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Review

From Cyber–Physical Convergence to Digital Twins: A Review on Edge Computing Use Case Designs

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Abstract: As a result of the new telecommunication ecosystem landscape, wireless communication has become an interdisciplinary field whose future is shaped by several interacting dimensions. These interacting dimensions, which form the cyber–physical convergence, closely link the technological perspective to its social, economic, and cognitive sciences counterparts. Beyond the current operational framework of the Internet of Things (IoT), network devices will be equipped with capabilities for learning, thinking, and understanding so that they can autonomously make decisions and take appropriate actions. Through this autonomous operation, wireless networking will be ushered into a paradigm that is primarily inspired by the efficient and effective use of (i) AI strategies, (ii) big data analytics, as well as (iii) cognition. This is the Cognitive Internet of People Processes Data and Things (CIoPPD&T), which can be defined in terms of the cyber–physical convergence. In this article, through the discussion of how the cyber–physical convergence and the interacting dynamics of the socio-technical ecosystem are enablers of digital twins (DTs), the network DT (NDT) is discussed in the context of 6G networks. Then, the design and realization of edge computing-based NDTs are discussed, which culminate with the vehicle-to-edge (V2E) use cases.

Keywords: 6G; artificial intelligence; big data; Big data analytics; cyber–physical convergence; day 3; digital twin; edge computing; network digital twin; open RAN

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1. Introduction

The introduction of fifth generation (5G) networks was a response to problems related to the exponential growth of mobile data from the new generation of wireless services. This enormous growth of mobile data was envisioned to overwhelm the network in terms of its ability to provide resources to support data-generating application with high flexibility [1]. Since provisioning of resources with high flexibility requires extensive upgrades to the technologies existing in the current network infrastructure, this presents itself as a huge challenge to a lot of mobile network operators (MNOs) [2]. The sixth generation (6G) of wireless communication has high expectations in terms of improved quality of service (QoS), i.e., providing network coverage, minimum latency, cost-effective deployments, and low energy consumption, as well as high fidelity [3]. This QoS can be further improved by incorporating proper resource management techniques through artificial intelligence (AI) and machine learning (ML) procedures. Resource management in 6G networks and beyond is envisioned to require massive big data analytics for knowledge discovery in order to achieve high-level intelligence in terms of decision making and on-demand service provisioning. Due to this postulation, this review investigates ways of exploiting the cyber–physical convergence to realize the digital twin (DT) technology, with specific focus on deriving DT technologies specifically tailored for 6G networks and beyond.

The expansive and sporadic growth of mobile data applications suggests that the 6G wireless landscape will be characterized by plug-and-play deployments driven by massive

Internet of Things (mIoT) [4]. These deployments are all driven by the desire for better user experience, which will be achieved through higher QoS attainment. As the surge towards massive IoT continues to gain momentum, wireless network deployments are beginning to manifest in the following forms: (i) the login time, (ii) the logging subscriber, (iii) the location at which the login activity occurred, and (iv) the application that was used. The volume of network traffic received at each wireless access point (AP) is increasing, and in order to keep up with this increase, the computational capacity of the APs and other related infrastructure at the network edge require urgent improvement. Bandwidth demand is increasing daily, and it reaches an all-time high with each passing day due to the rapid proliferation of data-intensive applications and services, which contribute to overloading the frequency bands and the inefficiency of the current spectrum management techniques [5]. This situation presents network designers and performance analysts with a host of new challenges. The most pervasive problem is that the required transmission speeds tend to be so high that the ratio of propagation delay to packet transmission may become significantly greater than unity [6]. However, with the introduction of AI strategies into wireless communication, solutions for most of the pervasive challenges and problems can be attained.

1.1. Research Motivation

Through the integration of AI and big data analytics into the core of wireless devices and infrastructure, the IoT has completely transformed from the Cognitive IoT (CIoT) to the Cognitive Internet of People Processes Data & Things (CIoPPD&T). However, there are still aspects that need to be addressed in terms of (i) network maturity and diversity and (ii) network flexibility towards digital transformation.

- Network Maturity and Diversity: The on-going deployment of 5G networks is showing that wireless communication has greatly matured from the previous two generations in terms of coverage and offered services. Parallel to maturity is the level of network diversity that has been reached, which comes from different perspectives.
    1. From the technology perspective, millimeter wave (mmWave) communications and the network backhaul technology are the main aspects that determine network maturity in the evolution towards 6G. There are actually three significant classes of this technological perspective, defined according to use case situations: (i) extreme/enhanced mobile broadband (eMBB), (ii) ultra-reliable low-latency communication (URLLC), and (iii) massive machine-type communication (mMTC). These are network augmentations, among which mixes of utilization situations will revolve to quickly prosper 6G networks into realization in no time [7].
    2. From the element management system (EMS) and business perspectives, the relevant aspects are business models, such as (i) ecosystem maturity, (ii) coordination of industry verticals, and (iii) the regulation aspects, including those related to spectrum management and fragmentation.
    3. From the network intelligence perspective, the determination towards realizing 6G networks can be viewed as a dispersed neural system that connects (i) the physical, (ii) the cyber, as well as (iii) the biological universes, which genuinely introduces a period wherein all network operations will be recognized as linked and smart [3].

  These perspectives of network maturity and diversity have set a solid foundation for all things intelligent.
- Network Flexibility Towards Digital Transformation: With the introduction of some underlying technologies through AI, digital transformation is becoming a reality. The whole idea of digital transformation is the orchestration of network automation technologies to make the design and maintenance processes comprehensible and more natural to apply [8]. Further entrenchment of big data through the increase in digitally available data means that new methodologies to formulate and understand the

transient behavior of network systems need to be developed. That is why, as network data operations continue to soar, network data analytics need to be incorporated into the operations of wireless networks, more especially the network components that are pushing significantly large amounts of multimedia traffic to the internet [4]. Therefore, effective ways to improve the computational capabilities of the relevant network infrastructure will bring the necessary capacity to meet the unprecedented computational demands of future network users. The current network design and control methods based on deep neural network (DNN) architectures are not enough for 5G problems, hence they may not be adequate for the "tsunami" of use cases and multi-platform environments brought by 6G networks. To this effect, when it comes to network big data, network infrastructure should become a major priority among enterprise executives. Despite the popularity of AI strategies with diverse capabilities that have improved connectivity and network flexibility for the dynamic virtual environments, rapid scalability is needed to handle the intermittent nature of big data loads [9].

Towards realization of the DT technology in wireless networks, it is believed that the incorporation of AI strategies in network infrastructure can improve their operational efficiency [10]. Therefore, a comprehensive representation of the transition from the convergence of cyber–physical systems towards opening the way to real-time monitoring and synchronization using DT is the motivation of this research work.

1.2. Novelty and Summary of Contributions

The contributions of this review, which are to bridge the gap between AI strategies and DTs using the concept of the cyber–physical convergence, are outlined as follows:

- Blurring of Lines and the Cyber–Physical Convergence: With the convergence of several disciplines, research in wireless and mobile communications has become an interdisciplinary field, shaped by several interacting dimensions. This is called the the blurring of lines [11], i.e., the blurring of the traditional boundaries between the digital, physical, and biological worlds, which has led to cyber–physical convergence. To this effect, the fourth industrial revolution (4IR) is a set of technological advancements that have exploited the convergence of these technologies. As the lines between the different fields of research continue to blur, MNOs have already begun finding transitions beyond the traditional services, such as voice to actually monetize the new valuable assets such as data and multimedia content. Therefore, in this contribution, it is shown how digital transformation is blurring the lines between all these interacting dynamics that build up and finally converge into a behavioral psychology concept called RL. Then, the proxies of cyber–physical convergence are discussed in terms of (i) quantum physics and quantum computing and (ii) data science and big data.
- Adoption of Cyber–Physical Convergence Towards Realizing DTs: Since the emergence of AI strategies has already begun shaping an increasing range of industry sectors, their potential impacts in terms of sustainable development are expected to impact the global operation of the telecommunication industry, both in the short term and in the long term. In this way, network operators are able to profitably manage and operate the dizzingly complex next-generation IoT networks [12]. However, there is currently no published research on the systematic assessment of the extent to which AI strategies will impact all the aspects of sustainable development. Regarding the sustainable development goals agreed upon in the 2030 international agenda, telecommunication companies are under immense pressure to properly leverage AI for 6G networks. IoT and digital transformation require high levels of intelligence in order to improve efficiency and increase profitability. Possible ways to address this pressure resulted in the CIoPPD&T paradigm, which has been defined by CISCO as a monster paradigm. In terms of digital transformation, the CIoPPD&T is an industry-ripe paradigm for AI-driven solutions, wherein MNOs have already begun to experiment in terms of solution deployment and deployment [13]. Their main aim

of this contribution is on leveraging AI capabilities in terms of fast, scalable interpretation, analytics, and prediction towards providing the convergence to drive the adoption of the cyber–physical convergence towards the realization of DTs.

- Edge-Based Big Data-Inspired Digital Twin: As the IoT, intelligent networks, and social media are increasingly becoming prevalent, data volumes are explosively increasing, and the velocity at which the data are generated has a profound impact on society and social interactions. This means that big data has already been woven into the fabric of everyday operations [14]. Application-level data have quickly become the primary source of mobile big data, and these data can escalate into terabytes [15]. Research entities and industry experts have envisaged that through the use of network big data, 6G networking will take communication closer to 2030 vision, which is the Internet of Everything (IoE) [9]. Therefore, as big data is hurtling towards the wireless communication enterprise, data-aided models may help in finding key insights from the network data that improve predictive analytics. Meanwhile, cyber–physical systems are a key concept of the 4IR architecture. The physical and software components of cyber–physical systems are deeply intertwined and are able to operate on different spatial and temporal scales. That is, they are able to (i) exhibit multiple and distinct behavioral modalities and (ii) interact with one another in ways that are capable of changing with context. As the integration of the big data technology and DT continue to cover a wide range of applications in wireless communication, the main aim of this contribution is to discuss the application of big data computing and big data analytics in DTs. However, big data is a double-edged sword with particular keenness on both sides, which is to say that as it presents opportunities for enterprise development, it simultaneously brings with it challenges. In this case, this discussion will only focus on the application of big data in predictive analytics (the predictive DT), as well as in day 3 edge network operations.
- Digital Twin-inspired Vehicle-to-Edge (V2E) 6G Use Case: AI has already surpassed expectations in opening up different possibilities for machines to collaborate in digital transformation. Edge computing, as a new interdisciplinary paradigm of edge intelligence, performs computations in order to reduce latency, improve service availability, as well as save system bandwidth [16]. As edge computing and AI carry the promise of bringing intelligence to the edge of the network, they have since received tremendous amounts of research interest from the vehicular communication community. Therefore, in order to advance the DT technology at the edge, in terms of URLLC processes, the vehicular communication use case is considered, where a cellular vehicle-to-edge (C-V2E) DT is considered. With the assumption that the advisory information to vehicle controls are provided using advanced driver assistance systems (ADAS), this contribution elaborates on the DT concept at the edge by systematically splitting the DT design into different aspects, such as (i) requirements, (ii) AI agent, (iii) mapping, (iv) central controller, and (v) inter-twin communication. Regarding current and next-generation computational intelligence, this DT concept is discussed together with the prospective deployment strategy of an open radio access network (Open RAN)—tailored to meet the monitoring and control required in 6G edge computing networks.

1.3. Organization of the Article

The remainder of this article is organized as follows: Section 2 discusses the challenges facing the digital transformation towards the realization of DTs. Section 3 brings together a discussion on the pillars that make the cyber–physical convergence possible. Section 4 gives an extensive discussion on the different fields of study whose interactions result in the cyber–physical convergence as well as the proxies that merge as the cornerstone of the application of the DT in 6G networks. Section 5 gives an overview of the AI market in terms of the global AI software forecast and the forecast on revenue generation. The current state of the telecommunication industry is discussed, initially focusing on the emergence of over-the-top (OTT) services, which bring out the need to incorporate DT in wireless networks. Section 6 introduces the application of the DT technology into wireless networks in terms of inter-twin communication and how an end-to-end network DT is achieved. Section 7 brings out the need for edge intelligence in 6G networks and discusses the potential application use cases of DT-assisted edge computational intelligence. Section 8 discusses the incorporation of big data and big data analytics in edge computing towards achieving big data-inspired edge-based DTs. Section 9 discusses the edge-based DT with respect to the vehicular communication use case for both traditional and open RAN scenarios. Finally, Section 10 gives the concluding remarks of this article.

2. Challenges Facing Digital Transformation

With the massive number of mobile devices that are currently in use and the plethora of use cases and use case situations, whose heterogeneity is continuing to place stress on the already stretched network resources [17], there is a need to transform the current resource provisioning strategies. This transformation requires the incorporation of emerging technologies, such as AI and big data analytics, into the solution processes. However, the fact is that the incorporation of these technologies into the intricate operation of communication networks has been marred by several critical challenges that cannot be overlooked. The problems related to interactive computing and algorithmic dependencies are discussed below.

2.1. Lack of Interactive Processing

In ML, interactive processing refers to the ability of computers to learn from humans by interacting with them using natural language as well as by observing their behavior [18]. Among the emerging technologies that need to enhance interactive processing, AI, cloud-edge computing, big data computing, and computer vision are heavily mentioned as the defining technologies on the road towards 6G. However, the recent bliss of technological advancement and its acceptance, more especially in human-centered AI, has come with huge challenges relating to the mining of multi-modal, multidimensional, and complex data. As a response to these challenges, interdisciplinary approaches have been triggered, which has led into cutting-edge ML-based analytical tools being developed [19]. There are already documented successes in the use of artificial neural networks (ANNs) and other deep architectures in working with complex data at reduced computational algorithmic costs. Algorithm computational costs have dropped, computational power has surged, and data storage devices have become available at reasonable prices. This has allowed for the combination of different learning techniques to achieve even more powerful computational tools, e.g., ANNs combining with reinforcement learning (RL) resulting in deep RL (DRL) and other deep architectures.

To this effect, the computational capabilities of machines have been reshaped to understand and decipher complex patterns in big data. With the rise in interdisciplinary approaches, the analysis and the modeling of networks and dynamic networked systems has also attracted huge interdisciplinary research interest over the past few years. This analysis and modeling is mostly done using complex systems theory [20]. To this effect, a new telecommunication ecosystem landscape has emerged such that research in wireless networks has become an interdisciplinary field shaped by several interacting dimensions. In spite of all these achievements in computational prowess, algorithms for interactive processing are still lacking towards the attainment of comprehensive digital transformation.

2.2. Existence of Long-Range Algorithmic Dependencies

From a system analysis perspective, it can be concluded that the design of a DT is complex. Due to the lack of interactive processing and the tasks that need to be accomplished, the analysis of its operation and maintenance throughout its lifetime requires a definitively different approach. Because of the different interacting dynamics from several knowledge bases, a functional DT-based wireless network can be achieved in the most peculiar context.

However, this requires a complex systems design approach. With so many interacting dimensions in a DT, algorithmic computing has been transformed to interactive computing, and the pervasive problem of the existence of long-range algorithmic dependencies is critical since it is a property that degrades the performance of DTs. Thus, the discovery of the existence of long-range algorithmic dependencies is very important. There are several solutions attempting to address this problem in wireless communications, but they focus on user behavior and its influence on the traffic and they are based on Markovian approaches, while future networks require solutions that can also handle non-Markovian network behavior [21,22]. If the network workload is characterized by aggregate packet arrival processes, which might be resulting from a superposition of different packet streams emanating from multiple sources, the instantaneous rates of packet arrivals can be modeled as a function of the number of such sources in their burst states.

In this way, the network states might end up fluctuating with high variability since this kind of traffic is usually far from a renewal process due to the positive dependence between successive arrival times. The escalation of such a situation, which is as a result of moderate-to-high traffic levels, can quickly lead to the degradation of the overall network performance [23]. As a consequence of this, a catastrophe of heavy burst packet losses may result. This may render the whole network unusable, as it might degenerate into a chaos of packet loss scenarios. As such, this kind of network behavior makes the long-term prediction of network behavior a serious challenge, hence newer models need to be brought forward to describe the relevant transient analyses and probabilistic models [24].

2.3. Tentative Solutions to the Digital Transformation Challenges

The answers to the above challenges can be given from the perspective of the rise in AI strategies over the past decade.

2.3.1. Introducing Cutting-Edge AI Algorithms

Cutting-edge AI algorithms that are capable of automating wireless network operations include, among others, (i) RL, which is useful in computer vision, and (ii) data mining, which is a very important tool in natural language processing (NLP) as well as other large language models (LLMs) [25]. Since smartphone evolution, AI strategies have had a wide adoption—a move that has huge implications for every industry vertical. As a result, it is the one that will lead to the next great technological shift, i.e., the fourth industrial revolution (4IR). The rapid advances in AI have opened up new possibilities to unleash new and effective solutions through improved storage and processing. Employing AI solutions in telecommunications can help MNOs to continue accelerating their growth and place themselves in highly competitive spaces. However, as much as AI is making tremendous milestones in technology, it has hit a series of roadblocks in the telecommunications industry. At surface value, it might seem as though AI is widespread in the telecommunications industry, but the only familiar application of AI is the voice-activated menu systems that respond to verbal commands. Using this, AI in the telecommunication market is increasingly helping MNOs in managing, optimizing, as well as maintaining infrastructure and customer support operations.

2.3.2. Introducing Big Data Computing Tools

As big data tools and their applications become more available and more sophisticated, the future of AI in the telecommunication industry is quickly developing. With this quick development, network optimization, predictive maintenance, virtual assistants, and other new AI use cases in telecommunications are already making a huge difference in delivering added value solutions to network users [26]. In order to realize DT, newer data models and newer data structures are needed in order to represent the observations (states) and the relations of the real-world assets (physical objects of interest). Then, these models need to be populated with knowledge. For instance, it is the actual data from the assets that are required in creating the actual DT instance. Therefore, the data collection process must be performed continuously in order to enable uninterrupted, accurate, and up-to-date system observation. In addition, the tools to operate on the data in order to add value to them, which are key in unlocking the DT capabilities and benefits, are required. Blockchain and federated machine learning (FML), and other analytical tools, are arguably the most prominent algorithmic tools and strategies for adding improved security of twinning the real-world processes and also extracting insights from the DT. This spans from simple data retrieval to complex algorithms and simulating different scenarios and other analytics tasks to predict future network behavior, used in the prediction of future network behavior.

3. The Pillars of the CIoPPD&T Paradigm

The CIoPPD&T paradigm can be defined as the IoE in innumerable ways since it will be built upon billions of connections to the internet. In the 2030s, wireless network size is estimated to increase proportionately to the square of the amount of network users, which will create unprecedented opportunities through the exponential power of networks in connecting people. In this case, IoE will represent the network of networks. CISCO theorized that, "as the evolution of the internet continues, the IoE will also evolve into a paradigm that brings together five pillars, i.e., cognitive, people, process, data, and things". Even though this is said to be a CISCO invention, it is not solely owned by them and does not describe a specific architecture due to the continuing evolution of the internet. By turning information into useful actions that will create more opportunities than ever before, the pillars of the CIoPPD&T will make the networked connections more relevant and even more valuable. In summary, this is a paradigm that describes the intelligent connection of (i) the people, (ii) their processes, (iii) the data they produce/consume, and (iv) the things that can be viewed as a world where billions of devices will be equipped with sensors to be able to detect, measure, and also assess their status and the status of the network [27]. These pillars are brought together to make possible the networked connections and the harnessing of raw data to describe several processes as follows.

3.1. Cognitive Science and Cognition

Cognitive systems have recently received great research attention in spectrum management algorithms for solving complex opportunistic access decision-making through computerized cognitive processes. Cognitive science, in its own rights, is an interdisciplinary scientific study whose processes deal with inputs from linguistics, psychology, neuroscience, philosophy, as well as computer science or AI. Its task is to examine the nature, tasks, and the function of cognition [28]. In the 6G context, the convergence of these processes, i.e., the data and the things, will create unprecedented opportunities for industries, businesses, and people [29]. With the emergence of the interdisciplinary field known as cognitive choice modeling, which integrates theory from decision processes and choice behavior [30], systems will be able to process sensory information based on certain computational rules in order to form representations of their environments and, subsequently, form the basis for decisions and choices [31].

3.2. The Internet and the People

People use their devices when connecting to the internet in a variety of ways, and the most prevalent way is via social media. The people connected to the internet become nodes and tend to produce information with trends that generate data resonating with different social activity systems. The recent advances in wireless sensor technology have already changed the way in which people connect to the internet, and this will proceed to enable them to connect via wearable devices as well as their clothing [32]. For example, miniature sensors may be placed on the surface of the skin or even sewn into clothes to provide information to medical practitioners about the vital signs of home-based care patients [33]. In addition, as the field of molecular communications matures, people will be connected in more relevant and valuable ways including body internal and external tele-medicine sensors [34]. In other futuristic drug delivery use cases, patients might be able to ingest a pill that will be able to sense and report the condition of the whole digestive tract to a medical practitioner over a secure internet connection [35,36].

3.3. The Processes and the Data

Processes occur when all the pillars of the CIoPPD&T cooperate with one another in delivering value to the world, e.g., delivering valuable information to the relevant person at the appropriate time. One example of such a process is the uniform parcel delivery system in a smart city, which offers services to different types of consumers in the city including individuals, departments, as well as manufacturers [37]. These processes are more vital, and, if done correctly, the connections may become even more relevant and valuable. This is possible when the right information is delivered to the right destination at the right time and in the most appropriate way. Data refer to a representation of facts about these processes, and they suitable for the communication of knowledge in a formalized manner. Devices typically gather information produced by several processes and this information is actually the data that will be converted into the intelligence responsible for making better decisions [38]. When the data are combined with the relevant analytics, actionable information can be delivered to people as well as machines to make better decisions that will achieve better results.

3.4. The Things

In the context of the IoT, a thing can be defined as an entity that has a unique identifier, an embedded system, as well as the ability to transfer data over the network [39]. These entities are the physical devices that are usually or always connected to the internet in order to assist one another in terms of intelligent decision-making. Such devices may include sensors, which are either disposable or non-disposable, consumer devices, and enterprise assets that are both interconnected and also connected to the internet. For context awareness, these devices sense and collect network data to analyze and obtain insight. Increasing the number of devices provides more valuable information that can aid people and machines in making better decisions. Therefore, the more expansive concept of the IoE includes (i) machine-to-machine (M2M) communication, which is a modality of communication between machines or devices without any human interaction or intervention [40]; (ii) machine-to-people (M2P) communication, where machines exchange information with people in order to improve their processes; as well as (iii) technology-assisted people-to-people (P2P) interactions.

4. The Interacting Dimensions of this Complex Socio-Technical Ecosystem

The cyber–physical convergence states that the physical world, which is the network users and their devices, and the cyber world, which consists of the internet applications and services, are becoming more integrated and converging [41]. The IoE concept has since evolved from its traditional definition due to the convergence of multiple technologies, i.e., (i) real-time analytics, (ii) ML, (iii) commodity sensors, and (iv) embedded systems. This is how the competitive dynamics of the interacting dimensions shape the cyber–physical convergence [42]. Since the adoption of the IoT as a tentative strategy for deployment in future generations of wireless communications [25], the concept of cyber–physical convergence is no longer breaking news. What is required now are different efforts for harnessing the network effects through the new and deeper connections that are afforded by the cyber–physical convergence. One of the main features of the cyber–physical convergence is that wireless network users as well as their behavior are the pinnacle of the technical communication systems. Because of this, the users and their devices are the actors in this complex socio-technical ecosystem that define their behavior in terms of (i) how much bandwidth they require, (ii) the kind of content they usually consume, and (iii) in what location of the network they are usually found. Therefore, the different interacting dynamics that define the realization of DT in terms of the operation of future wireless communication networks are discussed below.

4.1. Information and Communications Technology

Information and communications technology (ICT) is actually the convergence of several aspects including computing, telecommunications, as well as governance policies relating to how the information must be securely accessed and processed so that it can either be transmitted or stored [43]. ICT has always been behind every remarkable revolution in communication technologies, and its ecosystem has had a huge role in unleashing high-performance technologies and will soon be the biggest enabler of 6G networks [44]. Research work in ICT has already begun developing potential use cases for 6G, and each one of these use cases ais enabled by a set of technical requirements that have formed the basis of the technical work required for 6G. As a result, there is a wide application of ICT in the IoT and blockchain technology, which will drive the legacy of 6G networks.

4.2. Group Dynamics and User Behavior

A group is defined as several individuals who come and/or work together with the objective of accomplishing a particular task, while group dynamics refers to the attitudinal and behavioral characteristics of that particular group. Group dynamics usually concerns how groups are formed, i.e., their structure and processes, as well as how they function [45]. In the telecommunication context, group dynamics are a very common entity in the study of user/device behavior in heterogeneous networks. Services requested by different users in heterogeneous cellular networks tend to vary and change dynamically, either spatially or temporarily. For example, large amounts of traffic from similar applications/services might be requested by device users distributed over certain regions of the network. This creates a social pattern among the users that is known as service groups. The users/devices within those service groups might differ in terms of network usage, i.e., the user behavior known as group dynamics. From a macrocell perspective, the number of these network users requesting similar data or multimedia streams in a certain network location, within a certain time window, may be quite large. This might probably be advantageous in terms of identifying user patterns since such user patterns exhibit strong phenomena, i.e., user behavior, which characterizes their general behavior.

4.2.1. Describing User Behavior

In order to describe user behavior for inference purposes, the Gini coefficient can be used. The Gini coefficient [46] is actually a concept borrowed from statistics and economics used as a measure of statistical dispersion. Depending on the usage context, it is sometimes referred to as the Gini index or the Gini ratio. For instance, the Gini coefficient was used in [47] in measuring the participation inequality in treatment-focused digital health social networks. In that usage context, it was referred to as an index. Based on the Gini coefficient, user social patterns were studied and utilized as a method for optimizing system performance. In communication systems, this model can be exploited through social-aware networking protocols, as was proven in [48], and it is very efficient in supporting communication in user-centric mobile networks. However, user behavior and traffic characteristics are difficult to capture in wireless networks without using parametric techniques [49]. This means that collecting enough previous data from telecommunications service providers in order to obtain the statistics and inference of user behavior may not help in teaching a system how to learn a sequence of network behaviors. Even if parametric data could be abundantly available at our disposal, it might as well be more of a mere representation of past events. It may also not be very useful in the objective of interest, which is to obtain the current behavior for purposes of future network traffic behavior prediction. Therefore, in order to capture the traffic patterns, one needs to first deal with the user behavior since it has a direct influence on traffic patterns. This might help in the prediction of future prediction purposes, and mathematical modeling is a useful tool that can be utilized for this non-parametric traffic prediction due to the fact that it will be able to account for user behavior in terms of their mobility patterns.

4.2.2. Group Dynamics in Cognitive Radio Networks

The design of adaptive optimization algorithms for improving network operation and performance requires the use of advanced data collection and analytics techniques. For instance, secondary user (SU) behavior in a cognitive radio network (CRN) somehow exhibits a strong analogy to human behavior, and to explain this analogy, such a behavior is exemplary of a group of individuals living and/or shopping together [50]. On the one hand, such a group has some characteristics that may be categorized according to either individual behavior or group behavior. In terms of individual behavior, individuals can be seen as being self-interested, rational, and irrational. For example, in neo-classical economic theory, the authors in [51] studied maximization and the act of choice, whereby the author concludes that the behavior of a rational individual is to maximize a certain objective function over some set of appropriate choices. This is known as acting for private gain. However, on the other hand, group behavior refers to groupings that are/were created with the objective of achieving a common public good. Its characteristics include surviving through the evolution of time in the midst of resource constraints and stability reasons over time [52]. In human society, people are the ones that provide the choices as well as alternatives to the individuals and groups. However, there are always trade-offs between private gain and public good. Such trade-offs are usually modeled using prospect-theoretic discrete choice experiments [53]. In wireless communications, such trade-offs are usually measured and addressed using utility theory, where the different aspects of individuals and of groups can be well represented as utility functions [54].

4.3. Behavioral and Cognitive Psychology, Micro- and Behavioral Economics

In the behavioral and/or cognitive psychology field, principles relating to human learning and development are used together with their cognitive processing in overcoming problematic behavior emanating from emotional thinking [55]. This describes, among other things, (i) how human subjects perceive data and the way they interact with them, (ii) their assessment of the relevance of the information obtained from the data, (iii) the way in which they exchange this information through interactions with one another, as well as (iv) how they extract knowledge from that information. This is where the RL theory comes from, i.e., behavioral psychology. It is through such knowledge exchange that supermarket psychology-based RL strategies, which account for the high density of future wireless networks that leverage the data available with low overhead, are formulated. In the context of gNB sharing, this entails the modeling of how network providers negotiate the use of wireless network infrastructure and content resources in terms of trading and/or sharing them, i.e., the modeling of how subjects make decisions under different situations. This brings this discussion to how supermarket psychology inspires user behavior in mobile and wireless networks.

Example 1. *Suppose a customer is entering a supermarket; they generally navigate a route around its perimeter (the macrocell), before dipping into any of the central aisles (small cells) according to their specific needs (requirements). The perimeter design of a supermarket is in such a way that it has a wide walkway for accommodating large amounts of footfall. This is to encourage customer behavior due to their natural tendency of migrating towards traversing open spaces, hence avoiding congestion and confinement. Almost all retailers know this fact, as they always ensure that they position their key products there, i.e., fresh produce or perishables. The central isles, however, because their walkways are less wide and less frequently visited by customers, account for proportionately less sales for a typical supermarket. In this case, the products in the central isles actually sell in low volumes compared to all the products in the supermarket. As a consequence of this, the central isles are said to be lower in terms of sales density. Therefore, the majority of the products placed here are known as the long tail of the product offering, i.e., the non-perishables. This, however, this does not mean that this long tail of the product offering is inconsequential. As much as there can be relatively few units of each product in the long tail that are or may be sold each day, they actually serve the purpose of catering to every eventuality. In doing so, they also give the customers* *a sense of variety, and this variety is the one that drives them to choose certain supermarkets over others. Therefore, it is worth mentioning that the design of small cells follows from this idea. Small cells actually offer the users with specific needs such as video streaming, i.e., both delay-tolerant such as video conferencing and delay-intolerant such as movie downloads.*

4.4. Nature-Inspired Computational Approaches, Neurosciences, and Neural Computing

Nature-inspired computational approaches, also known as evolution strategies, are regarded as a sub-class of direct search algorithms and optimization methods. They operate by mutation, recombination, and selection, which they apply to a population that contains candidate solutions. They evolve iteratively to achieve better and better solutions, hence they are said to belong to a sub-class of evolutionary algorithms [56]. In computer science, these strategies are used as optimization techniques belonging to a general class known as evolutionary computation methods or as artificial evolution methods. These strategies operate by using the natural problem-dependent representations. These are primarily mutation and selection and search operators that are applied in an iteration loop. Each iteration of a loop is referred to as a generation, and each sequence of generations is continued until pre-defined criteria—termination criteria—are met. It is worth noting that the RL theory provides a normative account of concepts deeply rooted in the psychological as well as the neuro-scientific perspectives of animal behavior. An example of this is based on the behavior of algorithm agents when optimizing the control of their environment. In addition, neural computing has been identified as a perfect alternative computing technique of the post-Moore's Law era, even though much of the research attention has been directed to specialized applications [57]. The RL theory, through incorporating neural computing, gave rise to the development of the DRL strategy, as well as other AI strategies with usefulness in situations that are approaching real-world complexity, such as in robot navigation. In DRL, the computing agents are developed through the training DNNs in order to tackle the difficult task of deriving efficient environmental representations using high-dimensional sensory inputs, which they use in generalizing previous experiences to create new ones. Some deep architectures of DRL, such as the deep Q-learning networks (DQNs), even go to the extent of storing their past results and experience for later replay when encountering recurring problems.

Example 2. *Group behavior has had manifestations in wireless communications, with solutions from nature-inspired algorithms, such as (i) genetic algorithms, (ii) particle-swarm optimization, as well as (iii) DNNs, where cognitive radios (CRs) make decisions that not only control their fate but also the fate of others. In a similar way to human society, CR society is also a hierarchical society that has attributes that are similar to those possessed by human beings. One of their outstanding human-like attributes is self-organization [58]. In addition, similar to the central government of a country with specific reference to its system of law enforcement, a CR society also has basic etiquettes that all nodes in the CRN need to comply with. In both cases, more especially in the CRN, the main objective of having these etiquettes is to minimize unwarranted as well as excessive interference, i.e., listen before transmitting. In addition, during channel access, these etiquettes promote efficient channel access, e.g., one must never hold a channel unnecessarily if there are no packets to transmit. However, some shortcomings in CRNs have been studied using micro-economic game-theoretical analysis and have been addressed using psychological models derived directly from human behavior, e.g., game theory and RL. Therefore, a CRN can mimic a human society since it may behave rationally when it is competing and cooperating for resources in order to achieve survival as well as social efficiency, the same way as in the human society [52]. However, it must be noted that despite all these laws of behavior, irrational behavior due to Byzantine failures may also be exhibited by SUs [59], leading to security vulnerabilities as well as loss of spectral efficiency and instability in the CRN.*

4.5. Statistical and Discrete Mathematics

Discrete mathematics techniques such as graph theory, game theory, and queuing theory are very useful tools for deriving models in complex network analysis. Graph theory, which is used in studying the random phenomena in either two dimensions or higher dimensions, is one of the richest branches of applied probability. In terms of operation, graph theory is similar to stochastic geometry, which is also intrinsically associated with the theory of point processes [60]. It is often used in situations involving social relations containing compact graph descriptions that are amenable in characterizing properties of human behavior and exploiting them in designing wireless network solutions. On the other hand, in game theory and in queuing theory, discrete mathematics is used in describing network economics such as the utility. Even though game theoretic techniques are leaning towards the direction of RL strategies, it is often used to complete the list of discrete mathematical tools used in network analysis. Therefore, problems in queuing theory can be viewed in the light of both statistical and stochastic behaviors when faced with challenges relating to the development of mathematical tools to describe the behavior of arrival and departure processes of a given system [61]. Therefore, the study of point processes and the relationship between stationary and non-stationary quantities with special and non-special inputs can be examined using both graph and queuing mathematics. Therefore, it is in this way that the existence and the continuity statements, as well as the relationships between time and stationary quantities having special inputs, can be emphasized.

4.5.1. Learning and Queuing Theory in Stochastic Optimization

Learning and queuing theory actually result in the emergence of a newer class of random processes that is connected to point processes. This new class seems to be more suitable for describing queuing systems such that it can be used in data traffic analysis. The analysis of data traffic is somehow synonymous with the analysis of heavy traffic, whose queuing theory approximations can be performed on general arrival and service time models such as the $G/G/1$ queue [62]. In queuing theory, a $G/G/1$ queue is a representation of the queue length of a single server system with general (arbitrary) inter-arrival time distributions and general (different) service time distributions. Several research works, such as [63], have attempted to investigate the role that learning and regret plays in queuing theory. However, they omitted the assessment of the impact of parameter learning on queue performance. Regret can be defined as the difference between the aggregate performance of a particular algorithm and the aggregate performance of the best decision that the algorithm made. Learning deep generative models capable of representing complex service time distributions can be an effective way of learning parameters [64]. In this case, a better performing algorithm is the one with an aggregate approaching zero at a faster rate, i.e., fastest convergence towards zero. There exist regret-minimizing algorithms that are a consequence of Blackwell's Approachability Theorem [65]. However, it must be noted that the fundamental result of this approachability theorem is considered to have resulted in online learning. Therefore, a single server queuing model can be considered for sequential decision-making where a scheduler makes service decisions that affect the service rate. If the service rates are assumed to be unknown, the aggregate performance of the different service decisions would be predicted and then optimized using an online learning algorithm.

4.5.2. Learning and Graph Theory for Deep Learning

Usually, the point where graph theory meets deep learning is in graph neural networks (GNNs), where NNs are the architecture being referred to when deep learning (DL) is mentioned [66]. The NN architecture is built upon the concept of perceptrons, which are inspired by the interaction of neurons in the human brain. In the graph, there are a couple of different types of traversals, i.e., directed and undirected. If the graph is directed, the traversal follows a single direction, otherwise it is undirected. Building on the concept of traversals, let an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ be representative of a set of vertices $\mathcal{V} = \{1, 2, \cdots, V\}$, which represent the set of gNBs to which users can connect and the edge set $\mathcal{E} = \{1, 2, \cdots, E\}$ represent the possible connection links between gNBs and users. The state of a given user at a given time slot can be defined using the characteristic parameters concerning its association with the gNB to which it is connected. In addition, user–gNB association, which is a stochastic process, has been studied extensively in the literature using matching theory with parallels to game theory in [67], as an optimization problem in [68], and modeled as a stochastic game in [69].

The attractiveness of these approaches is the long-term biased received power of the respective BS. However, 6G will comprise dense and hyper-dense deployments of small cells and a frustratingly high number of mobile devices that want to connect to the internet via these gNBs. Therefore, a deeper understanding of the user–gNB association mechanisms as well as the more complex schemes that provide the best QoS is a requisite. In this regard, future user–gNB associations need not aim only at improving system utility, sum rate, and fairness but also how quickly and efficiently those are attained in hyper-dense deployments. Therefore, the efficiency in addressing this as a primary objective should be performed with the idea that due to the IoT, the scale of the network may increase in terms of its heterogeneity [69]. In addition, the amount of information that the network infrastructure is expected to process at each particular instant increases. Both the gNB and the user devices need to be equipped with learning capabilities so that they can be able to learn from their previous experiences. Learning from previous experiences and comparing them with current information is used to achieve better resource usage performance in the infinite horizon. In order to decide how many resources to be allocated to each cluster, a policy of maximizing the expected gain per unit resource and an unbounded knapsack problem can be formulated and a greedy policy utilized.

4.6. Quantum Physics, Quantum Computing, and Quantum Machine Learning

The incorporation of quantum computing and quantum machine learning (QML) algorithms in 6G networks is aimed at enhancing the processing capabilities of network infrastructure compared to the traditional ML techniques [70]. The rapidly increasing wave of data services that is pushing the boundaries of processing power of the communication networks is not passive. The data are increasing pervasively and at an exponential rate and the data traffic presents imminent challenges to all the aspects of wireless systems design. This then inspired the advent of quantum computing in wireless communication. The quantum computing concept, which is aimed at fundamentally changing the telecommunication landscape using quantum physics properties, has since inspired a whole new generation of researchers. These properties are used by quantum computers to store data and perform complex computations [71]. As a result, the quantum computing community has since achieved major breakthroughs by building systems that are stretching the limits of classical simulations to enable cloud-based research. Apart from enabling communication technologies and bringing advantages to all the layers of the protocol stack, quantum computing has become a catalyst in the seamless communication ecosystem for the cyber–physical convergence. The ideas of quantum physics were applied in a spectrum occupancy reconstruction problem often encountered in CRNs [72].

4.7. Data, Data Science, and Big Data Analytics

The data that are generated by wireless communication networks are not just any data, they are system-level data. System-level data include cellular-level data and core network-level data [73], which can be interpreted for the purpose of decision-making in both spectrum and computational resource allocation (RA) [74]. Since interpreting the enormous amounts of data, structured and unstructured, for decision-making purposes has proven to be cumbersome in terms of computational and time complexity, data science emerged as a solution. It was mentioned previously that it is the increase in the amount of data available that has led to the emergence of big data analytics. Therefore, data science, as a field of big data, was/is aimed at providing meaningful insights from the large amounts of complex data through the combination of the different fields of the cyber–physical convergence. The fields of work in statistics and computation are used in the interpretation of these data for purposes of better decision-making [75]. The continuously increasing datasets and ease of access have since been made possible through a collaboration of companies known as Fintech [76]. When it comes to obtaining big data networking requirements, database applications, and processing upgrades, there is no shortage of advice. A single casual internet search will show a plethora of options. However, neither the data themselves nor the intelligence can be of any value if this advise cannot obtain the proper processing in a reasonable amount of time to turn it into useful computational algorithms. In order to achieve useful computational algorithms and have systems running on both the twin and the physical object, one must be able to describe the characteristics into a mathematical model then create systems that have the capability to traverse the data and come up with useful information to enhance the processes of the DT with extremely high flexibility.

4.8. The Proxies of Cyber–Physical Convergence

In the cyber–physical convergence environment, the user devices are actually referred to as the proxies of their users in the cyber world. This is because the user devices are used to (i) communicate, (ii) exchange, as well as (iii) manage the network data by emulating the way in which the users would be when they are interacting with one another in the physical world. Therefore, in the design of effective 6G communication systems, user behavior needs to be taken into consideration strictly as a structural paradigm instead of just an afterthought. In doing so, network users will no longer be treated as passive internet entities but as active role players [77]. This is because in anticipating the effects of device behavior on their users or in order to understand the reaction of the users when they are exposed to certain situations, a socio-technical analysis is required. In a socio-technical analysis, users are viewed as entities of the wireless communication ecosystem with a behavior that can be modeled and clearly predicted to a certain extent [78]. In addition, the resources that it brings are exploited in the optimization of system operations such as in crowd-sourcing systems where complex problems are synergistically solved with the use of computers. However, since crowd sourcing is one of the main components of the complex internet socio-technical system, as it is based on device-to-device (D2D), device-to-human (D2H), as well as human-to-human (H2H), it is used as a very primitive example.

4.8.1. The Human Proxy and User Experience Proxy

The human proxy paradigm and the user experience paradigm merge as the other two cornerstones in the design of cyber–physical convergence in mobile and wireless communications through quality of experience (QoE). On the one hand, the human proxy paradigm is primarily based on the communication between the user personal devices. The user devices communicate with one another and act as the proxies to their human users. On the other hand, the user experience proxy is defined based on the interactions that take place between the users and their devices. Here, device behavior is designed by considering how the users react to the network services as well as the QoE [79]. The QoE is then used to model the interactions between the users and the services using a user-centric approach. Here, the expectations of the users in terms of the QoS and the reactions to its variations are considered. In this way, it can be easy for the QoE models to be integrated into the design of wireless network systems in order to improve the level of user satisfaction. However, an emphasis must be made that the proposed human-centric design approach is not just another bio-inspired wave of wireless network design. Instead, it is user devices acting as proxies of their users by embedding certain models of human behavior in the design of wireless networking systems. In other words, it is a natural way of making user devices behave in almost a similar fashion to their user when faced with certain situations [31].

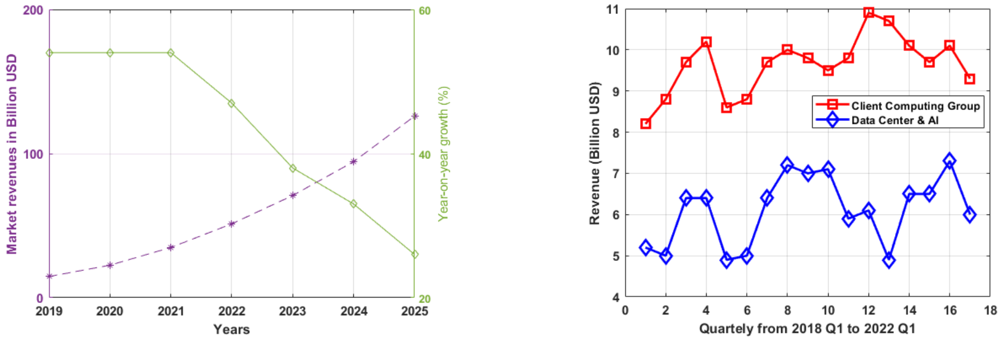
4.8.2. Integrating the Human Proxy with Deep Reinforcement Learning

DRL from human feedback is when systems or machines learn to behave by using some little assistance from humans, which can actually bring out the best from both humans and the machines [80]. Building AI systems that align with human values, i.e., human-centered AI, in which DRL strategies can be used in the design of social mechanisms preferred by humans, is still an open research topic [81]. What is quite remarkable from the above discussion on human proxies is that most of the solutions to these problems are found through the harmonious combination of RL strategies and hierarchical sensory processing systems. An integration of choice modeling and mathematical psychology with DRL strategies was reported [31], where a prospect theoretic DRL strategy was realized. A graphical example of this approach will be shown later in this article, where a human behavior model is infused into the decision-making of a data center in Figure 5b. In addition, data-centric communications can benefit from the wealth of neural data that reveal notable parallels between the phasic signals that are emitted by dopaminergic neurons and temporal-difference (TD) RL algorithms. Data-centric communications, which refer to data-centric computing as well as data-centric networking, can be described as the information systems in which the data are stored independently of the applications. Actually, data-centric communication systems have already started exploiting these models to efficiently guide information diffusion among human users [82]. Through this information diffusion, human users may be able to collaborate with one another and leverage both the storage and the processing capabilities that are locally available to them for gNB association and RA mechanisms—all through DRL strategies.

5. Overview of the AI Market and Current State of the Telecommunications Industry

The main functionality of AI, which is the ability to analyze large volumes of data and extract information that gives useful insights to high-quality decision-making, is going to be paramount in 6G. This is because the adoption of IoT devices in the global market has grown tremendously in parallel to the data that they produce. The growth of network big data and the increased adoption of cloud/edge-based services and applications, as well as the escalating demand for intelligent virtual assistants, are the major driving factors that have increased the global market share of AI. The size of the AI market is expected to grow from USD 86.9 billion, which was recorded in 2022, to a whopping USD 407 billion by the year 2027. This is at an estimated compound annual growth rate (CAGR) of 36.2% during this period [83]. However, the AI market seems to be facing some critical challenges as the key restraints to market: (i) the limited number of AI technology experts and (ii) data privacy issues as well as the unreliability of AI algorithms. Because of these challenges, the possible opportunities of the AI market mainly include the improvement of the operational efficiency in wireless communications as well as AI adoption in improving customer services. The forecast of the global AI software market is shown in Figure 1 below.

The forecast of the global AI software market, as shown in Figure 1a, is expected to be on a rapid growth for the next three years. It is expected to reach USD 126 billion in revenues by the year 2025. Due to the increasing need for new use cases, the current state of the AI market includes a wide range of applications, which, among others, include NLP and robotic process automation, that will grow tremendously. As can be seen from the forecast of the global AI software market in Figure 1a, an approximated 54% year-on-year increase is expected. The growing demand to access historical datasets in order to predict trends is expected to drive the AI market growth. Decision support, interactive gaming, and real-time recommendation systems are expected to drive the AI market growth. According to the Research and Market report [84], the global AI software market in telecommunications, which was estimated to be USD 1.2 billion in 2021, is expected to reach USD 6.3 billion in revenue by 2026. This is a CAGR of 38%. It is worth mentioning that AI in telecommunications includes, but is not limited to, the use of big data analytics in handling of huge volumes of data.



(a) (b)

Figure 1. Market forecast with respect to the AI market and Intel revenue forecast. (**a**) The global AI software market forecast from 2019 to 2025 [83]. (**b**) Intel revenues from two different company segments from 2018 to 2022 [84].

AI is also a huge player in coming up with solutions for problems such as (i) automatic detection and correction of failed transmissions, (ii) automated customer services, and (iii) complementing of the IoT. Counterpoint revenue earnings by Intel from the first quarter of 2018 to the first quarter of 2022 are shown in Figure 1b. The desktop revenues were standing at USD 2.6 billion, while notebook revenues stood at USD 6.0 billion, which indicate respective declines of 5% and 14% year-on-year. However, it is worth noting that during this period, the whole world was facing challenges in all industries due to the COVID-19 pandemic. Therefore, these declines can be attributed to demand waning due to the pandemic. It can also be observed that the Datacenter & AI Group has been the key revenue growth segment for Intel with 22% year-on-year growth.

5.1. Current State of the Telecommunications Industry

The telecommunication industry has become very competitive, and in this highly competitive landscape, very little separates telecommunication companies from one another. However, because the communication enterprises use similar infrastructure vendors, it is difficult to differentiate one from the other based on only their infrastructure and operations. It is, however, possible to differentiate enterprises based on the consumer expansion into the content arena as mobile content and video content become the most significant consumer use cases for 5G networks.

5.1.1. Consumer Expansion into the Content Arena

Since the emergence of smart phones, traffic patterns in wireless networks have had a dramatic change. This dramatic change is attributed mainly to the large number of applications introduced by 5G. Therefore, expanding into the content arena can be the simplest and most natural way for network providers that are seeking to grow in wireless communications, more so because user behavior and their traffic patterns are application-specific and they vary rapidly within short time intervals [4]. As a result, network providers have begun aggregating streaming platforms in parallel with launching their own services. The rising bandwidth requirements and the growth of the IoT means that network providers need to make near-constant upgrades to their infrastructure in order to keep up. Even though wireless infrastructure is quickly becoming less critical to profitability, the congestion in the radio spectrum has actually pushed the designers of 6G to adopt new spectrum bands to support 6G communications. Ultimately some network providers already have their own over-the-top (OTT) services or alternatives with favorable rates to their customers. To this effect, there has been a response from telecom companies in Sub-Saharan Africa, such as Vodacom, MTN, Airtel, Globacom, Orange, and Safaricom towards bolstering their OTT services. Based on market research, since 2017, MTN has been increasing the number of subscription offers in several countries in Africa south of the Sahara by launching various mobile applications such as access to television (TV) channels and streaming content. The company has been offering subscriptions that provide users with access to content only as well as a combination of access to content and internet data [85]. This means that algorithms for 6G communications must have higher performance than those of the existing 5G networks to operate on those various dimensions of 6G.

5.1.2. The Rise of Over-the-Top (OTT) Services

Suppose one has a data plan with their mobile operator to which they purchased a smartphone with which they can make GSM calls and short message service (SMS). One could be able to make Skype calls or any other voice-over-IP (VoIP) services for cheaper and free voice calls and chats over the network. Here, Skype is referred to as the OTT service. OTT services, namely voice and video services over the wireless network, have been revolutionized by smartphones since they have multimedia and advanced communication functions [86]. The network carrier utilized for an OTT service has (i) no control, (ii) no rights, (iii) no responsibilities, as well as (iv) no claim on the OTT served by its network infrastructure. What it does is only carry the internet protocol (IP) packets from source to destination. The network carrier can be aware of the packets and their contents but cannot do anything about it, which makes VoIP an alternative to expensive phone calls. In VoIP, the caller does not pay for the dedicated phone line but utilizes the existing internet without dedication. However, there have been restrictions imposed by network carriers on their networks on VoIP services. For instance, when Apple released the iPhone, AT&T imposed some restrictions over its user on its network. However, these restrictions were lifted due to pressure from the FCC, and since then, carrier networks realized that they should stop fighting and reap the benefits of offering good connectivity for users of OTT services.

5.1.3. Content-Based Applications and Social Networking

In addition to connected television and content applications such as TikTok, further undercutting their traditional business model has been the rise of OTT communications: (i) applications for social media networking, such as Facebook; (ii) applications for internet telephony, such as Skype; (iii) applcations for micro-blogging, such as Twitter, Posterous, FriendFeed, etc.; (iv) applications for instant messaging, such as WhatsApp, Facebook Messenger, WeChat, Viber, etc.). All these applications most predominantly consist of real-time content, hence they exhibit different traffic patterns compared to the usual voice, text messaging, emails, as well as web surfing [4]. These applications take up a huge share of the communications market, such that users no longer rely on carrier networks as much as they used to. The need to continuously invest in next-generation infrastructure and increasing commoditization of offerings is leading the telecommunication sector to the perfect storm. As digital players such as Google Fiber expand to infrastructure, carrier networks are becoming more worried about their survival in the wireless marketplace [87]. In order to improve their chances of survival and remain profitable, many communication service providers (CSPs) have begun embracing additional and sometimes unconventional revenue streams. For instance, Verizon attempted to increase its reach through media via its Verizon Media Group Holding in recent years to give it multiple additional revenue channels beyond traditional telecommunications offerings [88].

5.1.4. Looking Beyond Network Connectivity—The Confluence

By bridging the gap between the physical assets and digital worlds, a DT is realized. Due to the requirements of specialized processors that are able to process massive amounts of structured and unstructured data from different sources, DT has become a new approach for testing and assurance for AI workloads. A DT can be defined as a virtual copy of the physical asset of interest that provides an emulated software replica that enables continuous prototyping, testing, and optimization [89]. The visualization module of a DT is responsible for delivering data insights to end users, simulation, and intelligent operations, while the dashboards and commands rely on the visualization module for correct functionality. Through the amalgamation of the current communication and control technologies, the computing and data analytics techniques, as well as the modular manufacturing towards realizing the 4IR, cyber–physical convergence is promoted. This is evidence that at the confluence of AI, big data, and the cyber–physical convergence, there is the DT technology. Together with IoT and blockchains, they have redefined the future vision of globalization in terms of how it has to be imagined. Through the integration of the cyber–physical worlds via the convergence of cyber–physical systems, the ability of DTs in terms of monitoring, optimization, and prognostics of industrial processes will improve [90].

6. The Digital Twin Technology

A DT is actually more than a mere simulation. While a simulation is just a data-driven prediction of the behavior of a physical asset in terms of its processes, a DT spans the full life cycle of the asset, i.e., from design to service use cases. Defined in simple terms, in DTs, the digital replica of a physical device is the virtual part that eventually forms the DT. The interaction between the digital replica (digital image) and the physical device (physical process) is enabled with the aim of simulating, analyzing, and controlling the real-time operation of the physical process [91]. As the initiatives of the 4IR continue to gain momentum across different industrial segments, the focus has been on the automation of processes. The fourth industrial tevolution (4IR) is a revolution that is virtually built upon three primary technological advancements, i.e., IoT, big data, and edge computing. Even with the limitlessness of the potential of the IoT, designing IoT systems can be very daunting. Designing IoT systems usually requires a complex web infrastructure as well as multi-domain expertise [92]. In a more elaborate sense, a DT is a tool to safely test the impact of modifications made in network parameters on the twin of the physical asset without halting operations. For example, in testing a new version of software, it may be used to evaluate the planned steps for deploying it in order to make sure that the available resources are sufficient for optimal operation. If successful to the best possible operational level, a switch to this new version may be commissioned. The rising of digital industrial technologies that gather and analyze data across different domains has assisted in the rise of the DT version in the 4IR.

6.1. Digital Twins as a Concept of the CIoPPD&T

The cyber–physical convergence that led to the IoT and went beyond the perimeter of the IoT into the CIoT has now generalized the IoE by specifically addressing it as the CIoPPD&T. The CIoPPD&T concept is a CISCO invention [93], and it is actually a monster paradigm that has built on the foundations of the IoT by adding the likes of (i) wireless big data, (ii) network intelligence that allows for convergence, (iii) orchestration, as well as (iv) visibility across previously disparate systems. In this way, a monster paradigm that can be summarized to what is referred to as the DT technology is realized as a concept of the CIoPPD&T. A DT can be viewed as a virtual representation of a physical asset or person, whose processes can be understood by analyzing its data. It consists of three main components: (i) a digital definition of its counterpart, generated from computer-aided design (CAD); (ii) operational or exponential data of its counterpart that are generated from IoT; and (iii) the information model, such as a dashboard, that is used for presenting the data in order to drive decision making. Therefore, the key technologies towards the realization of DT in 4IR, where use cases and applications are defined in various dimensions, are shown in Figure 2 below [94].

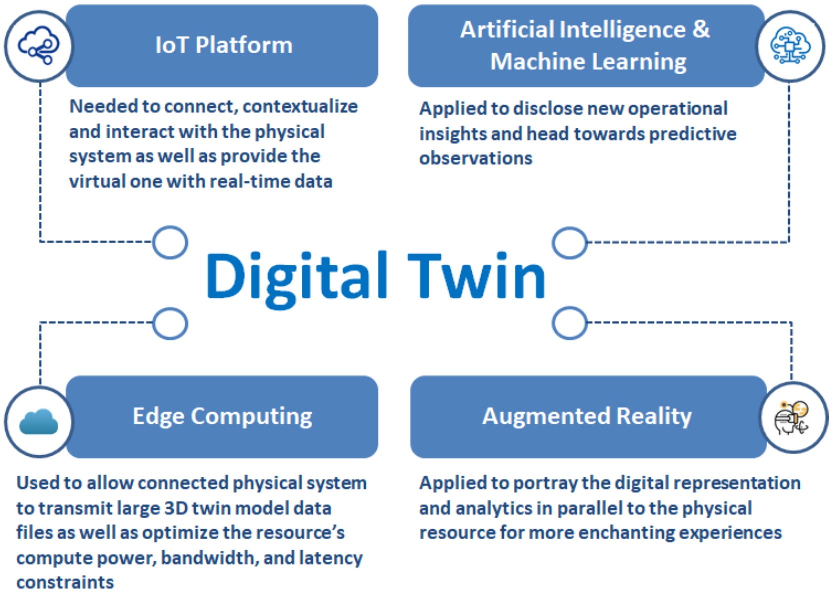


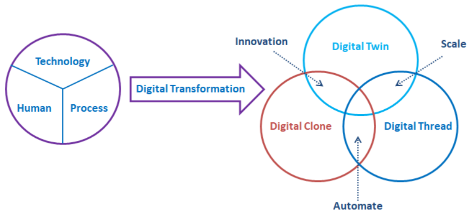
Figure 2. Digital twin components with respect to the technical contributions of the 4IR.

What is shown in Figure 2 above is the how 4IR signifies the transformation of legacy sites into promising autonomous network facilities driven by consistency, flexibility, and efficiency. The DT technology is rapidly being adopted across various use cases in industrial fields as its enhancements are consistent with the important technologies for the 4IR. The technical contributions of the 4IR that make up the DT are as follows [95]:

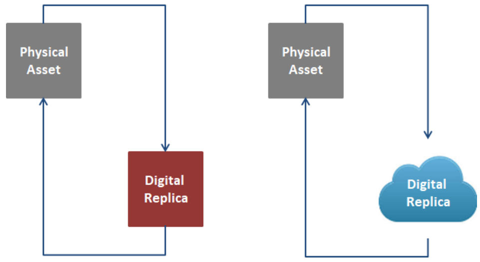
- IoT Platform: The incorporation of the IoT platform in the DT architecture is to enable connection, contextualization, and interaction with the physical system as well as to provide the virtual one with real-time data.
- Artificial Intelligence and Machine Learning: AI and ML are very critical DT components, and as such, they are expected to play very crucial roles in the self-organization, the self-healing, as well as the self-configuration of 6G networks. This will be made possible and even enhanced by other cutting-edge technologies such as QML and blockchain. Through these technologies, the digital counterpart of the real network will be able to provide seamless monitoring, analysis, evaluation, and prediction.
- Edge Computing: Edge computing, preferably with the use of distributed computing, allows connected physical systems to transmit large 3D twin model data files as well as optimize resources such as (i) computing power, (ii) bandwidth, and (iii) latency constraints.
- Augmented Reality: Augmented/virtual reality (A/VR) is applied to portray the digital representation and analytics in parallel with physical resources for more enchanting experiences.

6.2. The Digital Transformation

Due to the personalized techniques for capturing the dynamics of the physical assets, DT is well known as the major enabler of the digital transformation. In general terms, digital transformation can be defined as the adoption of digital technology and integrating into the business processes of an organization in order to fundamentally improve the operation of the organization [96]. There are different kinds of DTs, all differing from one another on the levels of integration. The process of digital transformation is shown in Figure 3 below.



(**a**) The process of digital transformation towards digital twinning.



(**b**) Difference between digital twin (left) and digital twin-predictive (right).

Figure 3. (**a**) Process of digital transformation and (**b**) difference between a digital twin and a digital twin-predictive.

Figure 3a above gives a general overview of digital transformation with specific focus towards digital twinning, while Figure 3b shows a comparative representation of a DT and a DT-predictive.

- Digital Clone: This is an emerging technology involving deep learning (DL) algorithms that are used in manipulation of currently existing hyper-realistic media, i.e., audios, photos, and videos. With various establishments making digital cloning technology available to the public, functionalities such as audio-visual, memory, personality, as well as consumer behavior cloning can be realized [97]. A consumer behavior clone, a DT version of user behavior, can be a user profile or a cluster of customers based on their demographics. It must be noted, as can be seen in Figure 3a above, that innovation is realized when DTs and digital cloning are integrated.
- Digital Thread: Since its aim is to signify the digitization and traceability of an asset throughout its lifespan, it can be defined as the foundation behind digital transformation [98]. This is made possible through linking all the DT capabilities, such as (i) its design, (ii) the performance data, (iii) the product data, (iv) the supply chain data, as well as (v) the software used in the creation of the product. Therefore, a digital thread, together with other DTs, can be used to meet certain design requirements, records, as well as all the data to be used.
- Digital Replica: As shown in Figure 3b, a DT is referred to as a digital replica of a physical asset that has a two-way dynamic mapping between the physical asset and its DT. This is to say that the replica consists of a structure of connected elements and meta-information.
- Digital Shadow: The definition of the digital shadow can be based on its purpose and existing relationship with the corresponding DT [99]. When the design objective is to serve a specific purpose, the digital shadow operates in isolation from the DT. In this way, the digital shadow provides a blueprint of the required data, its sources, the relationships between the various pieces of the data needed, as well as any data manipulations that need to be performed. The data are either forwarded directly from the digital shadow to the DT or the digital shadow performs some pre-processing and/or simulations itself. Therefore, based on the data that are delivered by the shadow, the DT integrates them into a complete digital reality for detailed processing, simulation, and analysis.
- Digital Twin-Predictive: With reference to Figure 3b, the ultimate goal of a predictive twin is beyond the DT, as it aims to achieve further analysis for the purpose of predictions and individualization through the use of big data and ML in cyberspace. Therefore, a DT-predictive is a digital replica that uses two-dimensional real-time data communication over cyberspace.

The above analyses show why a DT has several levels of integration, relating to the digital model and the digital shadow. These terms are most often used synonymously when in actual fact they are different in terms of data integration towards the physical, digital, and cyber layers [100]. With its current operational framework being the CIoT, which is characterized by (i) the perception–action cycle, (ii) massive data analytics, (iii) derivation of semantics and knowledge discovery, (iv) intelligent decision making, and (v) on-demand tasks for service provisioning, its framework is capable of bridging the physical and virtual. With objects and resources, it has a huge capability of bridging the physical world, and with human demand and social behavior—the social world, in addition to (i) enhancing smart RA, (ii) automatic network operation, and (iii) intelligent service provisioning.

6.2.1. The Network Digital Twin

The functional decomposition of a DT can either be (i) horizontal, i.e., life of a packet from the edge to the cloud, or (ii) vertical, which distributes decisions to improve overall efficiency, i.e., DT and multi-scale AI. In addition, the architecture of the network DT (NDT), similar to the traditional DT, essentially consists of both the physical and the digital and includes three layers [101]:

- hardware layer, which comprises the physical components of the DT, such as routers, actuator IoT sensors, as well as edge servers;
- middleware layer, which is all about data governance, processing, integration, visualization, modeling, connectivity, and control; and
- software layer, which consists of analytics engines, ML models, data dashboards, as well as modeling and simulation software.

The explosive growth of new use cases in (i) time-sensitive, (ii) safety critical scenarios, and (iii) stringent requirements have created a huge demand for cost-effective verification methods [102]. The NDT, as the DT technologies continues its rapid diffusion into numerous industries through interdisciplinary advances in the industrial IoT, cloud and edge computing, ML, AI, as well as through advanced analytics, is also permeating into wireless communication space. In wireless networking, DTs are utilized to drive the current network testing environments towards being sufficiently ready for the demands of the future. In the NDT is where the agents perform the configuration and function changes [33]. For instance, when new configurations are applied on a new AI model or applied on a new network software, it is of paramount importance to know its performance before it is commissioned to the whole network. The components of a DT in wireless networks can be defined in terms of two platforms, which are described as follows:

- Data Platform: A data platform is one of the main DT components, which ensures secure data ingestion and processing, as well as steady performance, normalization, management, ML, AI analytics, micro-services, and integration.
- Autonomous Network Platform: This is the digital domain of the DT framework on wireless communication consisting of four main components, i.e., network state prediction, expert knowledge, AI algorithm, and DT network. Therefore, in a DT exists an autonomous platform that enables a transition to a world in which computers use digital maps as a life-like representation of the physical network. The autonomous platform forms a foundation for simulations and virtual reality environments that are meant to fool the human mind and make it to believe that it is actually located where it is not. This module is between the physical network and the DT and enables the DT to analyze the outcome of a set of inputs and predict the outcome without affecting the physical network. If the outcomes are what is intended, then the new configurations can be transferred to the physical network as updates [103].

6.2.2. End-to-End Wireless Network Digital Twin

Wireless networks are designed according to the principle of end-to-end architecture in order to guarantee certain application-specific features such as reliability and security [104]. The expectation for 6G networks is that they will be more reliable and fast and be able to support a large number of ultra-low latency devices. For this to be possible, network agility is very key, as network providers will need to look beyond connectivity and complexity but towards new opportunities for growth in order to offer end-to-end solutions for both individual and enterprise consumers [105]. Some identified areas of interest where network DTs have interesting use cases are shown in Figure 4 below.

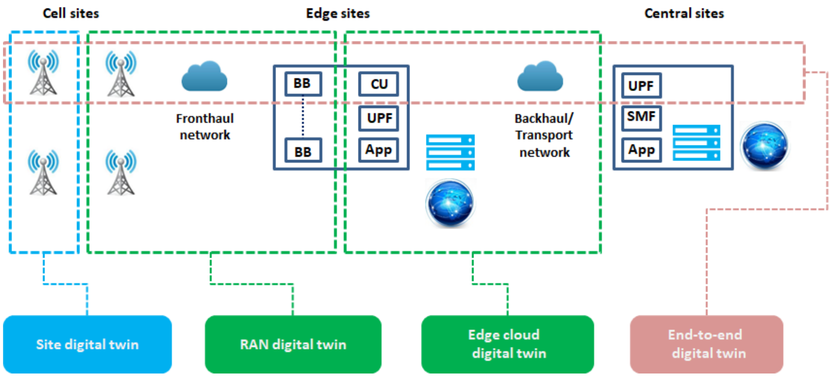


Figure 4. The different areas of interest and interesting use cases for digital twins in wireless networks.

In Figure 4 above, the twins of the different network substrates are shown: (i) the RAN, (ii) the edge network, (iii) the backhaul or transport network, and (iv) the network core. The positioning of the network functions (NFs), i.e., baseband units (BBU), user plane function (UPF), session management function (SMF), and application (App), is only for illustration purposes—it does not depict any form of new radio (NR) functional split.

- Cell Site Digital Twin: Since the process of installing, inspecting, and maintaining cellular towers is difficult and costly, the AR functionality can be enabled to visualize the cell tower. There is a plethora of use cases where the cell site DT can support MNOs or tower companies, i.e., (i) rollouts of new generation technology such as 6G, (ii) site survey on existing sites, (iii) upgrades, and (iv) maintenance activities [106]. Based on the assumption of perfect spectrum sensing in dynamic spectrum access (DSA), the information exchange that takes place between SUs and the gNBs is according to peer-to-peer information exchange.
    1. Infrastructure Digital Twin: Based on the specified kind of information exchange between the users and the network, the programmability of the network can allow for enhanced data management tasks (load management, compression, and data reduction). A programmable framework for advanced IoT and data-driven automation also allows for virtualized resource provisioning. The most prominent resource provisioning of this kind is known as containerization. Containers are created as images and allow users to package application code, dependencies, and configuration into a single object that can be deployed in any environment. However, they are only considered containers when they are running.
    2. Device Digital Twin: On the other hand, information exchange between users is governed by transfer learning and cooperation management, which considers source agent selection and target agent training. Information fidelity technologies such as federated learning and blockchain are incorporated with digital twinning to provide security for targeted services and advanced testing and facilitate deployment.
- Edge Site Digital Twin: Due to the use of higher frequencies, which are vulnerable to absorption, 6G networks will be limited in terms of transmission range. This means that edge platforms or sites will be a perfect solution to counteract this limitation, and computational resources will be docked at an aggregation site and launched on-demand to each edge site. However, it must be noted that the DT of the edge site includes both the access network and the backhaul network (transport). In order to meet the high computing demand of edge computing networks, new enabling technologies such as (i) the air interface and the transmission technologies as well as the novel network architecture, (ii) advanced multi-antenna technologies, (iii) network

slicing, (iv) cell-free architecture, and (v) cloud/fog/edge computing are already being developed [107].

- End-to-End Digital Twin: This kind of DT is mostly encountered in network slicing architectures where the relationships between the different slices are monitored using graph neural networks.

The contributions that applied the DT technology in 6G RAN problems are tabulated in Table 1 below.

Table 1. Application of the digital twin technology in 6G networks.

Objective	Technique	Algorithm	Considerations	Reference(s)
Describe a network DT architecture focusing on the RAN and also align with open RAN	Identify different application use cases and train algorithms under different conditions	Reinforcement learning	Aligning with open RAN for implementation used for training RL-based capacity-sharing solutions for network slicing	[106]
Design a DT technique for self-optimizing mobile networks	Combine expert knowledge with RL and DT	Reinforcement learning	Future network states must be predicted based on which optimization decisions are generated by expert knowledge	[108]

7. Edge Computing Digital Twins—Special Use Cases

With the 5G NR already commissioned in most parts of the world and still being commissioned in others, the era of network softwarization is already at its height. The 6G networks, which are affectionately referred to as the era of network intelligentization, are quickly making their way into the wireless communication space [109]. Through the digital transformation, the current 5G networks are quickly transforming themselves towards 6G through the transformation of their access and resource provisioning strategies. Edge computing, which is a strategy for provisioning computational resources at the edge of the network in order to advance the requirements of latency-critical services, enables MNOs to keep core NFs at the edge of the network. As a result, computational software in the form of NFs is kept in tens of thousands of remote locations all running consistently and with uniform security standards. With these NFs or network applications running close to the end users, network latency is reduced, which also allows service providers to offer new services that are not possible with cloud computing [110]. Most of the use cases and applications that require lower latencies, such as vehicular communications, can benefit from the faster, more reliable services compared to cloud computing [111]. Other benefits of edge computing include low latency, privacy protection, context awareness, and reduced bandwidth consumption. In a nutshell, the structure of the cloud–fog–edge continuum is as follows:

- The Cloud Layer: The cloud layer, which is also known as the core (regional data center) of the MNO. This layer is traditionally a non-edge tier, and it is most often owned and operated by the public cloud provider, a CSP, or even a larger enterprise [112]. It is responsible for processing big data, business logic, and data warehousing. Cloud computing is the most prevalent tool for user data management in this layer.
- The Fog Layer: The fog computing layer is a computing layer lying between the edge and the cloud. Since it is commonly owned and operated by a CSP, it is known as the

service provider edge. In other words, it is a tier located between the core (regional data centers) and the last mile, i.e., the access network where the network operator serves multiple customers [113]. The fog layer is also responsible for local network access, data analysis and data reduction, control response, as well as function virtualization.
- The Edge Layer: Also known as the end user premises edge, the edge layer is responsible for the real-time processing of large volumes of data. Edge computing, which refers to data computation that takes place at the edge of the network, is the most prevalent tool for user data management at this layer. Along with fog computing, edge computing has been used widely in increasing the speed and the efficiency of data processing, as well as bringing intelligence closer to the user devices.

7.1. A Choice Modeling-Based DT for Edge Computing Platforms

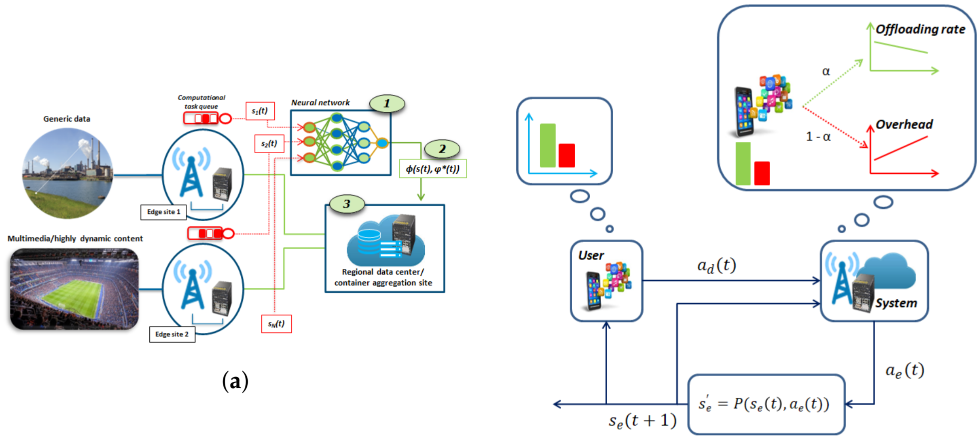
Edge computing and edge platforms are two of the most confusing and misused terms today, with edge computing platform even more confusing. Edge computing platforms are horizontal pieces of software that are designed to enable (i) the automated deployment, (ii) update, and (iii) management of distributed applications [114]. Many operations are quickly turning to edge technology because of its relevant advantages over the legacy cloud solutions. For instance, industries can make use of edge data centers to aggregate all the data collected from their sensors for quick processing by the edge cloud and turn them into useful edge indicators.

7.1.1. Modeling Behavioral Model for Day 3 Edge Computing Operations

Wireless networks have become complex, and the evolution from the current 5G networks to 6G networks is going to increase the complexity, making network management a daunting task. This requires day 3 management, which are more strategic approaches to network operations that focus on intent-based networking. In wireless communication, day 2 operations can be viewed in terms of system operations throughout its life cycle, with its behavior being analyzed and optimized continuously [115]. Thus, day 2 services are aimed at improving the QoS and sharing perception and awareness information. On the other hand, day 3 operations are intent-based operations, which means that there is an addition of further sophistication to day 2 operations such as sharing intentions [116]. This kind of intent-based or intent-sharing kind of operation supports negotiation and cooperation, which opens the door to cooperative perception in wireless networking. Edge platforms are an emerging edge computing paradigm widely recognized as a promising solution towards meeting the diverse edge computing demands [111].

Using this emerging paradigm, the operation of the traditional edge computing will be improved through the use of low-cost edge centers that use cognitive choice modeling. This is an intelligent edge management strategy for day 3 operations and beyond that use the concepts of cognitive choice modeling through prospect theory as shown in Figure 5 below.

In Figure 5a above, the operation of edge platforms in terms of day 3 and beyond operations, where edge platforms are leveraged for traffic optimization, is shown. The formulation of the edge platform for day 3 operations is aimed at (i) improving user and gNB–server cooperation towards intelligent decision making in terms of user–gNB for traffic offloading and (ii) improve resource provisioning through on-demand container provisioning by the data center [31]. It must be noted that the data center hosts a number of virtualized computational resources that account for the total computational resources of the whole system. With this kind of on-demand provisioning of containerized computational resources, (i) QoS can be improved in terms of latency minimization, (ii) bandwidth can be increased, and (iii) there is no under/over-provisioning of computational resources. In terms of day 3 and beyond edge operations, system state changes dynamically, hence the behavior of the system must be monitored continuously for proper analysis. For this purpose, a DNN agent monitors the states of the different edge sites, i.e., edge site 1, edge site 2, up to edge site N as follows:



(**a**) (**b**)

Figure 5. Container deployment at the edge based on prospect–theoretic DRL for day 3 operations. (**a**) A low-cost data center that manages the on-demand deployment of containerized computational resources to edge sites. (**b**) Concept of the prospect–theoretic DRL-based DT strategy for predictive resource provisioning in edge computing platforms.

$$s \triangleq \{s_1(t), s_2(t), \cdots, s_N(t)\}, \tag{1}$$

are fed into the DNN agent as inputs, where the process of computing the behavioral model proceeds as follows:

1. the DNN takes the states of the computational task queue, which are estimates of congestion as well as those of incident traffic types;
2. the output of the DNN is the behavioral model for the provisioning of the computational resources, which is as $\phi(s(t), \varphi^*(t))$, with $\varphi^*(t)$ as the control action that determines the provisioning of computational resources;
3. the behavioral model instructs the regional data center on the computational requirements of the different edge sites, which then launches containerized computational resources based on the respective demands.

Therefore, by taking into account (i) the workload size (determined by queue lengths), (ii) cycle uncertainties, and (iii) unpredictable emergencies, a DT for the RAN can be designed.

7.1.2. Choice Modeling and Mathematical Psychology

Here, it is assumed that the users and the edge infrastructure are equipped with intelligent modules for intent sharing and perception to aid the negotiation process. The prospect–theoretic DRL-based DT shown in Figure 5b uses prospect theory for modeling its offloading behavior. Under prospect theory, the underlying explanation for the behavior of the system is that due to the nature of their choices, i.e., independent and singular, the probability of gains and losses are assumed to be reasonably equal [117]. Hence, the $\alpha = 50\%$ models the gains in terms of the offloading rate, while $1 - \alpha$ models the losses in terms of increasing network overheads (risks). Evidence of this can be found using choice experiments, where choice modeling and mathematical psychology can then be used to realize a predictive DT based on prospect theory. Using this notion, the action $a_d(t)$ is taken by the user device when it is satisfied with the prospects from the gNB, while the action $a_e(t)$ is taken by gNB when admitting the offloading actions from the devices. The evaluation of the prospects towards decision making are based on subjective QoE measures in terms of task offloading rates and overheads. These are introduced in the discrete choice formulation when choosing edge sites to which traffic can be offloaded. After the actions $a_d(t)$ and $a_e(t)$ have been taken, the state of the edge system migrates from the present state $s_e(t)$ to the next state $s_e(t+1)$, which is defined as follows:

$$s_e(t+1) = s'_e = P(s_e(t), a_e(t)), \tag{2}$$

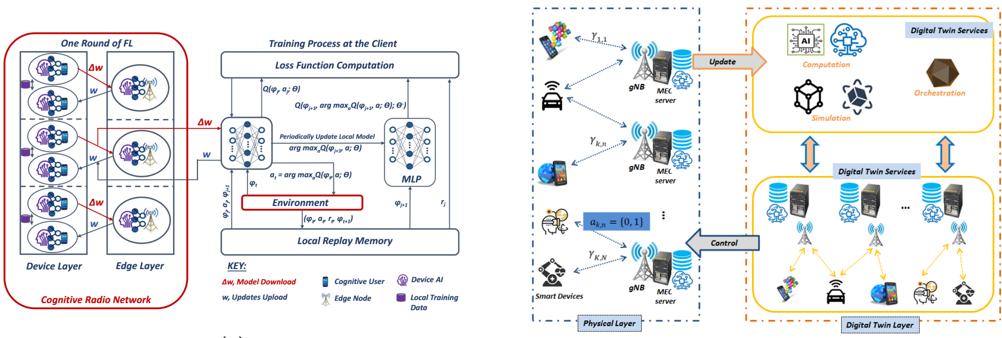
where the construct $P(\cdot)$ denotes the transition probability. This was followed by the introduction of a resource provisioning process where the DRL strategy was designed by incorporating Markov decision processes (MDPs) from the prospect–theoretic viewpoint. The striking novelty of this kind of DT is in the analysis of the data collected from the edge sites, which opens the door to the "predictive".

7.2. Federated Deep Reinforcement Learning-Based Digital Twin

Out of all the expectations of 6G networks, such as (i) improving global network coverage, (ii) improving spectral, energy, and cost efficiency, and (iii) enhancing network intelligence, data security is the most important one. In order to meet these requirements, network intelligentization is what 6G networks must rely on [118], more especially with the issue of the age of information (AoI) becoming more critical with URLLC applications such as vehicular technology. There is an urgent need to push the boundaries of AI and intelligentization to the edge of the network, which has resulted in edge intelligence [119]. Due to the promises of 6G in terms of offering a wide range of varied services through its heterogeneous devices, in the widely anticipated network intelligentization, edge computing comes into play in data fidelity and security. In data fidelity and security, data are used to train ML models using federated ML (FML), which is a combination of edge computing and AI strategies [120,121].

7.2.1. The Federated DRL Computational Offloading

Contrary to the traditional FML, techniques such as the federated DRL (FDRL) can be designed into edge intelligence frameworks for enabling edge devices to remember what they have learned together with other edge devices [122]. Therefore, edge intelligence can be applied in cases where there are multiple edge devices that need to make decisions in different environmental contexts. This means that in each environmental context, each edge device can build its own learning framework based on its context with assistance from other edge devices. Here, the basic assumption is that edge devices with limited computation capabilities and limited storage resources, but having various compute-intensive, time-critical, and privacy-sensitive applications, offload their data to the edge server [123]. Using the FDRL computational offloading scheme, the privacy-sensitive data are protected from malicious attacks by the federated intelligence shown in Figure 6 below.



(**a**) (**b**)

Figure 6. (**a**) A FDRL architecture for secure computational offloading in CRNs, and (**b**) a FDRL-inspired digital twin-empowered edge platform.

In Figure 6a above, a single round of FDRL in a CRN is illustrated, where edge devices on the device layer compute their local updates w using their local data without sharing them then upload their local updates to the edge server via the gNB in the form of a computed gradient. Then, the edge server in the edge layer combines all the gradient updates from the different edge devices and performs aggregate computation of global update Δw. Upon computing the global update, the edge server then broadcasts it back to the edge devices via the gNB. The processing delay of this FDRL computational offloading scheme is usually determined using the number of iterations required for the algorithm to converge [121]. The two-layer abstraction of the FDRL offloading architecture in Figure 6a above is discussed as follows:

- The Device Layer: The device layer operates according to vertical FML, where each edge device begins by partitioning a DNN model according to the current environmental factors, such as channel conditions and available bandwidth [123]. Then, an assumed set of edge devices share their local datasets with one another to cooperatively train their associated gNB by uploading gradients Δw. The transmission link for information exchange between devices is governed by device-to-device (D2D) protocols. In return, the edge server computes global updates and broadcasts an aggregated gradient as w through the gNB to globally train its associated devices [124].
- The Edge Layer: The edge layer consists of a gNB that is managed with a DNN model that is partitioned according to the workload of the edge server and executes according to device resource and intermediate data to the server. Here, features that describe the state of the edge servers and the requirements of the edge devices are fed to learn the DNN [125]. Through its generalization capabilities, the DNN trains the agent towards yielding general scheduling policies, which are not just tuned states that are encountered during the training process but are adaptive states that can be applied even to unknown states in the processes of predicting/prescribing.

The FDRL technique, as well as federated communication, can solve issues related to data privacy and latency in edge computing. However, a trade-off between the local computation delay and the communication delay is very crucial in minimizing the overall FDRL processing latency. In this context, the processing latency can be defined as a measure of the responsiveness of the computing devices (edge devices and the edge server), while responsiveness is used to measure the quality of the network by the number of round trips per minute. Therefore, processing latency results from the slowness of the hardware devices and the number of hops along the network. This can be achieved via joint transmission and computation optimization, where the state of the system $s(t) \triangleq \varphi(t)$ and the action $a(t)$ taken in each state can be given as follows:

$$a(t) \triangleq \arg\max_a Q(\varphi(t), a(t); \theta), \tag{3}$$

and the local function is periodically updated as $\arg\max_a Q(\varphi_{j+1}, a; \theta)$, where θ represents the network parameter. In the training process, based on (3), the local model is periodically updated as follows:

$$Q(\varphi_{j+1}, \arg\max_a Q(\varphi_{j+1}, a; \theta); \theta). \tag{4}$$

Then, the experience tuple $(\varphi(t), a(t), r(t), \varphi(t+1))$ is stored in the local memory as environmental experience for later replay.

7.2.2. Realizing the FDRL-Based Digital Twin

The general assumption of federated communication depicted in Figure 6a is adopted in order to realize the DT in Figure 6b. This is an edge-based DT that is inspired by FDRL that can enable secure offloading and processing of real-time applications provided by 6G networks. In the DT implementation of an FDRL architecture, a number of things can be monitored, such as (i) the devices and infrastructure, i.e., device DT and infrastructure DT, respectively, and (ii) the link state, i.e., link DT, defined according to the SINR $\gamma_{n,k}$. In terms of the link DT, network data analytics may be used for visualizing network performance in terms of key performance indicators (KPIs). Based on Figure 6b, the DT can be formulated as follows:

- Physical Layer: Since the value of the information that is obtained in IoE systems depends on the AoI, the time elapsed from the time that the raw data are generated by the applications to the time when the data are processed and delivered to the processes must be minimized [29]. User behavior and gNB association are the most critical processes of the physical layer (mostly the network edge), where the data producers frequently share with other parties such as edge servers for the training of their models [111].
- Digital Twin Layer and DT Services: The DT, found in the DT layer, is concerned with monitoring, capturing, and processing of the data in order to deliver insights for decision makers to act on. This means that the collection and storage of the status data and their subsequent processing is very important. In this case, the DT layer requires robust capacities of data storage and cloud-based ML platforms for analytics. The analytics are the most vital component of the DT platform since it translates the status data into analytics insights, which are then shaped into formats suitable for human perception.

8. Big Data and Big Data Analytics—The Final Frontier

The big data from large-scale wireless networks consists of several key features, i.e., (i) high volume, (ii) real-time velocity, as well as (iii) huge value that have led to unique research challenges that are extremely different from the current computing systems [126]. From the huge datasets that are generated by the extremely heterogeneous 5G network applications in diverse communication scenarios, 6G networks are expected to enable a plethora of newer AI-assisted smart applications. Big data, through the use of big data analytics, will also be used to completely transform the world of telecommunications, i.e., resource management. This has the potential of improving the efficiency of provisioning and distributing wireless resources. Due to the emergence of products such as cloud computing and storage, the data produced by the communication infrastructure are used to generate even more data that are also shared across other entities [73]. The data that are generated from interactions with servers through the IoT can be used to provide useful insights on how telecommunication businesses can manage their processes [127]. In terms of telecommunication business solutions, uploading data to the cloud platform for analysis can be an intensive process, and a lot of insights can be found at the edge. Real-time edge analytics can be used to deliver reaction-based business decisions on data predicting the future.

8.1. Big Data-Inspired, Edge-Based DT for Real-Time Network Diagnostics

In the big data and big data analytics context, a DT can be designed for the following purposes: (i) monitoring network operations, (ii) planning predictive maintenance, (iii) improving customer services, as well as (iv) resource management, i.e., optimizing RA [128]. Network operations in the current generation are already characterized by specifications of higher demands for data rates and higher quality of experience (QoE) on the user side. This, paralleled with the requirements for low complexity network architecture, and the continued reduction of costs on the RAN and network core, suggests that MNOs need to begin instantiating predictive analytics. Through the use of edge-based DT-based analytics, which entails the automation of network operations and maintenance through data analytics, network disruptions can be avoided and better QoE can be afforded to end users. In order to achieve this level of network automation, gNB functions and core network functions can be virtualized and arranged at the edge of the network to offer problem-specific solutions. A type of function virtualization for edge network diagnostics and prescriptive maintenance through intelligent virtual assistants is shown in Figure 7 below.

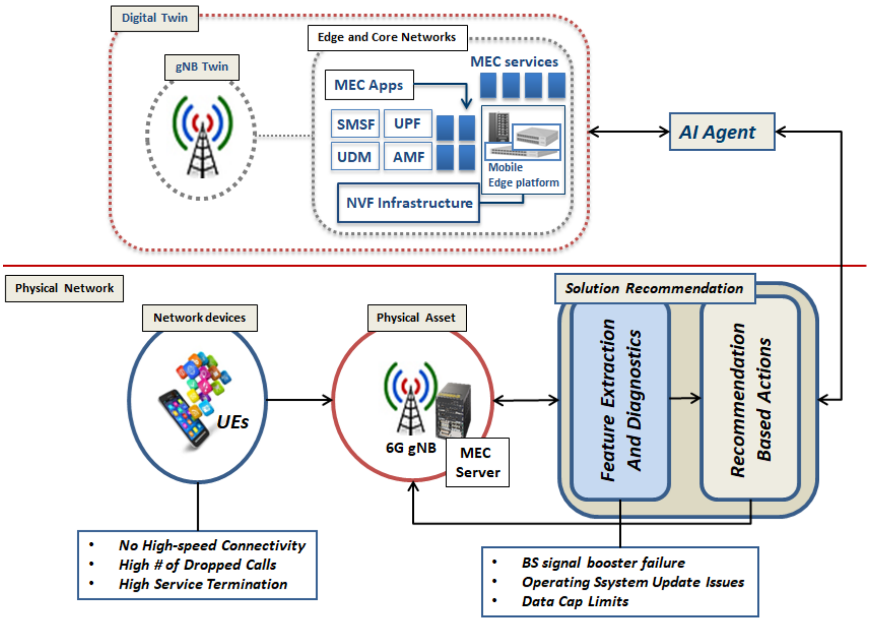


Figure 7. A digital twin representation of an intelligent virtual assistant for predictive and prescriptive maintenance in 6G networks.

Illustrated in Figure 7 above is a cloud–edge computing strategy to track QoE and service disruptions, whereby service providers can replace expensive site visits by running their networks with NFs using virtual machines (VMs) running on standard hardware at the network edge. MNOs might already be using the DT technology without them knowing, such as in customer service. For instance, a DT can be used in monitoring network conditions as a proxy measure of customer experience, where the origin of the issues affecting users can be predicted and addressed. Due to the need to deliver more personalized, anticipatory, and consistent services across all the physical assets in all network segments, the DT technology has a lot of potential in the customer service departments of MNOs [129]. Predictive and prescriptive analytics can be exploited in improving customer service. Service disruptions can be avoided by performing system diagnostics and making important maintenance decisions through customer service. Through the use of data mining techniques, DTs can enable better customer service by providing differentiated levels of service through the data obtained from customer reviews. To shed some light on this concept, an illustrative example is as follows:

Example 3. *Suppose the performance of the network has degraded to the point of inconveniencing network users. In this case, urgent and prompt intervention from the MNO is required. As shown in Figure 7 above, the service degradation from the subscribers that might be in the form of (i) poor network connectivity, (ii) high number of dropped calls, and (iii) high service termination can be intelligently detected and addressed before the subscribers begin logging their complaints. From a technical perspective, the kinds of complaints listed above may not differ greatly from one another, but based on proper analytics, they might require different technical solutions. On the other hand, from a customer service perspective, the similarities and/or differences in the complaints might not be clear, hence the requirement for proper data analytics to extract relevant features. For instance, if data mining techniques are used in mining the features from text and visualization techniques used, the best possible network diagnostics can be carried out and the accurate solution can be prescribed. Based on the complaints listed above, the corresponding problems might be (i) signal booster failure, (ii) operating update issues, and (iii) contract data cap limits [130]. Thus, assuming that the customer service department receives such complaints in larger volumes in real time, taking subscriber impatience into account, the process of going through such massive data, extracting patterns, diagnosing the problems, and assigning field technicians to the different sites might be labor* *intensive and time consuming. Therefore, the implementation of the DT-based real-time predictive maintenance solution proceeds as follows:*

- *Data Mining and Information Extraction: Using data mining techniques such as clustering algorithms, similar complaints can be grouped together for collective diagnosis. It must, however, be noted that the grievances received from the subscribers might be in text format, and some preliminary pre-processing might be required in order to be a dataset that is ready for processing and analysis. For the preliminary pre-processing step, a natural language processing and lexicon processing algorithm might be used to "mine" similar text structures. After, there is grouping of similar textual information using classification algorithms to observe some correlations in the text data for further processing.*
- *Data Analytics and Diagnostics: Using data mining techniques, a lot of information can be extracted and classified in terms of their similarities and differences, and diagnostic techniques can be applied in each cluster of information to diagnose problems. In the diagnostic step, the classified data are processed in order to obtain a good diagnostic visibility of the network problems. From the customer service side, this visibility can assist the service providers with information such as regions of the network, gNB sites, user behavior, and applications. Using this information, diagnosis of what the real problems might be can be performed.*
- *Solution Recommendation: Within a short space of time, potential solutions are evaluated and the best one is recommended and commissioned through the use of virtualized functions. For example, problems such as software maintenance and upgrades can be virtualized instead of allocating a technician on site. In this case, the software agent runs a solution recommendation module (SRM) and sends recommendations to the decision module, which proposes a network function virtualization (NFV) to the relevant gNB site [131]. However, due to the nature of the diagnosed problems, the recommendation processes differ from one another due to the difference in user behavior in different network regions. As a result, the agent that handles the recommendation process must reside at the edge server in order to dynamically launch tasks of relevant VM instances to resolve dynamic problems. Therefore, the VM launching can be managed using a DRL strategy as contemplated in [132].*

8.2. Big Data-Inspired DT for Real-Time Predictive Maintenance

There is a paradigm shift from the reactive system maintenance to the proactive one, which has led to the optimization of maintenance schedules [133]. This is called real-time predictive maintenance, which, by minimizing system downtime, improves the profitability and competitiveness of service providers. In real-time predictive maintenance, AI is used to analyze the operating condition of different network infrastructures. On the other hand, DT for predictive maintenance enables accurate recognition of equipment status and proactive fault prediction, which enhances system reliability. Therefore, in this case, real-time predictive maintenance is the competency of the system in distinguishing future scenarios that are likely to cause system failure and scheduing repairs before the system actually crashes [75]. In this way, the DT technology has greatly facilitated the development of predictive maintenance through predictive modeling. Predictive modeling, which is a predictive analytics tool, is a process that uses known results in the creation, processing, and validation of models that can be used in forecasting certain future outcomes [134]. On the one hand, predictive analytics is a data mining technique responsible for predicting future possibilities and prescribing future actions, hence the emergence of predictive and prescriptive analytics. A DT model for big data-inspired predictive maintenance is shown in Figure 8 below.

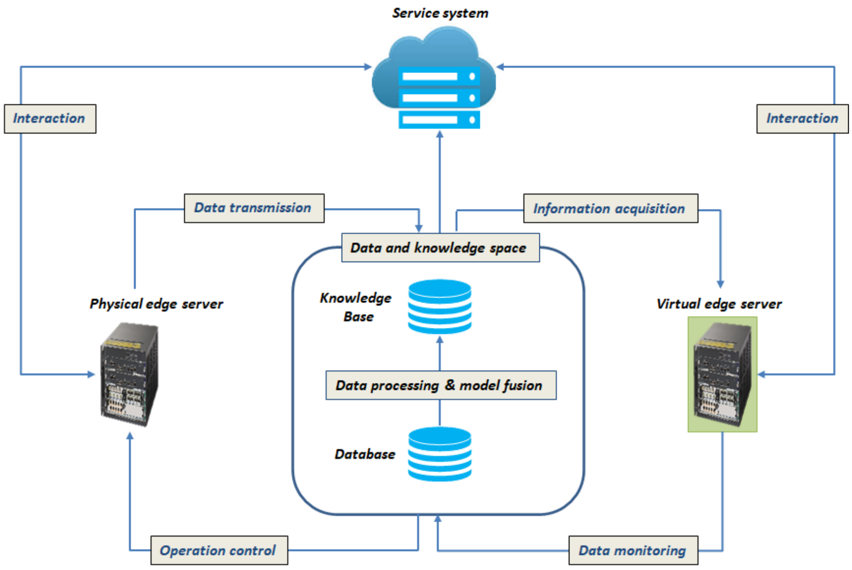


Figure 8. A digital twin-driven edge intelligent real-time predictive maintenance technique.

Shown in Figure 8 above is a closed-loop perception and control strategy between the physical edge server and the virtual edge server realized through the use of the big data technology.

- The virtual edge server: The virtual edge server then realizes the data monitoring and operation control for the physical edge server. In edge computing, edge-based predictive analytics solutions use the DT technology to prevent server downtime as a means of conserving and protecting QoS parameters and, subsequently, the QoE of users.
- The data and knowledge space: Here, the data are transferred to the database where they are stored and pre-processed. With the data and the model that are integrated and fused, the maintenance knowledge for decision making that is generated by ML algorithms is stored in the knowledge base [135].
- Inter-twin interaction: After establishing the knowledge base, the virtual edge server can then obtain the required information from the knowledge.

9. Network Digital Twin for Vehicle-to-Edge Communication

The network computational intelligence now resides at the edge instead of the core, and the most important infrastructure component is the MEC server. An efficient implementation of DT at the edge requires enabling high-quality edge intelligence service deployment.

9.1. Edge Computing-Based Digital Twin for Traditional RAN

Consider a cellular vehicle-to-edge network where a two-tier vehicular network on a one-dimensional road segment is considered. Here, the first tier consists of the macro-cell with a gNB, while the second tier consists of a set $\mathcal{N} = \{1, 2, \cdots, N\}$ of small cells, each one having a single roadside unit (RSU), RSU_n, as shown in Figure 9 below.

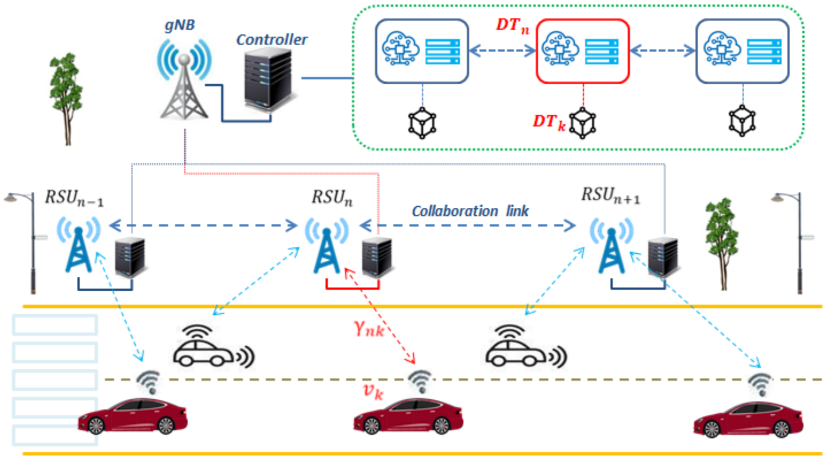


Figure 9. A network digital twin model of a multi-link communication in a cellular vehicle-to-edge offloading scenario.

In Figure 9 above, the gNB serves as a controller that manages the RSUs on the second tier by controlling their resources and also establishing offloading and computing policies. The RSUs are assumed to be connected to edge servers using the evolved common public radio interface (eCPRI) front-haul interfaces [136] to provide delay-constrained computing services. As it can be seen in Figure 9 above, a set $\mathcal{K} = \{1, 2, \cdots, K\}$ of vehicles are randomly distributed on a road segment, and each one of them periodically generates computing tasks that require results to the RSU via an offloading link characterized by γ_{nk}. Due to the safety-critical nature of vehicular communications, this is a site-specific DT for obtaining time-variant link behavior in terms of packet loss rates (PLR) for analyzing the reliability of vehicular communication scenarios. In this application, the use of a real-time geometry-based stochastic channel model, which was studied in [102], can be adopted in simulating doubly selective channel frequency responses.

Consider a scenario whereby the best offloading decision in a vehicle-to-edge (V2E) network needs to be found. This offloading decision that is sought must associate each tasks that is generated by vehicles with one of the available edge servers. Assuming that the objective goal of minimizing (i) the offloading error, (ii) processing latency, (iii) overall energy consumption, (iv) or a combination of these objectives, the question is how a perfect DT can be designed to solve this problem in the best possible way. One possible way is to split the DT design into two, as discussed below.

- Device/vehicle DT: The vehicle DT (vDT) can be thought of as the profile of the device, which may include (i) the travelling speed, (ii) the trajectory and real-time vehicle location, as well as (iii) the resource requirements.
    1. The requirements: The requirements may include (i) the size of the task (payload size), (ii) the required processing cycles, as well as (iii) the dependency and the priority among tasks.
    2. The AI agent: The AI agent then iteratively associates the device tasks with the servers and takes note of the reduction of the objective, i.e., records the resulting reward. The features that describe the status of the server as well as the device requirements are then fed to learn the DNN, which uses its generalization capabilities to yield general scheduling policies.

  In relation to the other DTs, the vehicle DT monitors the vehicle trajectory and vehicle speed optimization—to name a few. Other additional parameters that can be monitored are blind-spot and accident detection.
- Infrastructure DT: In edge computing, the infrastructure consists of (i) the RSUs, (ii) the edge server, and (iii) the vehicles themselves. The responsibility of the infrastructure DT (iDT) is monitoring and optimization of service provisioning to the devices. This means that the infrastructure DT manages device behavior in terms of their real-

time location and network behavior. Then, the state of each edge server can be described using its resources, i.e., (i) its computing speed and (ii) the quality of the communication channel. For an efficient infrastructure DT establishment, effective mapping between RSUs and vehicles must be established.

1. Mapping: The mapping between the physical twin and the virtual twin has three components: (i) data storage, which collects data from the physical network, such as vehicle state, RSU state, and wireless channel state, (ii) virtual model mapping, and (iii) inter-twin management.
2. The Central Controller: The central controller at the edge server can model the offloaded tasks and determines their resource demand status using the aggregated data in the device DT. It is this controller that assigns tasks through the computing task model.
3. Inter-Twin Communication: The knowledge transfer process between the two twins can be secured using blockchain in order to preserve knowledge integrity for the immutable and trackable contributions of each device. Blockchain is a comparatively newer technology that simplifies network management and enhances its performance by offering a variety of applications that considerably improve the security of authentication.

- Link DT: Due to these channel imperfections, more especially in urban environments, the concept of DT can be enabled as a city-aware DT model. The simulations of the city-aware DT model should allow for accurate modeling of ray reflections and signal attenuations [137].

9.2. Edge Computing-Based Digital Twin for Open RAN

The disaggregated and open architecture of open RAN is aimed at meeting the high demands for 6G wireless communications. The most important services in a multi-vendor disaggregated network environment require continuous measurements and testing for continuous assurance [138]. How these measurements and tests will be conducted from different vendor infrastructures as well as how they will proceed in tandem with 6G networks is a very important and challenging question. Having some parity between the virtualized network environment and a DT of the network would be crucial. Therefore, building accurate DTs for open RAN environments will be key for network testing to be performed without taking the network offline. MNOs will be called upon to (i) improve computational capability for serving latency-critical applications and (ii) extend coverage to under-served locations and communities. The major challenge here is that a software push from one vendor might potentially cause some disruptions in the mechanizations of other vendors in the radio system [26], since the inter-dependencies among the network equipment from different vendors could be very complex and add too much risk in the operation of the different software.

9.2.1. Edge-Based Vehicular Communications—A Primer for Open RAN DT

Improving computational capabilities to serve latency-intolerant services will present new opportunities for those service providers who will be prepared to embrace it [139]. For instance, most of the existing research contributions in vehicular-to-anything (V2X) communications assume either deterministic or static channel models, which might be unrealistic. Vehicular channels in urban environments are highly dynamic, owing to the influence of high-speed motion and intermittent connections. In line with the enterprise digitization enabled by 5G/6G networks [140], an edge intelligence system that allows a customized functional split to cater for 6G mission-critical services is shown in Figure 10 below.

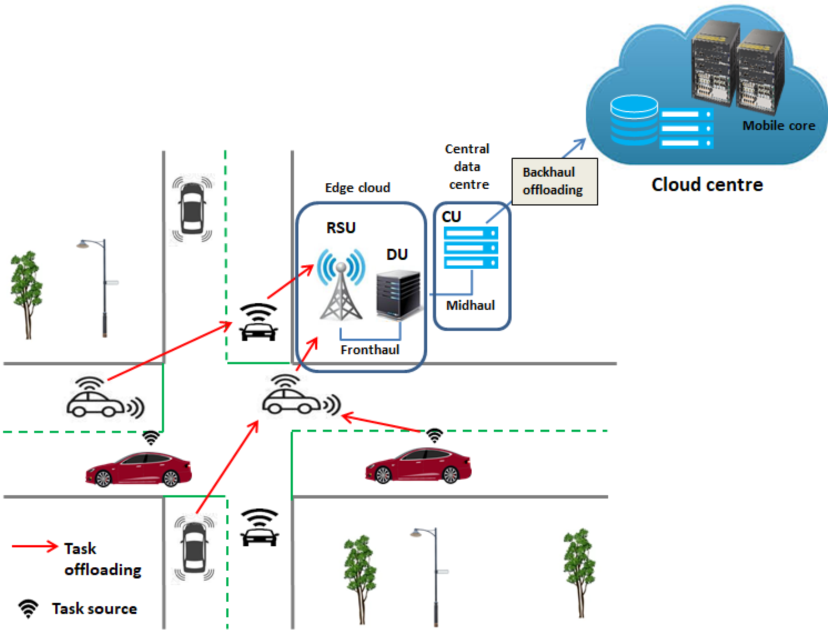


Figure 10. Edge intelligence on an open edge platform capable of handling vehicular communications.

Shown in Figure 10 above is a vehicular network with the support of the transportation infrastructure. Here, it is assumed that communication between the RSU and vehicles is based on 6G communications, and the coverage of the RSU determines the service zone. The edge intelligence system on the edge site is based on functional split, which is defined as follows [141]:

Definition 1. *In the context of open RAN, the functional split determines the number of gNB functions that can be left locally, i.e., closer to the user, in order to relax the bit rate and delay requirements of the fronthaul network. It also determines the number of gNB functions that can be centralized in order to achieve greater processing capabilities.*

According to the open RAN split architecture, the edge computing system consists of (i) a fixed RSU, (ii) a distributed unit (DU), and (iii) a centralized unit (CU), which complete the open architecture defined for edge computing.

- Distributed Unit: The DU is the lower-layer split of the open RAN protocol stack, while the fixed RSU together with the DU are considered as the edge cloud. According to the logical split 7.2x, the DU can be defined as the logical node that includes a portion of the gNB functions. It is tasked with controlling the operation of a number of RSUs.
- Centralized Unit: The CU is the upper-layer split of the open RAN protocol stack, and it is considered as the central data center. It is the logical node that includes a portion of the gNB functions, i.e., packet data convergence protocol (PDCP) and the radio link controller (RLC) layers of the protocol stack, as defined by logical split 2. The CU can also support a number of DUs. Therefore, by taking advantage of network function virtualization (NFV) techniques and running them at CUs, part of the network functions can be transferred into data centers instead of running them at the RSU.

In Figure 10 above, it is assumed that the open and flexible edge platform consists of node software that runs on devices at the edge, as well as a management system that runs on the edge–cloud continuum. Since the infrastructure nodes are wire connected via high-speed fronthaul connections, all the infrastructure nodes can be regarded as one giant node together. Both resource availability and resource requirements are quantified with resource units.

9.2.2. Open RAN-Inspired Edge Digital Twin—A Vehicular Communication Use Case

Even though the DT technology is specifically aimed for the simulation of future experiences, the calculation of context, and the development of a chain of outcomes, it can also be used in the real-time optimization of edge computing algorithms [142]. In safety-critical applications, such as autonomous driving, it can be used to create a progressively safer environment through V2E communication. For instance, for some of the challenges faced in autonomous driving such as drastic weather changes that may require a change in the route course, the edge can assist the DT to quickly compute the necessary changes that need to be made. Developing a DT of the terrain (infrastructure DT) and of the vehicle (device/vehicle DT) can help the edge computing technology in predicting and successfully executing a safe and successful journey. Therefore, in order to realize the full potential of open RAN at the edge, an edge DT (EDT) can be designed for real-time network modeling and optimization. To this effect, an EDT can be designed as a section of the NDT that is described for both pre- and post-deployment for supporting vehicular communications, designed as shown in Figure 11 below.

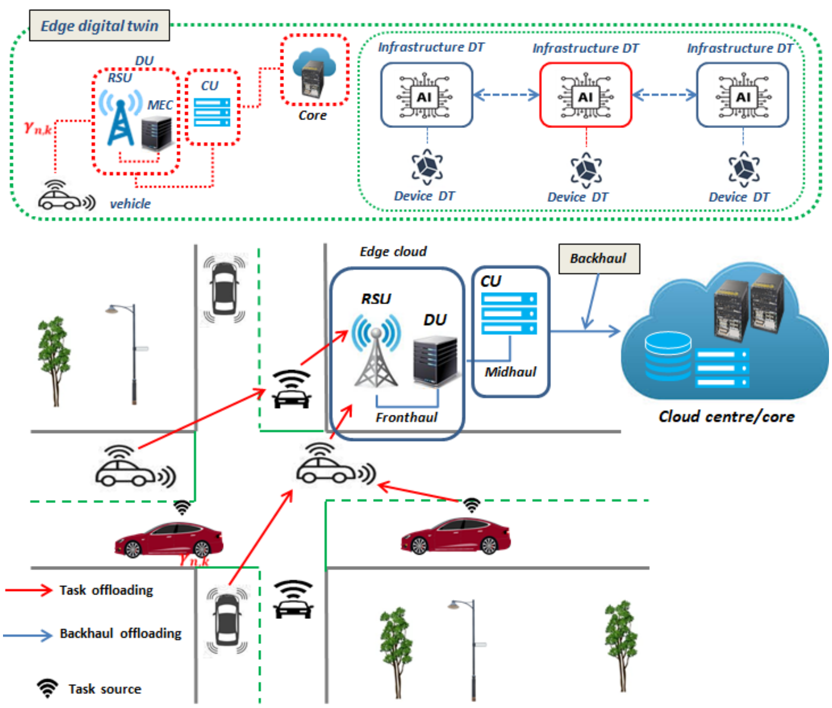


Figure 11. Digital twin implementation of a computation offloading scenario in an open edge platform capable of handling vehicular communications.

As shown in Figure 11 above, a DT-enabled V2E network is realized through two closed loops between physical V2E networks and the DTs. In the computation offloading scenario, the digital models of the vehicles and of the infrastructure interact via inter-twin communication managed through the blockchain technology. Based on the current contributions in the DT technology for edge computing problems, the research designs are conducted based on the tabulation shown in Table 2 below.

Table 2. Application of the digital twin technology in edge computing.

Objective	Technique	Algorithm	Considerations	Refs
Enabling new functionalities, e.g., hyper-connected experience and low latency	Formulate an edge association product w.r.t. network states and varying topology	Deep reinforcement learning	Use of transfer learning to solve DT migration problem	[143]
Incorporate DT into wireless networks to migrate real-time data processing and learning	Blockchain-empowered FML framework to run in the DT for collaborative computing	Multi-agent reinforcement learning	Improve system reliability, security, balance, learning, accuracy, and time cost	[144]
Ensure seamless handover among MEC servers and to avoid intermittent metaverse services	Real-time data collection and model training	C-Deep deterministic policy gradient	Interplay between local DT edge computing on local MEC and the global one on cloud due to the nature of network states	[145]
Develop RA model and establish a joint power optimization function, delay, and unbalanced RA rate	Design a greedy initialization strategy that will improve convergence speed of DT	Whale optimization algorithm	Demonstrate that RA and allocation objective function value, power consumption, and reduce RA imbalance rates	[146]
Address DT construction challenges and assisted resource scheduling, e.g., low accuracy and large iteration delay	Federated machine learning	Deep Q-learning network	Low-latency accurate, and secure DT to jointly optimize total iteration delay and loss function, and leverage model recognition	[147]
Blockchain proof of authority trust mechanism to provide quality services, e.g., data security and privacy	Combine a blockchain-based distributed network with DT for IIoT	Blockchain and deterministic pseudo-random generation (DPRG)	Enhance the authority of decentralized DT combined blockchain networks	[148]

10. Conclusions

This objective of this article was to highlight the different interdisciplinary research fields that interact to shape the cyber–physical convergence towards realizing the DT technology. By shaping a new telecommunication ecosystem landscape beyond the operational framework of the CIoT, a new kind of resource management to improve radio utilization in 6G networks was realized. This permitted the development and use of the DT technology as a virtual representation of physical assets. Therefore, towards the discussion of DT use case designs for edge computing, the challenges facing digital transformation were discussed together with prospective solution recommendations. The pillars of the CIoPPD&T were discussed with the aim of highlighting how they interact to form the complex socio-technical ecosystem defined according to the different fields of research. Then, the current state of the telecommunication landscape and the overview of the AI market were discussed with the aim of highlighting the need for an NDT. In bringing the autonomous network operations, the DT was introduced as a concept of the CIoPPD&T, and the digital transformation towards realizing the DT technology was highlighted. Through this introductory discussion of the DT, an NDT was introduced in the context of 6G networks.

10.1. Elucidation of Contributions

Regarding the edge computing use case designs, the contributions are as follows:

- Edge-Based DT for Day 3 Operations: The principles of choice modeling and mathematical psychology were brought from prospect theory, and discrete choice experiments were brought to model day 3 edge operations. To address the complexity of 6G networks, the traditional edge computing (as currently known in the 5G context) could be improved through the use of low-cost data centers (i.e., CU) that operate according to cognitive choice modeling.
- Big Data-Inspired Edge DT: Since 6G networks are expected to enable a plethora of newer AI-assisted smart applications, big data analytics could be utilized to completely transform the world of communication. In this way, the status of the edge systems in terms of an edge-resource device model can be realized through the deployment of big data-based DT models deployed at the edge server. With this modeling approach, parameter calibration between physical assets and DTs can be performed at regular intervals. In this way, the physical components can exchange real-time information with the DT, thus opening the door for predictive maintenance.
- Vehicle-to-Edge Use Case Design: The design and realization of the C-V2E offloading scheme was realized with the suggestion of splitting the NDT design to specifically focus on the vDT and the iDT that will monitor different network profiles. This kind of design is more suitable for vehicular services since it allows for the creation of a specific DT—tailored for monitoring a specific troublesome feature of the network, such as the connection link in urban environments. This is a performance-related and real-time constraint violation challenge, which is very critical in ensuring the dependability of the DT. The DT cannot entirely and accurately simulate the physical entity, as there will be specific errors, and the cumulative error will increase with time.
- Open RAN-Based Vehicle-to-Edge Use Case Design: With the vital role played by open RAN in improving the computational capabilities of the edge, vehicular applications could benefit from greatly reduced latency. To that effect, an EDT was designed based on the dis-aggregated RAN architecture, specifically for C-V2E applications. Here, a customized functional split of the edge was realized according to open RAN principles, such that the edge server was dis-aggregated into (i) edge cloud and (ii) central data center. This design architecture achieves reduced latency compared to the non-split architecture by orders of magnitude.

10.2. Recommendations for Future Research

With the recent rise of chat generative pre-trained transformer (ChatGPT), it has been postulated that 6G RAN will support GPT-based applications. OpenAI's ChatGPT is an

AI-powered language model capable of understanding and responding to natural language inputs [149]. This means that RAN will be redesigned for the emerging 6G GPT-based systems. However, for GPT models to function properly, a sizable amount of computing power and data storage are required. Since 6G networks are supposed to provide lower latencies than the current 5G networks, the time required for communication between the GPT and other devices must be as minimal as possible. Therefore, the open RAN principle of splitting the RAN (i.e., DU-CU) and rearranging the NFs to meet different computing and storage requirements may be adopted to partition the ultra-large GPT-based computing into a distributed computing and distributed networking architecture. This partitioning technique must be adopted to achieve the objective of optimizing the computing resources and connectivity resources in order to increase the network capacity when delivering the GPT-type services. In this way, a novel communication model between the GPT-based applications and the DT in the context of joint sensing and communication—depicted as a virtual reality showing multi-modal brain-computer interface—can be designed.

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