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Deploying Neural-Symbolic Hybrid Models for Adaptive Spectrum Management in 6G-Ready Networks

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ABSTRACT
The spectrum scarcity exacerbated by the increasing demand for connectivity from sectors such as the Internet of Things and Industry 4.0 has caused a shift in policy and regulation decisions towards a more flexible use of the spectrum. An example of this is the identification of tools such as Dynamic Spectrum Access which allow better outlets for unlicensed bands and the design of technology options capable of supporting it. This is the spirit of Cognitive Radio Technology but, to be practical, cultural issues must be addressed first; its application to commercial wireless networks is still a question mark. In wireless communication, Artificial Intelligence is now seen as a game changer, particularly in the way signals are defined and processed as well as in network management. The convergence of these two areas is seen by many as a natural path into the future, opening up new challenges and new business opportunities. Dynamic Spectrum Systems for Wireless Communication networks are at the core of this set of problems, Dynamic Access Spectrum is the new objective for designers and operators; the fulfillment of this objective allows the implementation of a new business in which Wireless Communication is ancillary to the production and commercialization of information. Cognitive Wireless Networks, built upon More than Moore paradigms (natural air interface processing, dynamic all-in-one network management), are seen as the exploitable fruit of the convergence of Artificial Intelligence with the current state-of-the-art in Radio Communication Theory applied to Wireless Networks. We explore these ideas, utilizing the current research activity and the lessons to be learned as a roadmap to the future..

Keyword: *Spectrum Scarcity, Dynamic Spectrum Access, Cognitive Radio, Wireless Communication, Artificial Intelligence, Internet of Things, Industry 4.0, Network Management, Signal Processing, Cultural Adoption, Commercial Wireless Networks, Dynamic Spectrum Systems, Business Opportunities, Converging Technologies, Natural Air Interface, More than Moore, Information Commercialization, Cognitive Wireless Networks, Radio Communication Theory, Future Connectivity*

1. INTRODUCTION

6G-ready networks require new management procedures. A step towards such networks with the ubiquitous, dense, and heterogeneous deployment of communications services can be achieved by the remarkable character of the wireless communication spectrum as a national resource to be shared by all. The electromagnetic spectrum, spanning 1 Hz - 100 THz in frequency, represents one of the main natural resources of the earth. Even though it is considered a public resource, it is usually exploited by private entities for a limited time in certain geographical areas. Wireless communications services compose a fundamental layer of our networks. If the spectrum is managed most efficiently, it can guarantee the most benefit for society. Current centralized and static ways of managing the spectrum have shown to be limited to the rapid and continuous rise of new communications services and demands. Satellite Internet, the Internet of Things, Industry 4.0, and Virtual Reality represent only a few of the new services that are redesigning the future of our wireless networks. The importance of a flexible and proactive solution is further enhanced by the increased demand for mobile telecommunication services after the pandemic.

In this discussion, a new category of what we define as Adaptive Spectrum Managers is described. Such new software components are embedded in the architecture of 6G-ready networks and can continuously monitor the exploitation of radio resources in the geographic area of interest. Moreover, they can evaluate how to encourage entities to dynamically abandon spectrum resources to be freed during their temporary under-utilization periods, directly optimizing social welfare, defined as the total benefit for society, jointly considering both public and private entities. Entities that have temporarily halted the exploitation of resources can give back the resources to be exploited by other public or private entities. Such a solution can also be applied in a static way to any set of already given public operations for the management of the territory.

1.1. Purpose and Scope of the Study

The innovation of the 6th generation (6G) networks lies in the transparent convergence between terrestrial and non-terrestrial networks, satisfying the demand for new verticals, such as intelligent transportation, digital twins, immersive communication, and wireless sensing. A critical enabler to fulfill the 6G vision is the ultra-wideband provided by enhanced and new spectral bands, including mobile satellite service, and new aerial service spectrum. However, deploying additional spectral bands to meet the demand of verticals at a large scale in smart cities, smart factories, or rural areas requires a deep understanding of the network environment, data analytics, and continued training to guarantee quality service provision at any time and under any circumstance.

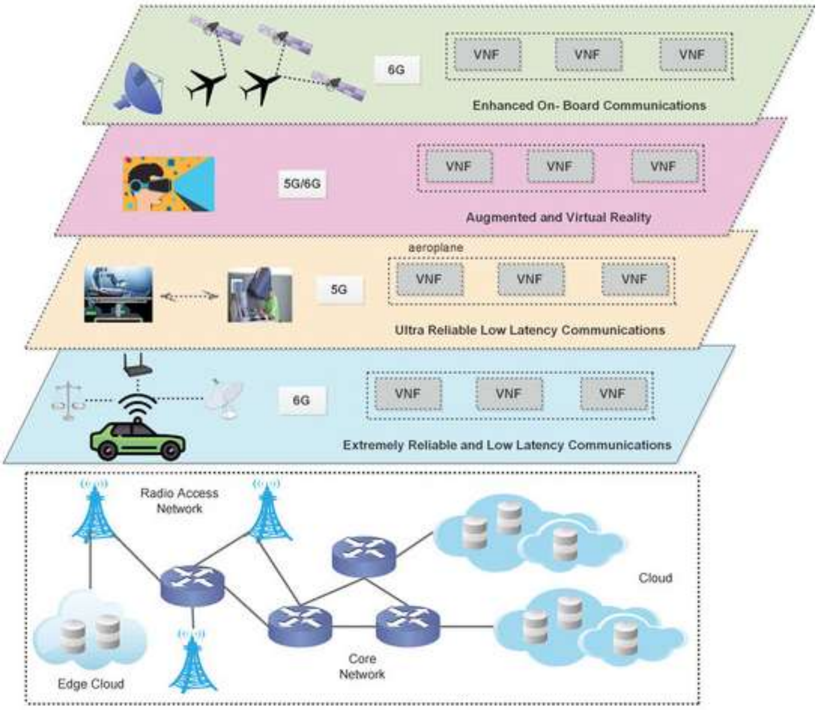

Fig 1 : 6G Mobile Networks

In this work, we show that the combination of symbolic and neural-based support for decision-making and decision-support systems, recently dubbed neuro-symbolic, provides a suitable framework for adaptive spectrum management and in particular for autonomous decisions on the allocation of services and resource blocks to each spectrum band, the demarcation of the service area of each band, and the selection of efforts in the continuation of the service. We first define the required concepts and properties of a DSS for spectrum management in 6G networks, emphasizing the complexity of the intelligent service networks due to the multiple services, spectral bands, and operator choices. Next, we present a neuro-symbolic architecture that fulfills the required properties of the DSS. The novelty of our work is the approach and the focus on the combination of symbolic and neural-based approaches for implementation in realistic contexts without large amounts of labeled datasets, effectively addressing the explainability-dependency trade-off typically observed in graphic domain applications, while also facing the criticism of symbolic-based approaches in the management of uncertainty and variability usually presented in wireless networks. Finally, we validate the neuro-symbolic architecture with a tangible implementation for a specific spectral management use case.

2. BACKGROUND AND MOTIVATION

The intelligent planning and management of the communication resources of a wireless network is an ever-growing and complex optimization problem that retains a key role in the area of wireless communications. Availability in the hardware and software implementations of advanced communication infrastructures and solutions, combined with the recent innovations in advanced algorithmic optimizations, have formed the so-called “intelligent networking” concept, an umbrella definition indicating the convergence of communications and information technologies. Reinforcing the intelligent networking concept, the upcoming 6G wireless systems are envisioned to be a Semantic Network, where all available entities inject into the network semantically meaningful information that can be shared, learned, and decided with advanced Artificial Intelligence and Machine algorithms.

Inspired by the communication technologies that will enable it, the intelligent networking framework presents great promises toward becoming an enabling and disruptive tool for the set of activities collectively referred to as Adaptive Network Management and Operations. Network operations involve planning the deployment of a telecommunication network and are performed by network planners. Network management involves monitoring and controlling the network during operation as well as detecting or recovering from any problems in the network. The joint interplay of the two faces of AM&O is becoming essential to ensure the seamless end-to-end quality for 6G services and applications, which will also benefit from the batch and real-time processing at the service time of datasets of very high-dimensionality and high velocity of advanced AI and Machine Learning algorithms. All these novel paradigms will also translate into the realization of inherently decentralized, cooperative, and player-oriented network and service management frameworks.

This paper delves into ML-enabled technical investigations of neural-symbolic hybrid methods, which allow the deployment of intelligent spectrum management and optimization solution frameworks for wireless systems. Such innovation will tackle the inherent complexity in the implementation of intelligent advanced solutions by combining the characteristics of the dissector-needed neural-based models with the proven efficacy and robustness of optimization-based strategies. These benefits will be also reflected in neural- and neural-symbolic-modeling solutions built on top of heuristically initialized system-inspired gradient-descent designs.

$$S_a = \alpha \cdot f_{NN}(X_t) + (1 - \alpha) \cdot f_{logic}(C)$$

Where

S_a: Spectrum Allocation Score

$f_{NN}(X_t)$: Neural Network Output from Real-Time Features X_t

$f_{logic}(C)$: Symbolic Logic Output from Constraints C

α: Blending Coefficient ($0 \leq \alpha \leq 1$)

Equation 1 : Hybrid Spectrum Allocation Score

2.1. Contextual Framework and Research Significance

Fifth Generation (5G) of wireless communication networks has been developed and further exploited as the global mobile broadband communication standard. However, despite the wide deployment and provision of such services, there exists an unprecedented demand for Wireless Network Service Requirements; specifically, i) mobile traffic volume; ii) number of connected devices per km2; iii) end-user experience data rate; iv) pervasive low latency communication and v) ultra-high dependency on network availability. The above demands push wireless communication networks beyond the limits that are already being imposed through the exploitation of the already deployed technologies for 5G communications. Such demands are forecasted to become even more strict in the coming years, thereby creating the need for the research and development of 6G networks.

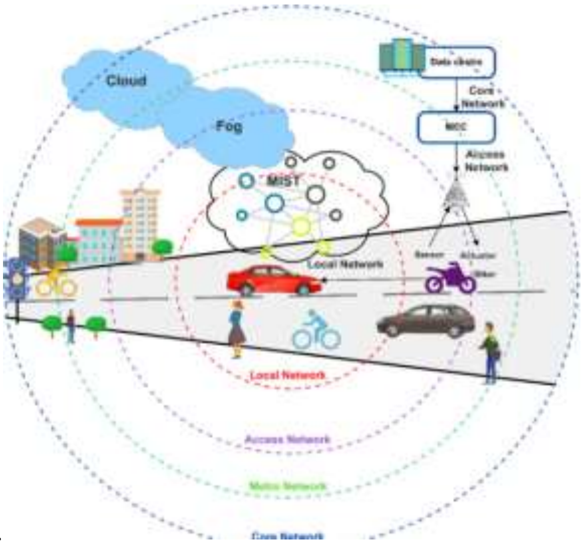

Fig 2 : 6G networks for artificial intelligence

The 6G networks promise to utilize high, as well as low-frequency bands as part of the communication infrastructure. Non-Terrestrial Networks technologies, such as LEO satellite networks, are also being utilized, in combination with Low Power Wide Area networks, to help advantage the effective provision of the services for the 6G communication networks. Adapting new technologies, however, creates additional challenges for the resource management components of mobile broadband communication networks. Availability is one of the main service criteria of the 6G-ready networks and, to be able to assure such a property, a plethora of radio resources may be challenged to be relied upon during the design and operation of the resource management engines. The above indicates the need for the development of the resource management engines that will be called upon to make important operational decisions based on radio resource availability, low user-km2 rate, device priority, low latency reception demand, and uncertainty on the conclusion of the uncertain tasks that rely on the utilization of heterogeneous networks. Such a conclusion can promise a well-established network operation with minimal skilled human interference through the exploitation of intelligent Resource Management Engines. Therefore, the question that embodies the motivation behind the content of this thesis stems from: How can Intelligent Resource Management Engines use the promising flexibility of Artificial Intelligence (AI) to ease the administrative burden?

3. OVERVIEW OF 6G NETWORKS

In response to the growing demand for differentiated Quality of Service (QoS) levels in various vertical industries, sixth-generation (6G) networks leverage the extensive deployment of multimedia sensors to gather a massive amount of context data from the physical environment. Such infrastructure creates the so-called Smart Dust concept. Such data can be exploited in a bidirectional manner by both vertical industries and the 6G network operator. On one side of the Smart Dust concept, advanced Artificial Intelligence (AI)-based technologies running on the 6G edge clouds can automate higher QoS network management by smart processing the raw data delivered by the verticals either in wireless mode from the multimedia sensors or more reliably through fiber-optic cables from the boundary nodes located close to the wireless deployment. On the other side of the Smart Dust concept, businesses aiming for the advanced usage of the 6G infrastructure can offer incentives to the 6G operator through the delivery of relevant raw data that can be exploited to forecast productivity-related KPIs in the areas of interest for the industries whose activities rely on the processing of the revealed information.

Compared to the earlier 5th generation (5G) networks, which turn towards the network slicing paradigm to customize the networking resources to the requirements of different verticals, 6G wireless networks are increasingly expected to be highly vertical-oriented and offer the vertical-specific level of guaranteed Service Level Agreements (SLAs) more efficiently, thanks to the interplay between the AI-based technologies and the Smart Dust concept. In this vision, to overcome the growing complexity in the QoS management of the mixed traffic, including one transferring super-critical data requiring compliance with very stringent delay deadlines using the ultra-reliable low-latency communications services and low-priority data done by devices collecting information to be periodically reported to the cloud for inferring analytics on the edge-enabled cloud servers through advanced machine learning, it is time to design and deploy a new generation of intelligent systems for the vertical awareness in the Infrastructure as a Service (IaaS)-enabled multi-service-oriented cloud-fog-5G network architecture.

3.1. Evolution and Key Features of 6G Networks

The sixth-generation (6G) mobile communication system is envisioned to evolve the 5G Mobile Communication System (MCS) toward a digital and networked society, unifying the physical and virtual world using high-dimensional intelligence and autonomous systems, and introducing new capabilities for a wide variety of vertical industries. To achieve these ambitious goals, 6G is requested to provide several revolutionary enablers that are still in the conceptual phase today. Consequently, it is not trivial to properly assess the development directions and levels of 6G. However, some key performance indicators (KPIs) are believed to be some performance prerequisites for 6G networks. The different and more stringent design goals of present and future wireless technologies are caused by the different characteristics of the services offered; indeed, the evolution in generations of wireless networks cannot be only seen as the increase of information delivered and the improvement of the quality of service for each service, order to fulfill such requirements, 6G systems will need a potentially visionary leap towards new generations of hardware and software systems: antennas and radio devices with ultra-wideband capabilities, SDN-based networks with ultra-low latency, intelligence to orchestration and optimization of all network resources, sensors and analytics from the edge to the cloud, and immersive technology, will all play a role in the value chain, along with new market verticals and players, redefining the dynamics of the Industry 4.0 and Digital Economies. The 6G era will be characterized by a complete revolution of traditional telecommunications, shifting from connecting things to connecting intelligence, and giving life to a new wave of transformative digital services and experiences.

4. SPECTRUM MANAGEMENT CHALLENGES

1. Key Issues in Spectrum Management

In information theory, a seminal work on channel capacity provides the basis for understanding most communication networks and allows characterization of the limits of capacity for additively Gaussian noise and a comparison of different modulation methods. Yet, it took several decades from the definition of information theory till the realization that a proper exploration of spatial information, not simply the volume of information, would allow the distribution of protocols within complex physical transport layers. Currently, information-theoretic design approaches are being explored as another branch of insight to improve the understanding of highly dispersed collaborations. This new paradigm states that encoding information in the individual parts, conveying information with the whole arrangement, and extracting information from the assembly is the key challenging task for the next generation of complex systems.

A combined radar and communications system design using Incoherent OFDM signaling is proposed and evaluated. The radar and communications systems share the same transmitter and are combined with the appropriate choice of communications signal and radar code. The radar system requires a time-dependent signature modulation and a carefully determined radar waveform coding to disentangle the superposition of reflected radar and communications signals. Different than prior integrated communication and radar systems, the approaches proposed here use multiuse codes for the joint communication and radar function in an integrated manner without the need for additional radar-orthogonal communication sequences. In this section, we shall discuss the challenges inherent to the design of spectrum management protocols dedicated to heterogeneous networks.

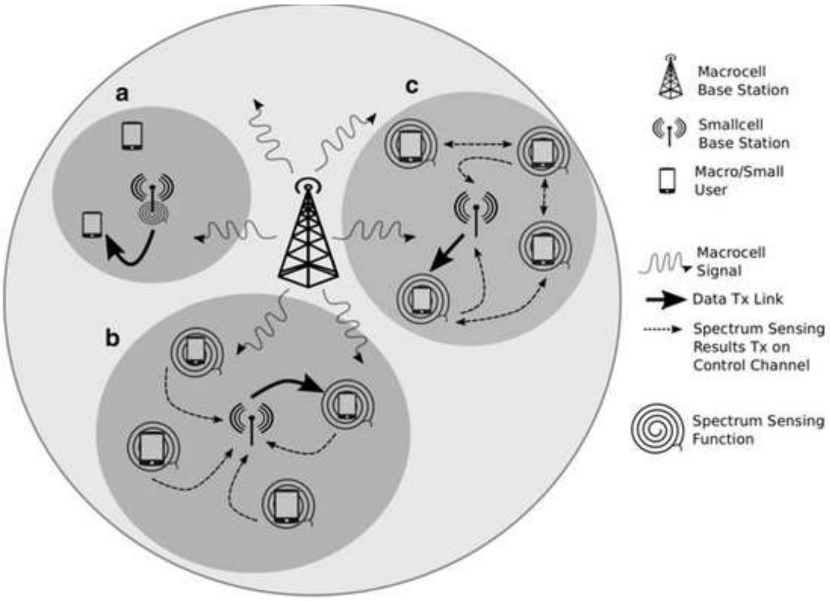

Fig 3 : Issues, Challenges, and Research Trends in Spectrum Management

4.1. Key Issues in Spectrum Management

To understand the challenges in physical layer spectrum management, consider the implications for the overall system. The critical question here is what decisions the various entities in the control plane should make about the assignment and coordination of spectrum management tasks. Several issues arise from such considerations. The first issue of fundamental importance in wireless networking revolves around self-management versus third-party management. In wired networks, the operating system depends on a centralized management system in most cases. Centralized management is common also in wireless ad-hoc networks. However, for wireless mesh networks, although still in the development stage, the most efficient in terms of resources seems to be a self-management approach complemented by centralized management. A decentralized and self-managed approach is also well suited to community mesh networks, where local management services can be complementary support created by volunteer users of the network.

This fact finds evidence in the interest shown by various companies for the deployment of unlicensed mesh systems that manage resources autonomously from a central authority for local access. The debate is still open. However, all the future scenarios for 5G and 6G networks assume cellless concepts, which would thus seem to facilitate self-management. Indeed, multiple actors will have to coexist in future networks with different types of business models. Dynamic spectrum access policies permit opportunistic use of poorly occupied frequency ranges. Thus, the coexistence of a large number of potential users and controllers makes dynamic spectrum access for the management of the allocation and coordination of spectrum management tasks through different interfaces and criteria during runtime, becoming a key aspect for future networks. As a consequence, it also appears that it will not be easy to define the amount of regulation and/or the incentives required for a decentralized approach that may work in the long run.

5. NEURAL-SYMBOLIC HYBRID MODELS

In general, hybrid systems combine the best features of symbolic and connectionist systems, enabling the former's reasoning skills and the latter's learning abilities. Bridging the gap between numerical and linguistic knowledge representation and reasoning are neural-symbolic hybrid models that combine neurocomputing methods with symbolic knowledge representation systems and reasoning methods. Key components of such systems are a symbolic knowledge representation formalism and related reasoning methods able to compute logic answers to queries efficiently and a neurocomputing model that can efficiently learn the parameters of a logic program representing knowledge on a specific application domain.

There are many reasons why developing neural-symbolic hybrid systems can be beneficial in artificial intelligence, especially natural language processing and computer vision applications. Traditional neural systems are capable of providing only soft answers when computing the output of a neural network (i.e., the output of a neural network about a sample being or not being classified in a target class, which is normally a number between zero and one). Thus, they are not designed to provide decisions that can be interpreted and justified. In contrast, traditional symbolic systems may be too demanding in terms of both reasoning speed and the amount of user knowledge, which may be lacking or difficult to specify in complex tasks. Furthermore, they are built manually and do not benefit from the ability of neural systems to learn from data, particularly in cases where it is too complex to build a symbolic knowledge representation of a given task. Finally, current hybrid models integrate rules and use supervised learning to minimize the difference between their soft answer and a known expected one.

5.1. Definition and Components

By neural-symbolic hybrid models, we mean models in which the relationships among some or all of the central components are given in a symbolic format, while the components take the form of neural networks. Therefore, by composition of neural and symbolic relationships, we create a new class of models in which both neural and symbolic parts take place. Within a hybrid model, different kinds of relationships may occur: a combination of a neural network with a symbolic input/output mapping, a neural network with symbolic linking relationships, hybrid relationships for both inputs and outputs, hybrid relationships for linking modules, and a symbolic module localizing a certain neural network. If not specified otherwise, we will use the term hybrid models to denote those with hybrid linking relationships or relationship linking modules. As a symbolic layer, we generally use a set of logical expressions or rules, as it is commonly done in the frameworks of symbolic logic programming for inductive logic programming or ontological knowledge representation. By themselves, logical expressions or rules do not form a layered structure, by which we mean that they do not describe an emphasis on a certain property or aspect of the relationship. However, lots of additional symbolic structures can be overlaid on these rules for a certain task, or a task can be specified by using additional properties of logical mapping or training, as we did for different tasks in the context of relational data. Therefore, from the modeling point of view, this kind of symbolic representation can be considered a relatively basic one, and by comparing different types of hybrid architecture used to build the model we find the growing level of layered symbolic representation as one of the increasing levels of hybridization about neural only or symbolic only models. The output of a purely neural model contains the vector of predictions for the learning task.

5.2. Advantages over Traditional Models

Subsequently, we give an overview of the advantages that Neural-Symbolic Hybrid Models have over traditional models and also the implications of using them for novel, yet important, challenges, such as the design of algorithms for Adaptive Spectrum Management in a 6G-Ready Networks. As already discussed, Neural-Symbolic Hybrid Models introduce meaningful inductive biases, expressed in the form of symbolic rules and relations, directly into the learning and representation processes, enabling a data-efficient and modular development of novel solutions for complicated tasks. The ability of the Neural-Symbolic Hybrid Models to constrain the learning process by adding relational bias into the ultimately learned relations is very promising for alleviating the data-hunger and data-inefficiency of Neuro-Inspired and Neural Models – in particular, of the DNNs and Deep Reinforcement Learning methods. When these are data-hungry, it may be hard or impossible to collect sufficiently large amounts of annotated data, or the annotation of the training dataset is too expensive to be affordable. Therefore, the generalization performance of DNNs and DRL methods learned on relatively small training data can be very poor, or upon deployment/test, the models can behave in an unreliable way, which may hinder the practical usefulness of such solutions based on DNNs/DRL methods. The above challenges can be alleviated via Neuro-Symbolic Hybrid Methods and other similar approaches, which try to leverage the advantages of learning from data via Neuro-Inspired Models and the advantages of encoding Symbolic Knowledge in the Symbolic Models, with the ultimate goal of improving the performance of pure Model-Free Learning.

Another advantage of the Neural-Symbolic Hybrid Models is that they provide a sophisticated and human-readable representation of the relationships between the variables/features. Consequently, these models might be appropriate for improving the qualitative understanding of the relationships between the variable features. The qualitative understanding of the relationships between the structure and some interesting features of the problem, is extremely important in many fields of science, including wireless communications, data science, energy efficiency, and environmental science, among many others.

$$U_s = \frac{R_b}{1 + I_c}$$

Where

U_s: Spectrum Utility

R_b: Achievable Bitrate

I_c: Interference Cost (aggregated from nearby allocations)

Equation 2 : Interference-Aware Utility Optimization

6. ADAPTIVE SPECTRUM MANAGEMENT TECHNIQUES

To dynamically and autonomously determine and optimize the spectrum allocation, modern cellular systems must be able to incorporate local information from end users and local administrative units to design the use of the spectrum according to the actual needs. For this purpose, some spectrum management models have proposed that private microwaves should be limited by the providers of these services. A new approach is considering microcell systems using the plant operated by the operator and asking it to share a small part of its spectrum. This idea would make it possible to put into play a small part of the broadband—telephone, for loading services during acute peak risk and for local use. The mechanism suggested is to pay the operators for using microwaves or compensate in kind, the concession to use the microwaves locally for all the services that they solicit.

Dynamic models for shorter prediction time intervals should also be developed for the dynamic management of the knowledge base. This is a statistical parameter-related algorithm that should use different adaptive mechanisms to update the knowledge system at a different speed. Adaptivity can be achieved in different ways. Adaptivity should occur on user loading changes, the use of the system probing, the corridor used by a user, the total average delay or the total average blocking, or the delay and blocking of the subsystems or the alternate corridors. These models should be then implemented in fuzzy decision-making systems based on dynamic spectral load indices to schedule the spectral use. Static fuzzy decision-making should be employed to access the infantilization of the bus connection in cellular systems with mobile services and lower error recognition coefficients. This system should be used to identify the busy segments and to ask the distributed users of the system to switch to a different bus segment without establishing a new connection to obtain lower transmission errors.

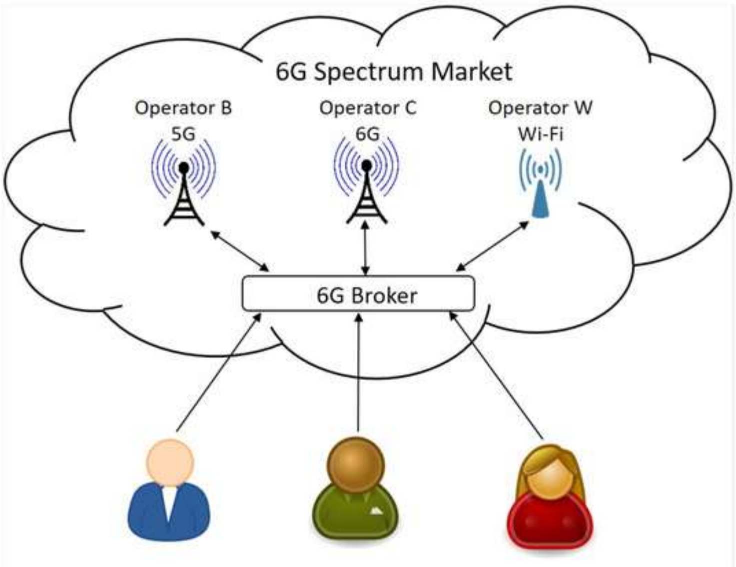

Fig 4 : Spectrum Management Platform Architecture

6.1. Dynamic Spectrum Allocation

In current wireless networks, static spectrum allocation models are employed for the promulgation of the demanded services. Frequency reuse techniques are utilized in cellular networks to provide the desired communication. This technique has operated for decades. However, despite its obvious advantages, the frequency reuse models employed today lead to an under-utilization of the available spectrum resources. This is because the provisioning of service requires more spectrum in some locations than in others, and the spectrum demand at various geographical locations does not necessarily share the same trends in time across all frequencies. Add to that other wireless systems and their influence on the network receivers through unwanted interference, and the result is that the challenge of interference has only increased over the years.

Imposing frequency reuse in heavily populated urbanized areas yields an increase in the energy emitted by neighboring cells. Therefore, a significant concentration of emissions inevitably leads to serious interference problems. Moreover, electromagnetic compatibility with other radio systems exploiting the same geographical location but differing in emission characteristics becomes even more critical. Thus, the dynamically controlled availability and sharing of spectrum resources according to the demand of service at the moment and in each area for all radio systems legitimately authorized to operate can be considered the most advisable solution for avoiding harmful interference and latent incompatibility problems. It offers an efficient method to re-establish compatibility conditions between mobile radio systems and the environment in which they operate. In addition to the technological and architectural solutions proposed and developed to favor the adaptive management of radio resources, information theory, and neural symbols have also been addressed.

6.2. Interference Mitigation Strategies

Interference mitigation methods are designed to alleviate the adverse effects of network interference on concerning users. Such techniques may take place on a per-user basis or in the network planning phase where related performance profiles are reconsidered. In contrast to dynamic spectrum allocation methods which require that a decision on spectrum resource allocation is taken by the operator on demand, these types of approaches use the assigned spectrum resources to enhance or restore the performance of users feeling the impact of nearby services.

An obvious but at the same time imperfect approach to ITM is power limitations. All wireless links are subjected to the Friis free-space equation which translates how far the signal travels in open air. Hence, in locations close to the transmitter, the received signal power is always stronger than the one received by users behind a larger distance. The closer the receiver users are to an active transmitter, the easier the interference generated to those users suffering from its influence can be controlled. In any case, the base station transmitting to a user falling in an area requiring power restrictions must lower its power output so that it does not affect others. Obviously, in addition to the actual power output limits, the effect of fading and natural obstacles changing the radio channel must also be considered. Radio network planning tools have been adopted for many years.

A more sophisticated approach to the problem is the use of directional antennas. This is the philosophy on which beamforming relies: by increasing the transmit antenna gain in the direction of the receiver, it is possible to increase the level of the received signal without raising the power output thus reducing the impact caused on those receiver users under the influence zone of the transmitter. Adaptive Beamforming as part of MIMO spatial diversity, is a technology already available in pressure environments and some commercial equipment.

7. IMPLEMENTATION FRAMEWORK

Building on the design principles that emerged from the previous section, we identified four common elements across the hybrid spectrum-related models we've envisaged in this work, which guided our implementation and would pave the way towards more concrete, impactful future contributions, in addition to being a building block for all the demonstrative models built according to each of the use cases presented in this Chapter. These elements are: (i) An on-premise Neural-Symbolic computing framework capable of hosting novel Neuro-Symbolic Spectrum Management models for wired and wireless systems, that exploits a CNN for feature extraction from digital/wireless sample input data; (ii) A "walled garden" approach to data that allows different players involved in resource allocation for both wired and wireless systems to keep control of their domain-specific data, but still achieve a win-win situation in the long run; (iii) A mesh-centered two-layer resource optimization architecture for stuck issue identification, which combines a top-down approach, for error correction and high-level guidance, with a bottom-up approach for misguided low and high contention ratio movement; and (iv) A reliable implementable process that supports every stakeholder's effort towards further monetization via ours or other mature N-S technology's solutions on top of theirs.

1. Model Architecture

Our model architecture can be summarized in four steps. First, training data and input features are provided to the model, either measured or synthetic. The model then trains to learn residual errors that optimize the input features over the measured overhead, outputting a reversible function. During model usage -- i.e., due to normal operation or a fault -- the known input features are fed to the model(s) along with overhead measurements so that the mesh-centered model first identifies the high contention ratio cells, then the root cause. If a fault is then detected in the top layer, the bottom-layer model then disambiguates the cause. Finally, a decided action is taken to resolve the fault. The mentioned decision can either be manual or be performed automatically by the model; in the latter case, if the problem is more serious than expected, the higher-up layer then decides what action to perform.

7.1. Model Architecture

We present a comprehensive model architecture that brings together the neural and symbolic subsystem components in a modular, systematic, and scalable approach. The components of our architecture can also deliver more complex aligned, symbolic, and symbolic-numeric insights when the approach is iterated. The modular approach is flexible and can be easily adapted to accommodate the problem that needs to be solved and the data that is available. Exposing increased complexity iteratively on need can manage resource contention and satisfy complexity and computational efficiency trade-offs. Our proposed architecture supports our key mobiles of Symbolic Learning and Symbolic De-embedding, in addition to more traditional learning and output-decision approaches. Formally, we define 3 sets Si, Os, and P, iϵI. Set Si of source representations is defined for each source Si, which uniquely identifies the unique relevant, source input features. The output set Os has the same dimensionality as the response variable. Each output is a numeric constant corresponding to template matching optimization and execution; the Po constants correspond to optimization constants corresponding to the functional control approach. P represents data and problem-specific numerical and symbolic variability. The content and dimensionality of Si, Os, and P depend on the data available and can vary for different input samples. This allows us to manage complexity and resource contention. P can be determined from a subset of examples and be included in the pre-processing transform until the predictive performance satisfies the desired specification. The individual modules can be developed and tuned based on simple performance heuristics, without solving the full inverse optimization problem each time. The methods can also unpack complex mappings down to simpler data-specific mappings, allowing efficient, customized exploitation for specific input data distributions which can further improve performance.

7.2. Data Integration and Processing

Automated data acquisition from different sources and at different time granularities is necessary to fulfill the solution requirements in terms of real-time decision-making and generalizability. Federation of distributed microservices, either provided in Cloud or Edge computing, is the most natural solution. The required data acquisition, fusion, storage, processing, normalization, and enrichment must be carried out autonomously by the proposed N-ISH. Data normalization is crucial since data coming from different sources can be sampled at different locations and time instants. Data collected for the same spatial locations at different time intervals can introduce significant noise due to the time-varying nature of the wireless propagation channel.

Because of the heterogeneity of the acquired data in terms of variables, measurements, time stamps, and space locations, a well-planned architecture is necessary to permit precise and effective smart decision-making with prediction models. The data integration layer is responsible for harmonizing data collected from distributed agents on the N-ISH. Such microservices have the role of collecting and sending back their measurements, which can include RF beacons, CN/USER positioning trackers, UAVs RPCI maps, SONs KPI measurements, user facemask images, and footprint root analysis. Microservices are associated with an optional data normalization/processing step, and a redundancy elimination step, where built-in filters would get rid of repeated or similar data.

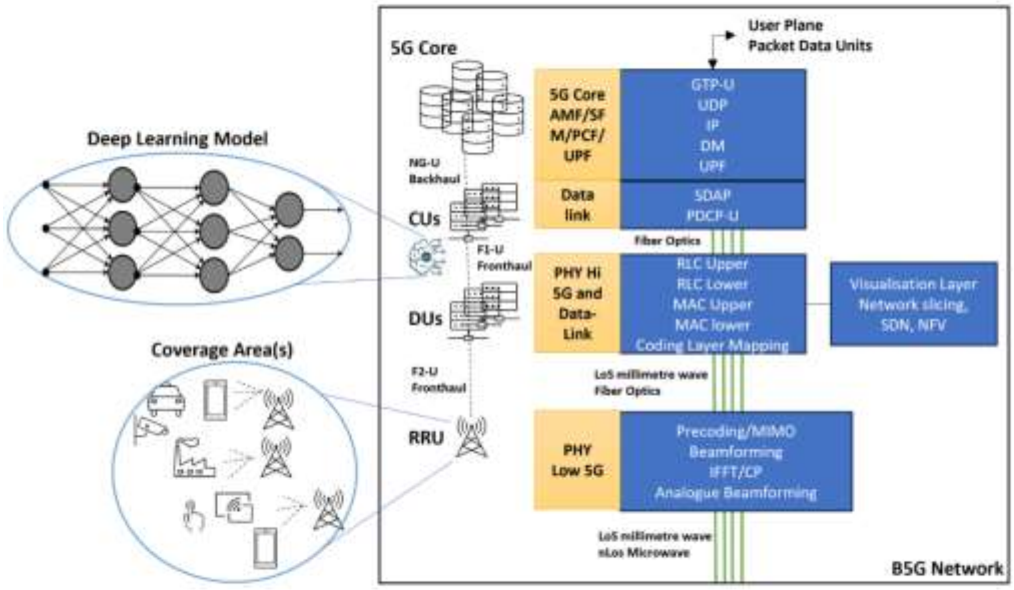

Fig 5 : Advanced Security Framework for 6G Networks

8. EVALUATION METRICS

To assess the effectiveness of our self-adaptive approach to spectrum management, a set of performance indicators is considered, ranging from the evaluation of the network to the end-user application, namely, the IoT-enabled video surveillance system. In addition, the results are benchmarked against existing solutions, allowing us to contrast the performance of our approach with those found in the analysis. The analysis conducted reveals the strengths and weaknesses of our self-adaptive approach and shows the trade-offs between performance and complexity in deploying Neural-Symbolic Hybrid Models for Adaptive Spectrum Management in 6G-ready Networks.

1. Performance Indicators

The performance indicators concerning the network are the end-to-end packet delay, which results from summing the queuing delay and transmission delay incurred by the packets generated by the IoT devices and the packets generated by the scheduler to convey the data gathered from the IoT devices to the control center, and the packet delivery ratio, defined as the ratio between the number of packets successfully delivered to the control center and the total number of packets generated by the network during the same time, that is, the duration of the replicant frames of the Neural-Symbolic Hybrid Model. Also, to assess the disruption perceived by users not serviced by the AP in the overlapping Basic Service Set with the network, we estimate the average packet delay of a video stream considering a codec, defined by: $td = b/f * (5 + 2 + 1) + 0.5$, where b and f are the encoded video bit rate and frame size, respectively, and t is the average packet delay. Since the largest task in 6G Network Slicing enabled networks will be that of transmitting high-definition video streams, it is safe to assume that for a 40 Mbps video stream, the average packet delay is about td = 80 ms.

8.1. Performance Indicators

The groundwork for assessing adaptive strategies rests in a coherent definition of performance metrics. A common criterion used in the literature assessing one or several UEs within its considered region is the capacity achieved across the considered duration. While simple to compute, this criterion is sensitive to situations where a very low capacity is achieved for a UE during a short period. This can easily happen in practical designs, especially when dealing with Q-Learning, where training is usually related to a long time window until the exploration of the space of actions is limited. An alternative approach selects a variant of the utility defined by weight functions that depend on the UE demand and not on their QoS. To be more precise, it adopts a utility defined based on the data throughput within the specific time slot.

A more general formulation is to select an overall utility that depends on the situation of each UE, in terms of its throughput, characteristic function, and demand, as follows. In its essence, users with violated QoS requirements generate penalties for the system, which decrease both for satisfied users as the QoS increases and for all UEs as more users enter the region. In this work, we employ utility functions of this type shaped according to proposed ratios of 10% for the most quality-sensitive 40% of the demands, 20% for the next 30%, and a flat ratio of 1 for all other users. In this way, a large significance can be given to small QoS violations for the users requiring the highest QoS, and extra penalties will be incurred while the demand threshold for entering the regions is crossed.

8.2. Benchmarking Against Existing Solutions

Nevertheless, despite all the previously discussed advantages in accuracy, time-convergence, and time efficiency, the deployment of the NSHMs over networks deployed in the field will still require to be configured for long-term performance, which competes with existing state-of-the-art, adaptive AI-based methods. For a lab setup with a NOMA scenario with a Downlink-NOMA deployment, we perform the comparison using a path loss model, where we compare the performance of the proposed NSHM models with our previously proposed AI-based, fully-Supervised and Reinforcement Learning based solution at a low-time convergence setup, in optimizing by following a Q-learning approach the network throughput, the jammed cell throughput and the jammed user throughput optimizations, FP and FP-RL methods. The performance for the architectural comparisons is obtained by using the same training dataset, the same tuning parameters, and the same test point for each method. The architectural variations for the proposed NSHM model utilized during these simulations include the Number of Neurons in the Hidden Layer and the activation of the Hidden Layer Neurons. For the Bayesian, Hybrid- and NSHM- Solution, we also evaluated 16 and 32 hidden neurons. For the Bayesian-Behaviour solution, we only evaluated, due to RAM limitations, the 8 Neuron one. Second, we are measuring the percent error for the defined network throughput, jammed user throughput, and throughput of the jammed cell.

With the proposed method in Lab-1, we report a speed-up factor of about 10,218X at a 15.95% throughput capacity measurement and 47,033X latency-simulation time factor at a 12.25% throughput capacity from the proposed AI-NOMA Solution. This makes Bazel-NOMA a true contender against existing solutions and able to be utilized in heavy computation scenarios.

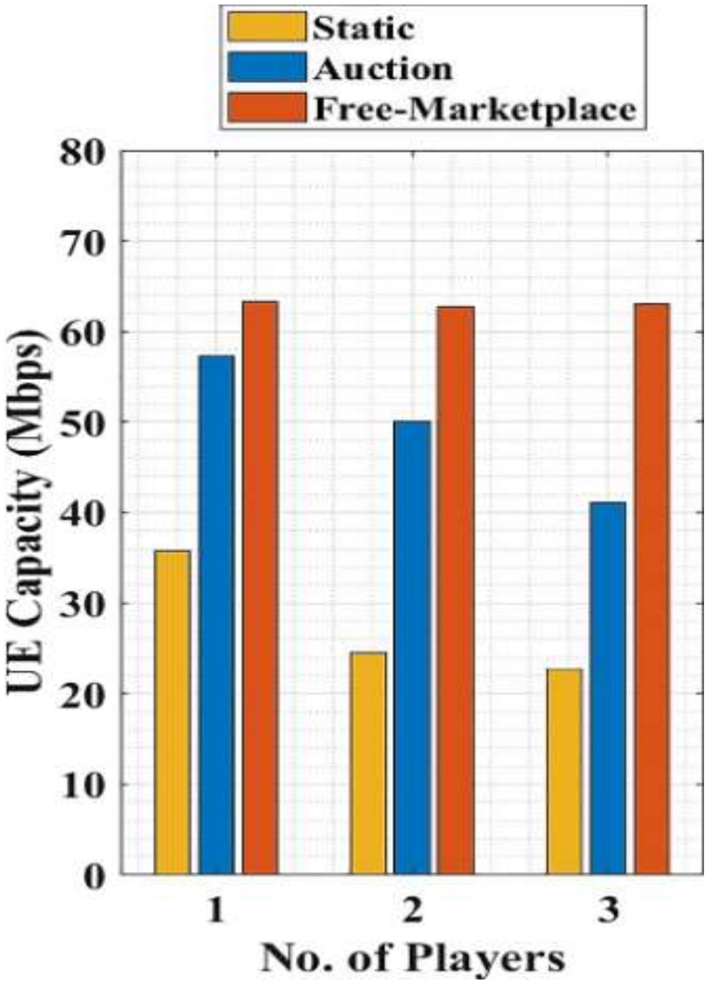

Fig 6 : Smart contract implementation on network sharing for 6G wireless networks

9. CONCLUSION

To fully capitalize on the technological breakthroughs expected from the sixth generation of mobile networks, future wireless service providers have to look to integrate and exploit the latest advances in artificial intelligence tools and technologies. These solutions must be specialized for future telecommunications. Not only must these solutions be tasked with meeting the expected growth in capacity requirements, and ensuring the ultra-reliable low-latency communication goals for advanced use cases, but also minimize the energy consumed in delivering the wireless services. This over-use of the radio spectrum has caused the emergence of a new malady of the information age, that of increased radio pollution, which has been directly correlated to a host of both physical and mental health issues among the world's population.

Despite the rich potential offered by AI and machine learning, the successful deployment of these tools for telecommunications-related tasks has remained limited, mainly because of the "data-hungry" nature of these solutions. The few successes reported so far relate to applications that are history. Moreover, any such old solutions cover only a narrow aspect of the tasks to be performed by the future wireless networks. For addressing the challenges of providing the next generation of telecommunication services, neural-symbolic computing paradigms, that allow expert knowledge or information to be integrated into the data-driven neural network solutions, must be looked to. The hybrid models proposed offer efficient solutions that are interpretable, less data-hungry, generalize better to unseen conditions, and are more stable. Such hybrid models may therefore be looked to for future practical use in the adaptive management of the radio spectrum but also networks.

$$\theta_{t+1} = \theta_t - \eta \cdot \nabla_\theta \left(\mathcal{L}_{NN} + \lambda \cdot \mathcal{L}_{logic} \right)$$

Where

θ: Model Parameters

η: Learning Rate

$\mathcal{L}_{NN}$: Neural Network Loss (prediction error)

$\mathcal{L}_{logic}$: Logic Consistency Loss

λ: Regularization Term for Symbolic Consistency

Equation 3 : Adaptive Learning Update Rule

9.1. Final Thoughts and Future Directions

The following exemplary customized processes and methods lay the foundation for future work. We will consider systems in more complexity: full-duplex radios rather than half-duplex radios, richer multi-user and multiple-input-multiple-output scenarios, and systems in areas of moving people and with passengers onboard vehicles. Sufficiently finite target statistics about the resource demand by communications users will not be available but only its shape will be known: communications usage will be self-similar but its traffic will have bursts of random enough dimension. The proposed neural-symbolic architecture will also include optimization engines based on correct sufficient statistics of the traffic shape rather than scalars informing about its average. The probabilistic interference forecast-based system at the neural level will allow for the online solution of a clusterization problem and, above all, the continuous learning of the nodes and edges of the network of potential information exchanges rather than for a one-time learning process (depending on the users of the traffic forecast window). This online learning is possible given the capability of bi-dimensional and higher-dimensional sensor nodes to make use of relative positioning techniques thanks to their increasing miniaturization.

Furthermore, compared to the current distributed node-based adaptive resource management based on measures allowing inefficient and uncoordinated local decisions, the use of a probabilistic teaching tool at the neural level will allow the learning of a centralized–-distributed control architecture for resource management (possibly hierarchical or at different time scales). Given its feasible implementation, the proposed neuro-symbolic architecture opens up new avenues for the efficiency of the design and implementation phases of 6G networks. This paves the way to the realization of user-driven and software-defined networks, in the vision of the Internet of the future

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