APPLICATIONS OF AI AND DEEP LEARNING TECHNIQUES TO COMMUNICATION SYSTEMS

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Abstract

Theincreasingnetworkdensityandunparalleledincreaseinnetworktrafficinducedbythe constantly increasing number of connected devices and online services necessitate intelligent network operations. The 5G and beyond 5G networks are being developed with various artificial intelligence techniques to provide higher data rates as well as better coverage, cost efficiency, security, adaptability, and scalability. A.i.(AI) has made remarkable advances in a wide range of fields, including speech processing, image classification, and drug discovery.In order to fulfil the demands of future communicating devices and services, machine learning (ML) has been used in various kinds of networks and networking technologies. In this article, we provided a complete survey of recent applications in communication systems and further discussion of challenges and future research directions is alsocovered.

I. Introduction

With the exponential increase in data and the continue to focus on improving of methodologies (e.g., deep learning), as well as the step-change improved performance of computing resources, artificial intelligence (AI) had also achieved breakthroughs in a wide range of applications, including language processing, image classification, and reinforcement learning [1]. AI is expected to have a significant impact on many vertical industries as well as our daily lives, such as intelligent transportation systems and haptic robots. Furthermore, it is predictedthatAI willaddapproximately16%,or approximately$13trillion,toglobalGDPby 2030whencomparedto2018[2].By2021,itispredictedthatallpeople,machines,andthings will generate nearly 85 Zettabytes of usable data, which will outnumber cloud data centre traffic (21 Exabytes) by a factor of four[3].

Furthermore,delay-sensitiveintelligentapplicationssuchasautonomousdriving,malware control mechanisms, and robotics necessitate rapid data processing [4]. Such exceptionally high internet speed and low latency requirements would put unprecedented strains on traditional cloud-based AI, in which massive sensors/embedded devices send collected data to the cloud often under varying network conditions (e.g., the bandwidth and latency) [5]. Futuristic wireless systems are primarily composed of ultradense edge nodes, such as edge servers at base stations and wireless access points, as well as edge devices[6].

Artificialintelligence(AI),ontheotherhand,hasbeendevelopedto"mimichumanintellect proceduresbymachines,particularlycomputersystems."Machinelearning(ML)isanoffshoot of AI that allows machines to learn from massive amounts of data and make judgmentsand/or perform actions without being given specific commands [7]. ML techniques have achieved great success in big data processing for many applications, such as image processing, natural language processing, and data mining, thanks to ever-increasing computing power [8]. As a result, ML techniques have been widely applied to a variety of problems in communications networks, and they are expected to be an integral part of next-generation communications systems[9].AmoredetaileddefinitionofAI is"atechnologythathasthepotentialtocorrectly interpret external data, learn from such data, using such learnings to achieve an objective and tasks through flexibleadaptation."

As a result, AI researchers are attempting to create intelligent agents in order to reach this aim. ML is a subset of AI that analyses algorithms computer programmes to improve themselves automatically through experience. ML can be divided into three types: supervised learning, unsupervised, and reinforcement learning. Deep learning (DL), a subset of ML, has received a lot of attention in recent times. The main difference between traditional ML and deep learning is how training data is used. Furthermore, deep neural networks (ANN) are the foundation of DL algorithms, whereas learning machines in traditional ML vary and are not limited to ANN [10].

Convolutionary Neural Network (CNN), Boltzman Machine (RBM), Long Short-Term Memory (LSTM), and other deep neural network (DNN) structures are widely used. With the no theorem, DL necessitates significantly more data and computing resources than traditional methods. Recognizing the concepts of AI and ML, a proper question is how AI and ML techniques can help with antenna and propagation research. The answer is that problems regarding must be formulated mathematically in order for AI/ML techniques to serve as solvers.ItshouldbenotedthatAI/MLmethodsarenottheonlywayofsolvingtheseproblems, but research shows that they have clear advantages over traditional methods, at least in certain circumstances. The mathematical problems addressed by AI/ML techniques are as follows: I regression, which identifies the relationships between such a dependent variable (i.e., output data) and one or more self reliant variables (i.e., input data); ii) classification, which uses a set of training data for which the feature and category membership or label is known to identify which of a set of categories a new instance belongs to; and iii) clustering, which naturally groups.

II. Over view of AI and ML in communicationsystems

O. Simeoneprovides an introduction to machine learning with applications to communications networks, in light of recent developments in the field [11]. The article covers the fundamentals of machine learning, with a focus on supervised and unsupervised learning, as well as how to apply machine learning to the physical layer at the edge and cloud computing.

X. Wang et. al. discusses the state-of-the-art techniques, as well as the challenges and opportunities of using ML in Hybrid Networks (HetNets) [12]. They describes machine learning-based techniques for smart HetNet systems and infrastructure, with a focus on self-configuration, self-healing, and self- optimization challenges. J. Wang, C. Jianget. al. discusses the history of machine learning (ML) over the last 30 years, as well as an outline of its applications in wirelessnetworks [13].

M. Wang et. al. explains how to apply machine learning to networking and provides a basic workflow with several steps [14]. The article focuses on measurement techniques, prediction, andtimetabling forconnectivityusingMLandsheds lightonrecentdevelopmentsinthefield. It also discusses the use of machine learning, specifically Artificial Neural Networks (ANN), in wireless networks. The article by M. Chen et. al.is a tutorial in nature, and it gives a detailed description of ANNalgorithmsandhowtheycanbeusedtosolveproblemsinwirelesscommunications [15].The use of various types of ANNs in Unmanned Aerial Vehicles (UAVs), cordless virtual reality, MEC, spectrum management, and the Internet of Things is discussed in detail. However, the physicallayeristheprimaryfocusofthelayered networkarchitecture.Nachmaniet al.(2016) propose a new approach for channel decoding that uses a "soft" Tanner graph based decoder. Theparitycheck matrix(expert knowledge)isusedto buildthenetwork[16].Forhighdensity parity codes, a well-trained network could help improve the performance of the belief spreading (BP) heuristic (HDPC). By properly weighting the reliability of the message, the small cycle effect can be mitigated and the approximation error can be compensated for in the mean time by adopting the min-sum algorithm[16].

C. Zhang et. al. presents a case study on government Deep Learning (DL) for mobile networks. The authors give a brief history of DL before delving into its application in mobile networks [17]. The article is worth reading because it provides insights into tailoring DL concepts for mobile networks as well as future research perspectives. The rest of the paper is divided as follows1)Introduction,2)OverviewofAIandMLincommunicationsystems,3)Background on AI and ML in optimization of Current networks, 4) Background on AI-ML in optimisation ofcurrentnetworks,5)AI-MLbasedapplications,6)Futureresearchdirections,7)Conclusion

III. Background on AI-ML in optimisation of current networks

Due to the obvious benefits of intelligent network operations, several studies, including survey articles, are available, as shown in Tables 1 and 2. As shown in Tables 1 and 2, the majority of the articles elaborate on AI and ML concepts and techniques and Table 3 summarizes the commonly used ML methods

TABLEI. Applications of AI and ML in communication networks

Publication Year	**Main focus of the article**	**Scope of limitation**
2020 [18]	It elaborates on the most significant roadblocks in AI4NETS and present a research agenda to address some of these issues, allowing for the natural adoption ofAI/ML for networking.	Doesn’t focus much on the limitations of AI4NETS to target the next wave of AI and ML in networking
2020 [19]	This article provides some background information on the proposed network customization technology and its accomplices.	The overall efficiency and the quality of output solutions for a fixed amount of resources canbe improved

2020 [20]	The survey covers a variety of topics related to wireless network design and optimization, such as channel measurements, modelling, and estimation, physical layer research, and network managementand optimization.	Discussion of challengesand potential future research directions aren't discussed in detail
2022 [21]	The use of (AI) (ML), inthe study of wireless propagation channels.	Demonstrates the early results of the experimentations.

TABLEII. Application of AI and ML in recent communication trends

Publication Year	Main focus of the article	Scope limitation
2020 [22]	An overview of machine learning techniques in wire-free networks	There was very little discussion of novel ideasand the issue of latency.
2020 [23]	A survey of machine learning techniques for edge and cloud platforms	Limited to ML in MEC platforms
2020 [24]	Data Driven optimization using ML	More focussed on Big data analytics
2020 [25]	An examination of federated learning in MEC platforms	MEC platforms only have limited discussion and surveys.
2020 [26]	White paper on the role of machine learning in 6G	There has been little discussion of existing technologies.

TABLEIII. Summary of ML-based communications applications

Category	Typical Algorithms	Applications
Regression (Supervised learning, unsupervised learning, Meta learning, Re-enforcementLearning)	Support vector Machine, Relevance Vector Machine, Artificial neural network, Bayesian learning, Boltzmann exploration algorithm, Deep transfer based learning algorithm.	ChannelParameter estimation Channel Characterization or modelling Channelprediction
Classification (Supervised and UnsupervisedLearning)	Support vector Machine, Relevance VectorMachine	LOS/NLOS identification
Clustering(Supervised and Unsupervised Learning)	Hidden Markov Model, K nearest neighbour, Fuzzy C means	MPC cluster identification LOS/NLOS identification

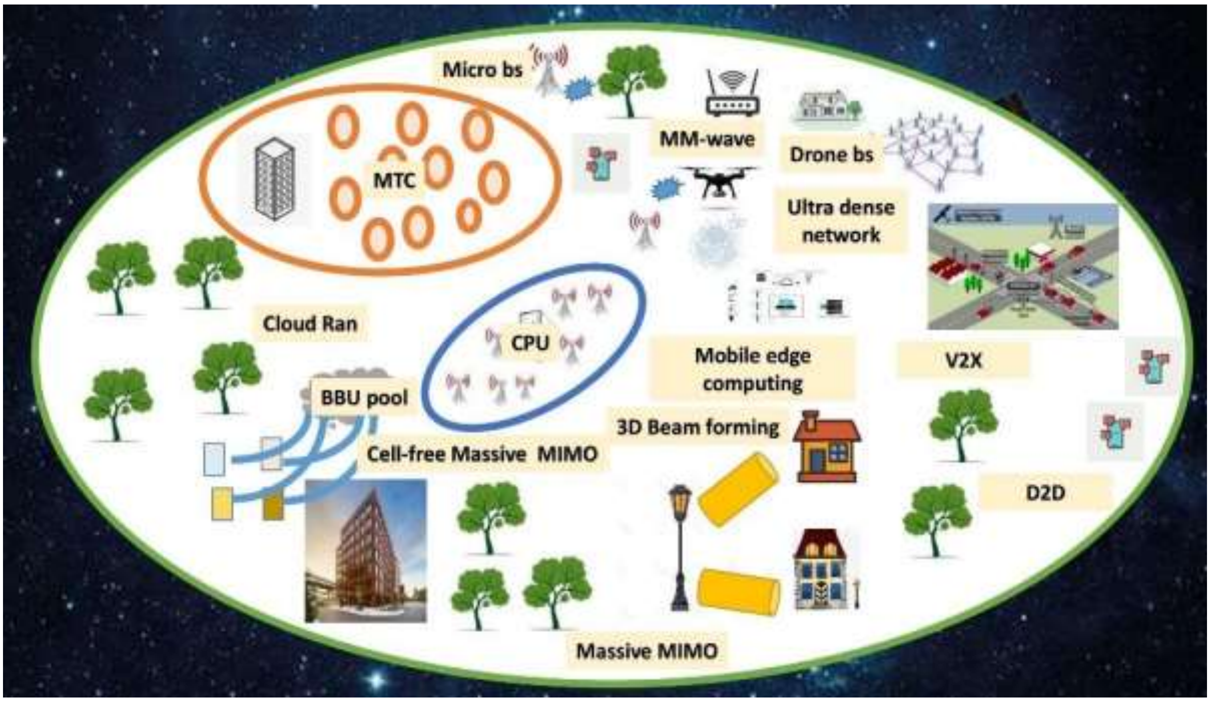
IV. AI and ML for Next generation wirelessnetworks

A single infrastructure in a customer next-generation network must conveniently and efficiently provide various types of services including enhanced mobile broadband, ultra- reliableandlow-latencycommunicationservices,andmassivemachine–typecommunication systems. It should also allow for simultaneous access to multiple standards, such as 5th generation (5G), long-term evolution (LTE), and Wi-Fi. It should also coordinate a diverse network types of ground stations (BSs), such as macro, micro, femto, and pico BSs, as well as various user devices and applications.

The challenge for a network operator is to efficiently operate a network capable of supporting such flexibility while meeting the demands of diverse services [27]. Furthermore, network operators face significant challenges in expanding their coverage and meeting ever- increasing capacity demands with a limited pool of investment and lack of resources such as spectrum. As a result, one of the primary concerns of network operators in terms of reducing operational expenses has been the mechanisation of multiple stakeholders and functions of cellular networks.

Fig.1. Graphical approach of future communication networks

With some technological elements, a graphical example of next communication network is shown in Fig. 1. Operators have always optimised their networks, but even presently,thesoughtandreceivedistoindependentlyoptimisesolitaryperformanceindicators (KPIs) or an element within the network, thus using a limited number of data sources.



NetworkoperatorsprimarilyrelyonKPIsaccumulatedatvariouslocations/partsofthe network and make decisions using various data analysis tools. Network management and enhancement are still typically conducted on old/recorded data, which severely limits their capacity.Ingeneral,networkoperatorsjusthaveaccesstoamassiveamountofdatafromtheir networks andsubscribers.

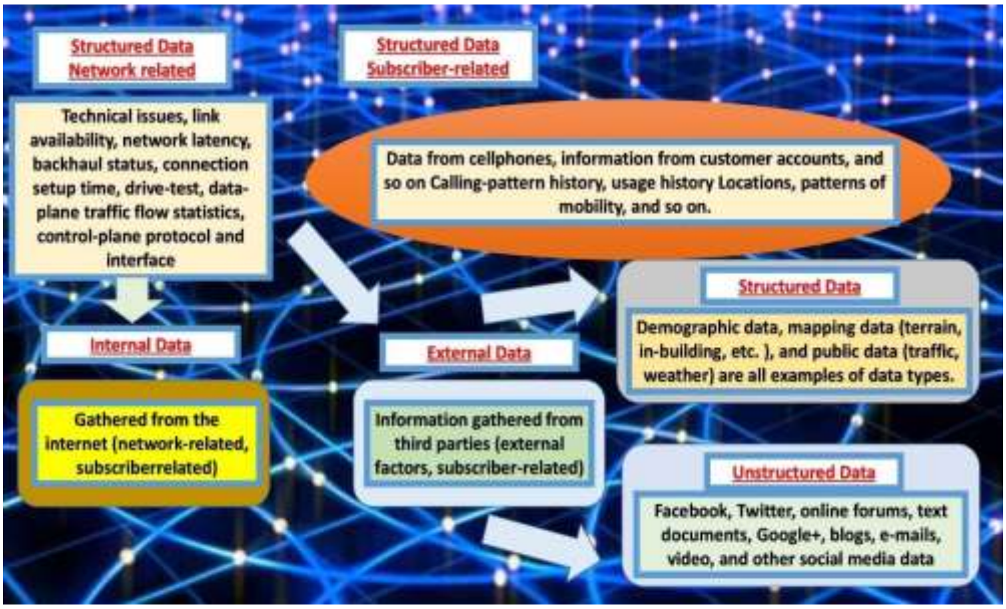


Fig.2. Data sets from sources for various technologies

For big data analytics, machine learning, and artificial intelligence, network operators have access to data sets and data sources in Fig. 2. Big data, when analysed properly, can convey a broader intuitiveness and comprehension because it pulls from multiple sources to reveal heretofore unrecognized patterns and correlations Analytics takes considerable work than traditional optimization because it broadens the multiple data sources, but it also offers a truly united and converged platform for innovation and organizational targets.

With the volume of data, the speed with which data flows in, and the variety and type of data sources, the network could go beyond prediction, i.e., it can facilitate and/or diagnose the operation & maintenance unit with decision options and the consequences of actions, and etc. Machine learning (ML) and artificial intelligence (AI) can assist in uncovering unknown propertiesofwirelessnetworks,identifyingcorrelationsanddiscrepanciesthatahumancannot see through inspection, and suggesting novel ways to optimise arrangements andoperations.

Althoughusingbigdataanalyticsforwirelessnetworkcontrolandoptimizationisvery appealing to network operators, it does come with some challenges.The process of managing and utilising massive amounts of data, designing methodologies for effective and flexible processing of large data sets, and then leveraging the insights from data analytics in networks can all present uniquechallenges.

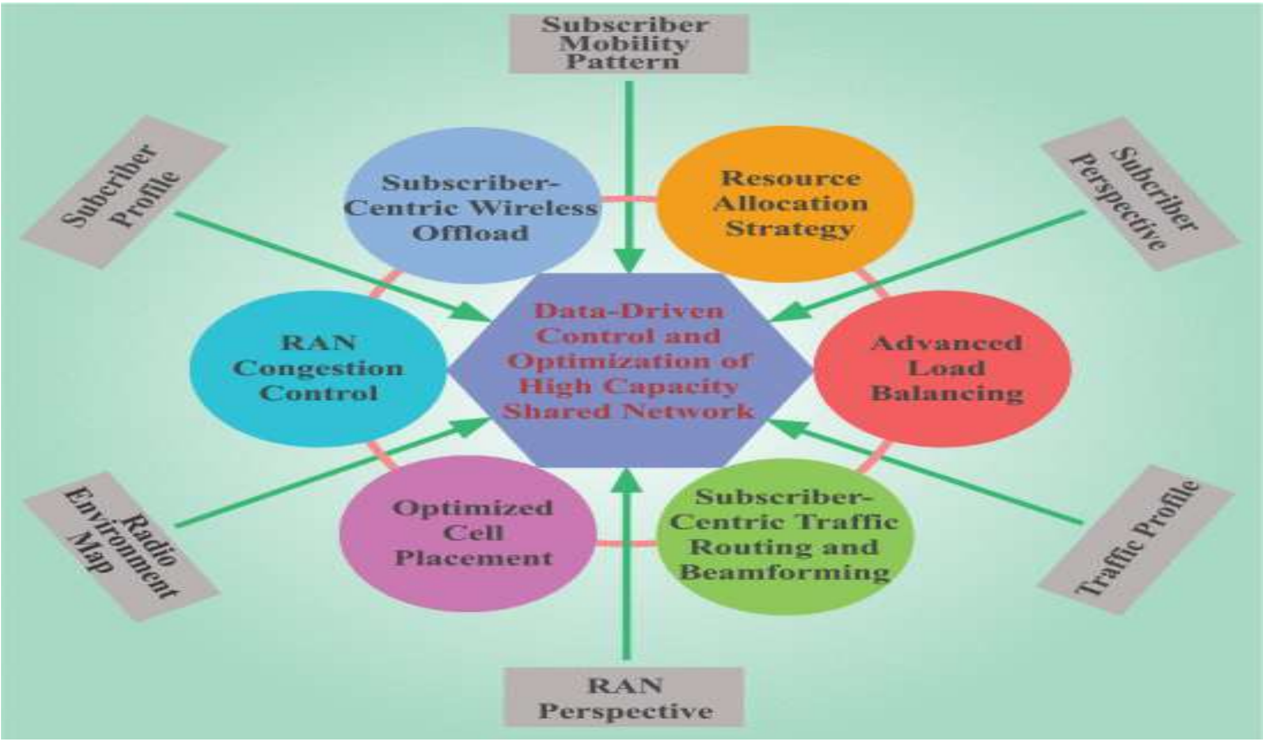


Fig.3. Application of Data anlaytics

A few data analytics and their applications in the next wireless communication system control and optimization in Fig. 3. The primary concerns for network operators stem from the amount of effort, skills, and labour needed to manage and start operating a big data platform. Even so, the most critical and difficult task is more likely to result from the network operators' continued direct control over the wireless network. Despite the challenges, network operators are more interested in data analytics platforms because the benefits outweigh the drawbacks.

Big data analytics improves the efficiency of service provisioning and end-to-end networkconnectivity.Analyticsaidsinthemanagementofsubscribersandtheimplementation of policies. It can assist network operators in implementing new traffic-handling techniques such as networkslicing (the method of slicing the network) and edge computing (i.e., the way to balance centralised and distributed functionality). On an overall basis the recent technologies could play an acute role in shaping communicationnetworks.

V. Communication based train control system using DeepLearning

Urban rail public transport systems are high-capacity modes of mass transit. To ensure thesafefunctioningofurbanrailtransitsystems,asafeanddependablerailroadcontrolsystem isdesired.Traincontrolsystems,built ontheprincipleoftraincontrolsafety, alsoimprovethe efficiency of rail transit operations. Train control systems have changed dramatically as communication and computer technologies have advanced. They are gradually moving away from Route Train Control (TBTC) and toward Communication-Based Train Control (CBTC) (CBTC).

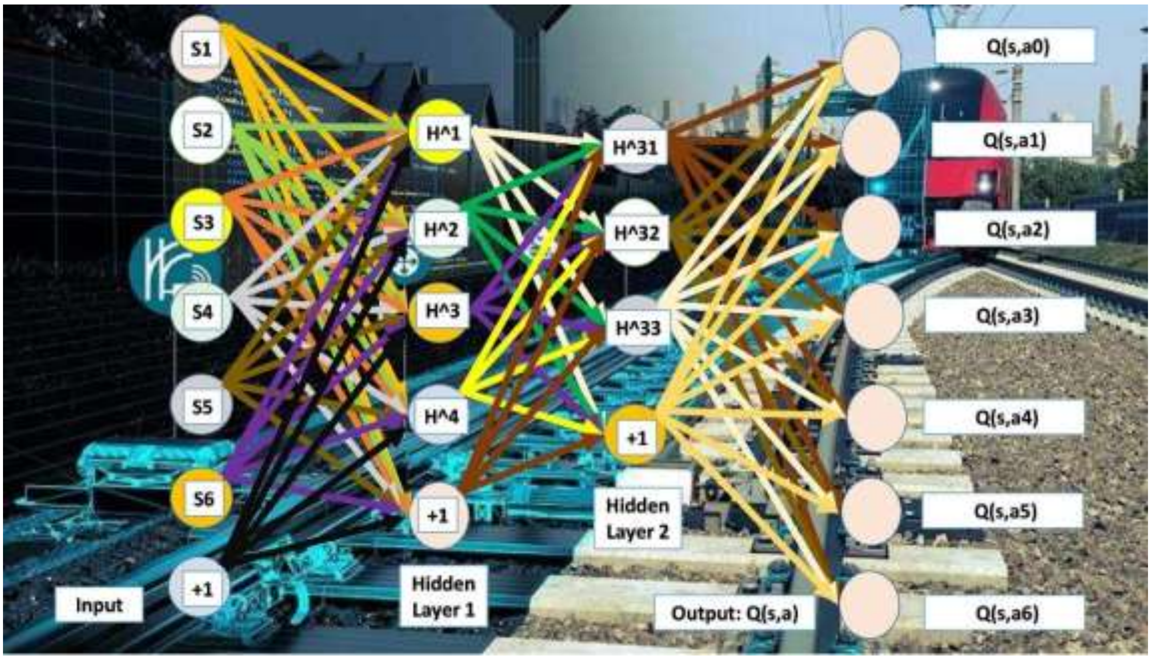


Fig. 4. Q-network used in the proposed application

Fig.4. shows Q-network used in the proposed application. Communication-Based Train Command (CBTC) systems are computer controlled train control systems that rely on bidirectional train-ground communications. CBTC is the future direction of train control systems[28].Complexchannelconditionsandfrequenthandoffcanhaveanegativeimpacton urban rail CBTC railroad communication performance and, as a result, CBTC operation efficiency. Linear Quadratic Price is determined as the control performance measure with the goal of minimising the optimal operation profile position error and energy consumption. The optimization model constrains train control strategies related to safety in order to ensure train operation safety. Furthermore, Deep Reinforcement Learning is used to jointly optimise the handoff decision and train control policy based on stochastic channel conditions and realtime train positioninformation.

Simulations results based on real-world field channel measurements show that the proposedoptimalcontrolmethodcansignificantlyimprovetrainperformanceofthecontroller inCBTCsystems,andthatCBTCsystemsmustsacrificesomeperformanceandensuresystem safety.

The deep reinforcement learning methodology is used to estimate the value functionin the CBTC achievement optimization process . The ideal policy can sometimes be understood using 2 deep Q networks. Google Deepmind uses this method on certain games and achieves very good results. Reinforcement learning can also be used to find the best handoff and train control policies in CBTC systems. . In CBTC railroad communication systems, channel informationisobtainedfromreal-worldchannelmeasurementsandusedtopreparethedeepQ network. . The linear quadratic cost is characterised as the control performance measure with the goal of minimising the optimised travel profile tracking error and energyconsumption.

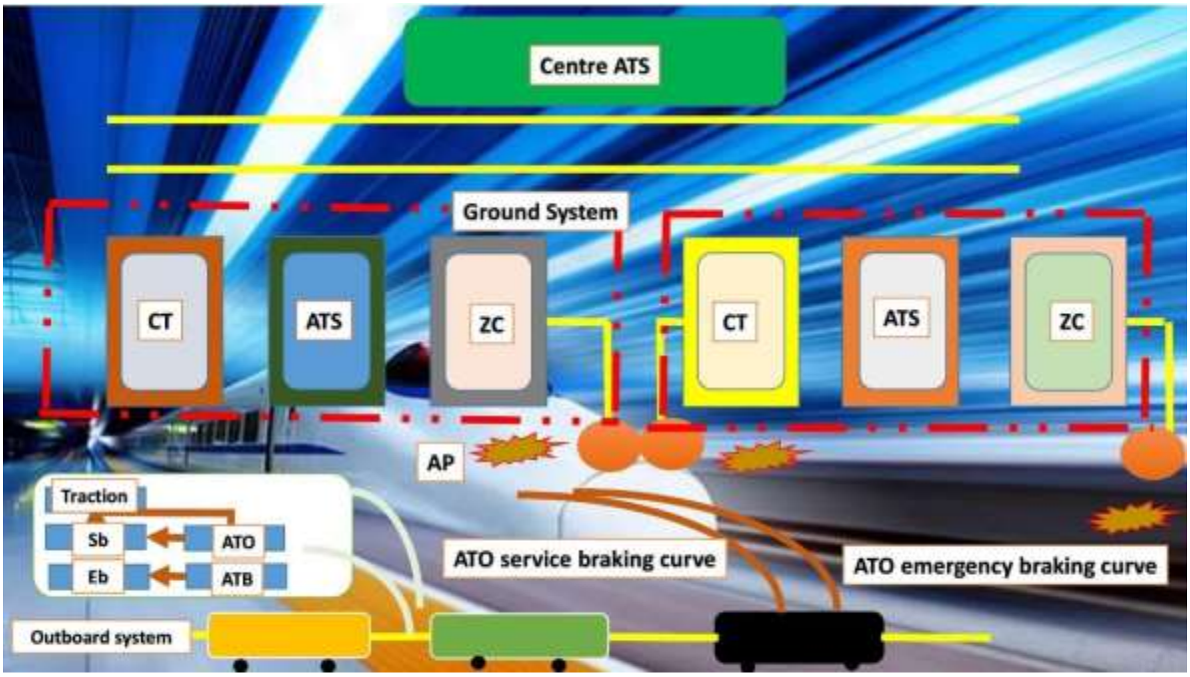
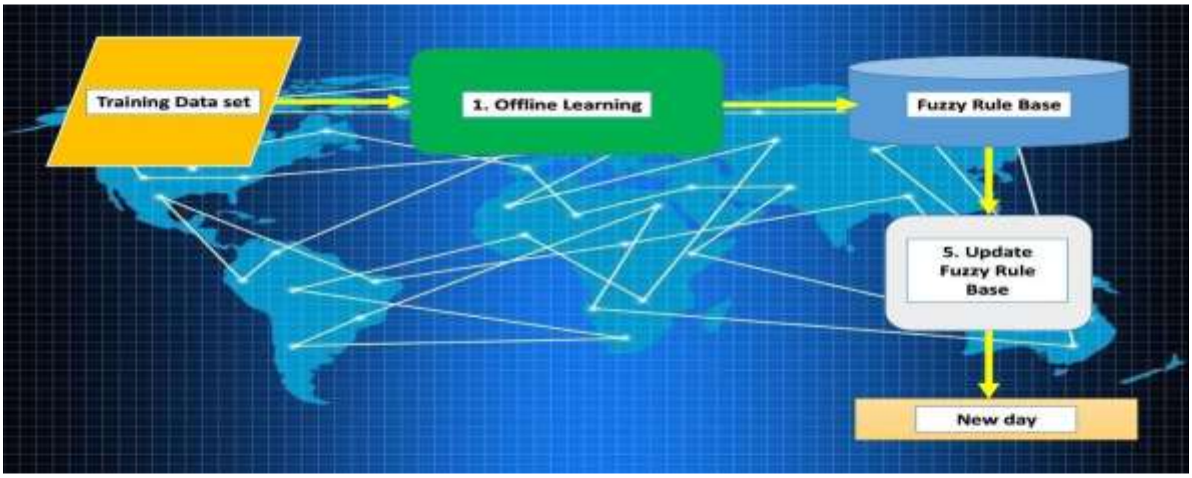


Fig.5. A typical CBTC system

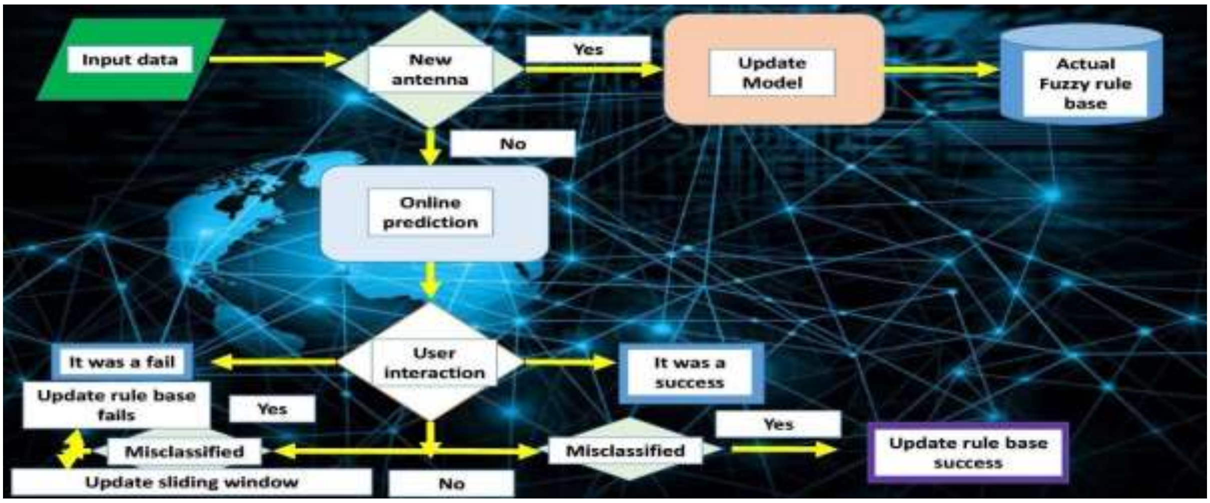
AusualsystemofCBTCisshowninFig.5.Theoptimizationmodelconstrainsboth handoffandtraincontrolstrategiesrelatedtosafetyinordertomakesuretrainoperationsafety. In the proposed framework, the account machine-to-machine (M2M) communications will be consideredinfutureworks.Intrain-groundcommunicationsystems,theconnectdelayofM2M communication systems will be calculated. It is also intended to train a back - propagation learning model to determine the best M2M access policy for CBTC systems.

VI. Fuzzy Logic based system for indoor localisation using wifisignals

Ambient Intelligence is an important information paradigm in which people are empowered by a digital environment that is "aware" of their existence and context, as well as sensitive,adaptable,andresponsive[29].Asaresult,oneoftheimportantcriteriaforAmbient Intelligent Surroundings (AIEs) is the skill to localise the user's location within the AIE in attempt to face her/his needs. In order to protect consumer privacy, use of cameras is indeed not desirable in AIEs, so non-intrusive sensors must be used. For outdoor spaces, there are various localisation methods available, such as those that rely on signal strength triangulation. These outdoor localisation methods, however, could be used in indoor environments. The majority of non-intrusive and non-camera-based indoor localisation systems necessitate the installationofadditionalhardwaresuchasultrasonicemitters/antennas,RFIDantennas,andso on.



(i)



(ii)

Fig. 6. (i) and (ii) shows the overview of the proposed technology

Fig. 6. gives a brief details about the proposed framework. To aid to these issues a framework indoor localization system based on WiFi signals is introduced. The system is free toreceiveandabundantinthemajorityofdomesticspaces.ThefreeWiFisignals,ontheother hand,arenoisyanduncertain, andtheirstrengthandavailabilityareconstantlychanging. Asa result, a fuzzy logic-based system is presented, that uses freely accessible WiFi signals to centralise a given user inAIEs.

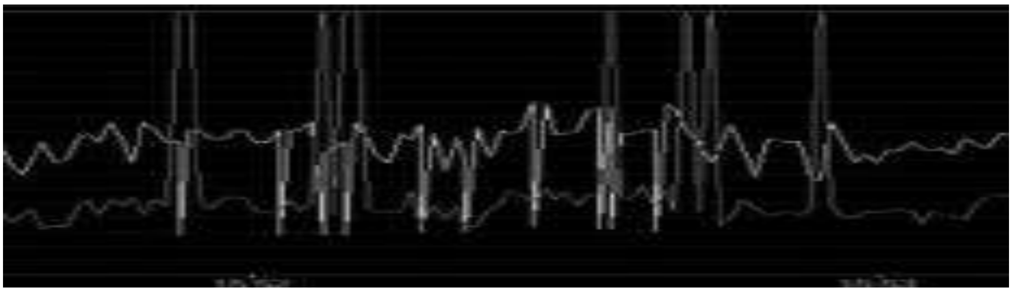


Fig.7. RSSI Measuring

Fig.7.showstheRSSI measuringTheaboveframeworkreceivesWiFisignalsfrom a large number of current WiFi Access Points (up to 170 Access Points) with no prior knowledge of the access points' locations or environment. To provide a zero-cost localisation systemwithhighaccuracyinreal-worldlivingspaces,thesystememploysanincrementallife-longlearningmethodtoadjustitsbehaviourtorangingandchangingWiFisignals.Thesystem was compared to other relevant methods in the literature in both simulated and real environments, and it is discovered that the present system is efficient than the other suggested frameworks in the asynchronous learning process. The new methodology was tested in a real-world centre apartment to office block. In all of these experimentations, the system detected the user with high accuracy in the given AIEs, and the framework was capable of adapting its behaviourpatternstochangesinsidetheAIEorWiFisignals.Itisenvisionedthattheproposed systemplaysabigroleinAIEs,particularlyinprivacy-sensitivesituationssuchaselderlycare scenarios. In the future, it is intended to use more sophisticated postprocessing techniques to provide higher accuracy while maintaining the zero-cost and non-intrusive solution. These methodologies will be driven by consumer moves in indoor environments, which would provide helpful data to the system with really no prior knowledge. In addition, it is also focussed on expanding the existing system, which is based on type-1 fuzzy systems, to type-2 fuzzy systems. This augmentation provides a better template for modelling and dealing with the short and long-term uncertainties that arise in WiFienvironments.

VII. Cognitive C4ISR application to Military communicationsystem

CognitiveArtificialIntelligence(CAI)isanewapproachtoArtificialIntelligence(AI) that aims to mimic how the human brain generates knowledge. Humans become intelligent as a result of knowledge that accumulates in their brains over time. He can understand how the world works (environment) and make decisions and/or make decisions based on his extensive knowledge.Ontheotherhand,strategicdecisionsthataffectthecontinuationofhavinganation and having a state are critical and crucial, and they must be made precisely and quickly, especially in the case of a contingency and when faced with multiple-data multiple-decision- alternative problems. The most precise decision must be based on knowledge derived from comprehensive information. Many methods for assisting decision making have been developed, with the majority of them coming from the field of Operational Research (OR). In this case, a different approach is taken. The approach is taken from the field of Artificial Intelligence (AI)[30].

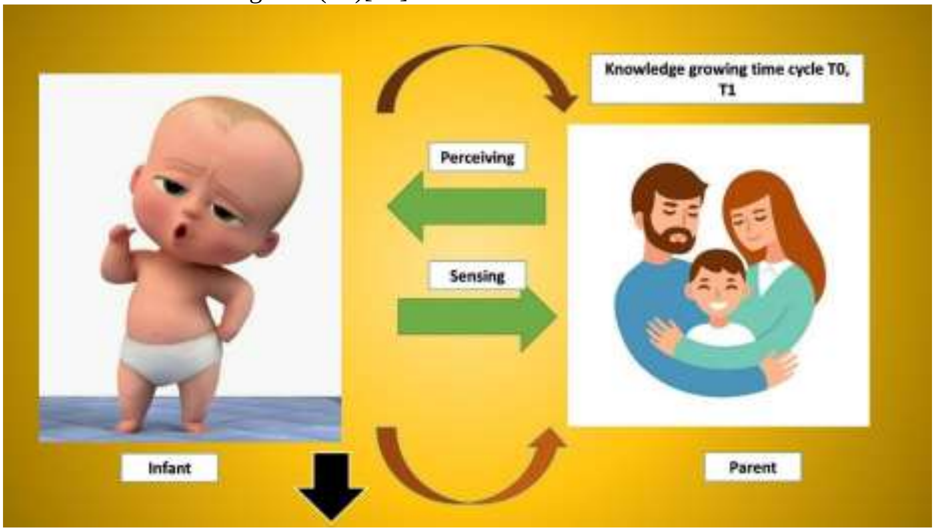
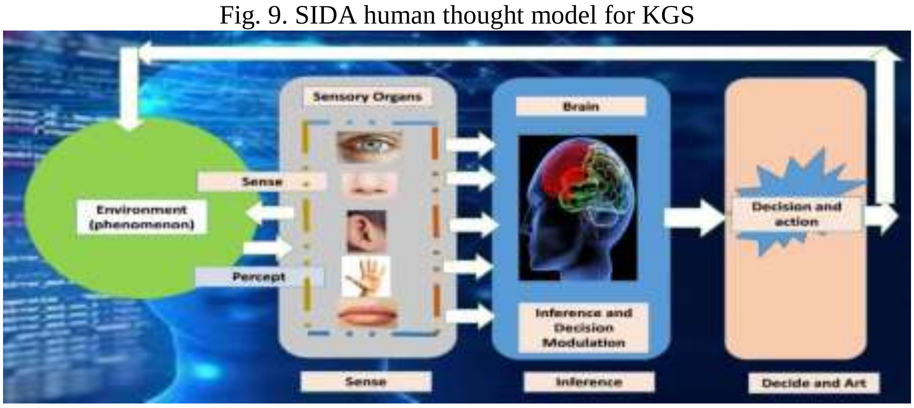


Fig.8. Illustration of knowledge cycle in humans

Fig. 8. shows the flow of knowledge in a particular interaction time. Why? Because itispresumedthattheprecisionofadecisionisdeterminedbythedecisionmaker'sknowledge. Knowledge does not appear out of nowhere; rather, there is indeed a process by which knowledge develops as well as exists inside the brain. It's why approaching decision making fromanAI perspective isanaturalthingto do.Tomakeuseofthebackgroundknowledge,the brain must extract it and use it as the basis for making a judgement. There have been multiple research stratergies on an agent with cognitive capability, with the goal of providing solutions formultiple-data,multiple-decision-alternativecases.Thiscognitiveagentisreferredtoasthe Knowledge-Growing System (KGS). Largely, KGS is a device which is capable of expanding its knowledge in tandem with the information accumulation over time.

Meanwhile, expertise extraction is the process of creating knowledge. In the meantime, knowledge extraction is a processofcreatingknowledge.Thatis,newknowledgewillbecreatedasaresultofknowledge extraction.

Fig. 9. SIDA human thought model for KGS

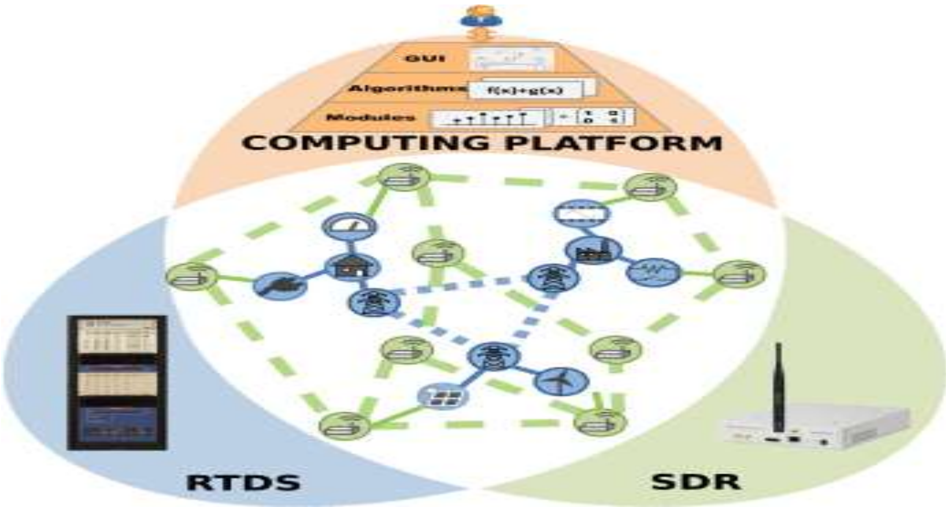


But, in essence, all of these processes accomplish the same thing: they acquire new knowledge.Fig.9.ShowstheSiDAmodelforKGS.Inareallycomplexscenarioinvolving IPolEcSoCDefSec, it is clear that the proposed Cognitive C4ISR can demonstrate its benefits, namely: (1) accelerating the decision-making cycle and (2) delivering knowledge as the basis for making a decision. From our simple example, it is clear that our Perceptual C4ISR is capable of demonstrating these benefits. The main requirement is that the inputs be in binary form, as a decision would be made based on ambiguous inputs. DoCis a measurement parameter that measures how much knowledge the system obtains and the percentage of decision success when it is executed. There are further attempts in exploring many opportunities to applyCAI.

VIII. Software defined radio based wireless communicationsystem

The current power grid is undergoing significant transition to the Smart Grid, which brings with it a slew of different challenges, such as the incorporation of renewable resources and smart devices. These changes also place strain on information and communication technologies (ICT) systems, which must support a variety of Smart Grid services with varying performance requirements.

Manufacturing wireless networking technology is expected to play a key role in emerging Smart Grid applications, particularly in critical scenarios such as Monitoring And control(SCADA)andgeographicallyrestrictedareas,toprovidealow-costandflexibleanswer for grid-wide information exchange. Furthermore, wireless communication technologies in fifth-generation (5G) systems are expected to address many challenges in future Smart Grid, such as distributed voltage regulation, grid fault and service disruption management, precise load control for critical elevated direct current (HVDC) transmission faults, and support for

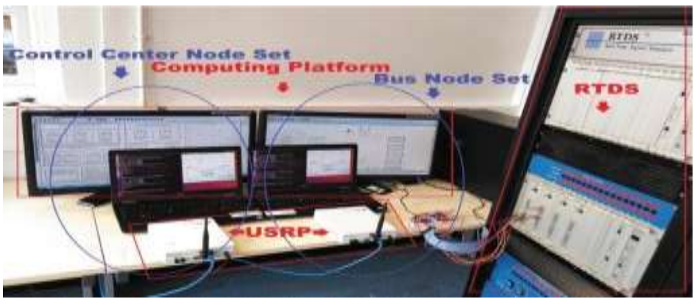


automation protocols such as IEC 61850. In contrast to wired Smart Grid testbeds, most wireless Smart Grid testing are based on numerical outcomes and simulation models[31].

Fig.10. The proposed frame work (Adapted from [31])

Fig.10.showstheproposedframework.Therearestillnotestbedswithtruewireless communication systems, nor is there a generalized design method for integrating these transceiversintoreal-timeevaluations.Withthispointinfocus,aSoftwareDefinedSmartGrid testbed architecture is described. It combines real-world wireless communication systems and Artificial Intelligence methodologies to provide a re-configurable framework to meet various real-time Smart Grid testbed designrequirements.

The architecture has shown great promise in attempting to address co-evaluation challenges of ICT systems and power systems, as well as supporting real-time Smart Grid evaluations through prototyping and experiments. The SDSG testbed framework is proposed, which includes the RTDS, SDR, and AI-enhanced computing platform. Its design



techniques in general-purpose hardware support, software - defined modules, and modular design, in particular, show great promise in supporting a variety of real Smart Grid test - bed designs. These current techniques use of architectures are demonstrated via developing and testing the structure into a presentation testbed.

Fig.11. The prototype of the proposed frame work

Fig.11. Shows the implemented prototype. Realworld experimental studies on AI- enhanced voltage stability controls demonstrate that the suggested SDSG architecture is competent integrate the elements from both ICT systems and power systems to support direct SmartGridapplications.TheflexibleSDSGtestbedframeworkandtheimplementedprototype willbeusedinfutureworktosupportadditionalresearchtopicsintheSmart Gridcontext,such as highly decentralized schemes, diverse data generation sources, and heterogeneous data transmission prerequisites. Utility scale grid models will be considered for the RTDS, while real electric grid components such as energy storage, Photovoltaics (PV), and controllers will be connected to the testbed via RTDS interfaces. The IEEE 802.11 protocol will include and implement automation protocols such as IEC 61850. More Smart Grid applications, including real-timeandnon-real-timeSmartGridapplicationssuchasDemandSideManagement(DSM) and metering, will be implemented on the power system side. More AI algorithms, such as deep learning algorithms, will be integrated into the Computing Platform to address uncertainties from both ICT systems and power structures, such as renewable energy and load forecasting.

IX. Multi-cap signal system using SVMdetector

CAP instrumentation could double the total capacity of a Nyquist-PAM system using the same pairs of opto-electronic devices by using orthogonality multiplexing with FIR filters. As a result, CAP provides significant benefits in bandwidth-limited systems, with relatively high spectrum efficiency, moderate complexity, and high flexibility.

Bandpass filter pairs, in specific, can be used to allocate signals adaptively in a multiband CAP scheme. Using 20-GHz class devices, 100-Gbps transmit power is accomplished over SMF and MMF links. To achieve a high enough capacity in a Multi-CAP scheme,high-densityCAPsignalsmustbeallocatedinthelow-frequencyband.However,even aftermatchedfiltering,thetraditionalharddecisionmethodalwayshasbottlenecksindecoding PAM-N elements with nonlinear distortion. To deal with it, signal distortion can be learned using the machine learning principle in a training process-enabled system . As a result, adaptable signal decoding can be implemented based on optimal results guided by computer vision.

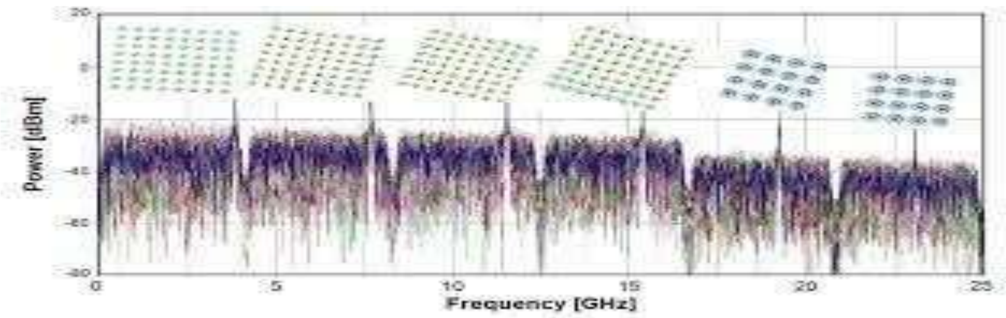


Fig. 12. Electrical spectrum of 122-Gbps Multi-CAP in optical B2B case. (Adapted [32])

AmachinelearningdetectorbasedonSupportVectorMachine(SVM) isproposedand simulatedina122-GbpsMulti-CAPsystem[32].TheSVMdetectorbenefitssignificantlyfrom theabsenceofde-rotatingconstellations,withover2-ordersBERreductionrequiredtoachieve the FEC limitation (3.8e-3) after 3-km SMF transmission.as shown in Figure 12. On the VPItransmissionmakers platform, the electro - optic Multi-CAP system is physically simulated. Key parameters of opto-electronic devices are set as practically as possible based on available equipment. The Multi-CAP wave is produced offline with a 13-fold upsampling factor. The CAP shaping filters are calculated by multiplying sinusoidal sequences by an elevated cosine function with a roll-off factor of 0.02. Matlabis used to perform the Multi- CAP demodulation. To ensure accurate BER measurement, sampled sequences are 800000 in length.

Thesupport vectorsaregeneratedthroughatraining processwithalengthof1000.The obtained decision line with the greatest margin is then used to decode the demodulated CAP signal'selectricalspectrum.SVM,ontheotherhand,doesnotrequiresuchacorrectorbecause it performs signal decision directly using support vectors, completely ignoring rotated constellations. The Ber is then evaluated using offline Matlab measurements. Linear interpolation, resampling, matched filtering, down-sampling, and the hard decision to the two quadraturePAM-NcomponentsareallpartoftheharddecisionprocessforMultiCAPsignals. The results show that BER reduction for high-density CAP signals is noticeable in the low- frequencyband.

X. Future of AI and ML in communicationsystems

A diverse set of services and devices should be supported by next-generation wireless communicationsystems.uRLLCandmMTC,forexample,arenew in5G;anotherofthemain motivators behind 5G there is a need for humongous machine-type communications. Meanwhile,withtherapidadvancementofAisystems,machineknowledgeacquisitionwillbe present everywhere, including in devices, at the edge, as well as on the cloud, transforming communication from linked iot-of-things to connected iot-of-intelligence. A deep integration of AI and communications will almost certainly emerge, with two components: AI-enabled mobile and wireless technology for AI. The current deployments of 5G wireless networks primarily support eMBB services, but it is anticipated that 5G/6G networks will penetrate various vertical industries and offer a plethora of personalised services and applications. On theonehand,verticalshavealreadyrecognisedseveralprofitableusecasesthattakeadvantage of emerging networks' unprecedented high data rates, low latencies, and large number of connecteddevices.

Communication service providers, on the other hand, have determined that AI/ML-based network orchestration is really the only way to quickly and dynamically support strict and diverse technical expectations of different use cases across the same unified physical infrastructure. Deep integration of wireless technology and Ai tools will be critical in the creation of this intelligent world.

XI. Conclusion

In this paper, we have reviewed several AI-ML based applications in the current communication systems, for reference, AI-ML uses in next generation wireless networks, CommunicationbasedtraincontrolsystemusingDeepLearning,Fuzzylogicbasedsystemfor indoorlocalizationusingwifisignals,CognitiveC4ISRapplicationtoMilitarycommunicationsystem, Software defined radio based wireless communication system, and Multi-cap signal systemusingSVMdetector.TheseexamplesdemonstratethatAiandMLsystemsareessential tools for not only boosting the effectiveness of existing wireless communication systems but also trying to define future wirelessnetworks.

References

[1] P.V.R.Ferreiraetal.,"MultiobjectiveReinforcementLearningforCognitiveSatellite CommunicationsUsingDeepNeuralNetworkEnsembles," inIEEEJournalonSelectedAreas in Communications, vol. 36, no. 5, pp. 1030-1041, May 2018, doi: 10.1109/JSAC.2018.2832820.

[2] Y. Shi, K. Yang, T. Jiang, J. Zhang and K. B. Letaief, "Communication-Efficient Edge AI: Algorithms and Systems," in IEEE Communications Surveys & Tutorials, vol. 22, no. 4, pp. 2167-2191, Fourthquarter 2020, doi:10.1109/COMST.2020.3007787.

[3] F.Shu,S.Chen,F.Li, J.ZhangandJ.Chen,"Researchandimplementationofnetwork attack and defense countermeasure technology based on artificial intelligence technology," 2020 IEEE 5th Information Technology and Mechatronics Engineering Conference (ITOEC), 2020, pp. 475-478, doi:10.1109/ITOEC49072.2020.9141751.

[4] T. L. Pham, T. Nguyen, M. D. Thieu, H. Nguyen, H. Nguyen and Y. M. Jang, "An Artificial Intelligence-based Error Correction for Optical Camera Communication," 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN), 2019, pp. 137-140, doi:10.1109/ICUFN.2019.8806169.

[5] T. -K. Kim, "Short Research on Voice Control System Based on Artificial Intelligence Assistant," 2020 International Conference on Electronics, Information, and Communication (ICEIC), 2020, pp. 1-2, doi:10.1109/ICEIC49074.2020.9051160.

[6] S. Ramos, J. Á. Pérez-López and R. Abreu, "An Analysis of the Importance of the Artificial Intelligence on the Information System of Police Forces," 2020 15th Iberian Conference on Information Systems and Technologies (CISTI), 2020, pp. 1-7, doi: 10.23919/CISTI49556.2020.9141006.

[7] T. Nakatsuji, S. Seki, S. Shibuya and T. Kaku, "Artificial intelligence approach for optimizing traffic signal timings on urban road network," Proceedings of VNIS'94 –1994Vehicle Navigation and Information Systems Conference, 1994, pp. 199-202, doi: 10.1109/VNIS.1994.396841.

[8] J. Park, J. Jang, G. Lee, H. Koh, C. Kim and T. W. Kim, "A Time Domain Artificial Intelligence Radar System Using 33-GHz Direct Sampling for Hand Gesture Recognition," in IEEE Journal of Solid-State Circuits, vol. 55, no. 4, pp. 879-888, April 2020, doi: 10.1109/JSSC.2020.2967547.

[9] T. V. Sethuraman, S. Elias and A. Ashok, "Demo: A Machine Learning based M-aryAmplitude Modulated Visible Light Communication System," 2020 International Conference on COMmunication Systems &NETworkS (COMSNETS), 2020, pp. 694-695, doi: 10.1109/COMSNETS48256.2020.9027292.

[10] B.Gao,B.Bu,W.ZhangandX.Li,"AnIntrusionDetectionMethodBasedonMachine Learning and State Observer for Train-Ground Communication Systems," in IEEE Transactions on Intelligent Transportation Systems, doi:10.1109/TITS.2021.3058553.

[11] O. Simeone, ''A very brief introduction to machine learning with applications to communicationsystems,''IEEETrans.Cognit.Commun.Netw.,vol.4,no.4,pp.648–664,
Dec. 2018

[12] X. Wang, X. Li, and V. C. M. Leung, ''Artificial intelligence-based techniques for emerging heterogeneous network: State of the arts, opportunities, and challenges,'' IEEE Access, vol. 3, pp. 1379–1391,2015.

[13] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, ''Thirty years of machine learning: The road to Pareto-optimal wireless networks,'' IEEE Commun. Surveys Tuts., vol. 22, no. 3, pp. 1472–1514, 3rd Quart.,2020.

[14] M. Wang, Y. Cui, X. Wang, S. Xiao, and J. Jiang, ''Machine learning for networking: Workflow, advances and opportunities,'' IEEE Netw., vol. 32, no. 2, pp. 92–99, Mar.2018.

[15] M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, ''Artificial neural networks-basedmachinelearningforwirelessnetworks:Atutorial,''IEEECommun.SurveysTuts.,vol. 21, no. 4, pp. 3039–3071, 4th Quart.,2019.

[16] NachmaniE,MarcianoE,LugoschL,etal.,2018.Deeplearningmethodsforimproved decoding of linear codes. IEEE J Sel Top Signal Process, 12(1):119-131. https://doi.org/10.1109/JSTSP.2017.2788405

[17] C. Zhang, P. Patras, and H. Haddadi, ''Deep learning in mobile and wireless networking: A survey,'' IEEE Commun. Surveys Tuts., vol. 21, no. 3, pp. 2224–2287, 3rd Quart.,2019.

[18] P. Casas, "Two Decades of AI4NETS - AI/ML for Data Networks: Challenges & Research Directions," NOMS 2020 - 2020 IEEE/IFIP Network Operations and Management Symposium, 2020, pp. 1-6, doi:10.1109/NOMS47738.2020.9110266.

[19] R. Alkurd, I. Y. Abualhaol and H. Yanikomeroglu, "Personalized Resource Allocation inWirelessNetworks:AnAI-EnabledandBigData-DrivenMulti-ObjectiveOptimization,"in IEEE Access, vol. 8, pp. 144592-144609, 2020, doi:10.1109/ACCESS.2020.3014301.

[20] R. Riggio et al., "AI@EDGE: A Secure and Reusable Artificial Intelligence Platform for Edge Computing," 2021 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit), 2021, pp. 610-615, doi: 10.1109/EuCNC/6GSummit51104.2021.9482440.

[21] I. Ahmad et al., "Machine Learning Meets Communication Networks: Current Trends and Future Challenges," in IEEE Access, vol. 8, pp. 223418-223460, 2020, doi: 10.1109/ACCESS.2020.3041765.

[22] J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, ''Thirty years of machine learning: The road to Pareto-optimal wireless networks,'' IEEE Commun. Surveys Tuts., vol. 22, no. 3, pp. 1472–1514, 3rd Quart.,2020

[23] T.K.Rodrigues,K.Suto,H.Nishiyama,J.Liu,andN.Kato,''Machinelearningmeets computation and communication control in evolving edge and cloud: Challenges and future perspective,'' IEEE Commun. Surveys Tuts., vol. 22, no. 1, pp. 38–67, 1st Quart.,2020.

[24] B. Ma, W. Guo, and J. Zhang, ''A survey of online data-driven proactive 5G network optimisation using machine learning,'' IEEE Access, vol. 8, pp. 35606–35637,2020.

[25] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, ''Federated learning in mobile edge networks: A comprehensive survey,'' IEEE Commun. Surveys Tuts., vol. 22, no. 3, pp. 2031–2063, 3rd Quart.,2020.

[26] S. Ali, ''6G white paper on machine learning in wireless communication networks,'' 2020, arXiv:2004.13875. [Online]. Available:http://arxiv.org/abs/2004.13875

[27] M. G. Kibria, K. Nguyen, G. P. Villardi, O. Zhao, K. Ishizu and F. Kojima, "Big Data Analytics, Machine Learning, and Artificial Intelligence in Next-Generation Wireless Networks," in IEEE Access, vol. 6, pp. 32328-32338, 2018, doi: 10.1109/ACCESS.2018.2837692.

[28] L. Zhu, Y. He, F. R. Yu, B. Ning, T. Tang and N. Zhao, "Communication-Based Train Control System Performance Optimization Using Deep Reinforcement Learning," in IEEE Transactions on Vehicular Technology, vol. 66, no. 12, pp. 10705-10717, Dec. 2017, doi:10.1109/TVT.2017.2724060.

[29] T. Garcia-Valverde, A. Garcia-Sola, H. Hagras, J. A. Dooley, V. Callaghan and J. A. Botia, "A Fuzzy Logic-

Based System for Indoor Localization Using WiFiin Ambient Intelligent Environments," in IEEE Transactions on Fuzzy Systems, vol. 21, no. 4, pp. 702- 718, Aug. 2013, doi:10.1109/TFUZZ.2012.2227975.

[30] A. D. Wahyudi Sumari, A. S. Ahmad and C. Artificial, "The application of cognitive artificial intelligence within C4ISR framework for national resilience," 2017 Fourth Asian Conference on Defence Technology - Japan (ACDT), 2017, pp. 1-8, doi: 10.1109/ACDTJ.2017.8259600.

[31] M. You, X. Zhang, G. Zheng, J. Jiang and H. Sun, "A Versatile Software Defined Smart Grid Testbed: Artificial Intelligence Enhanced Real-Time Co-Evaluation of ICT Systems and Power Systems," in IEEE Access, vol. 8, pp. 88651-88663, 2020, doi: 10.1109/ACCESS.2020.2992906.

[32] L. Sun, J. Du, G. Chen, Z. He, X. Chen and G. T. Reed, "Machine-learning detector based on support vector machine for 122-Gbps multi-CAP optical communication system," 2017 Opto-Electronics and Communications Conference (OECC) and Photonics Global Conference (PGC), 2017, pp. 1-3, doi:10.1109/OECC.2017.8114893.