Generalizing AI: Challenges and Opportunities for Plug and Play AI Solutions

Ismaeel Al Ridhawi, Safa Otoum, Moayad Aloqaily, and Azzedine Boukerche

Abstract

Artificial Intelligence (AI) has revolutionized today's Internet of Things (IoT) applications and services by introducing significant technological enhancements across a multitude of domains. With the deployment of the fifth generation (5G) mobile communication network, smart city visions of fast, on-demand, intelligent user-specific services are now becoming a reality. The concept of connected IoT is evolving into connected intelligent things. The advancements of both AI techniques, coupled with the sophistication of edge devices, is now leading to a new era of connected intelligence. Moving the intelligence toward end devices must account for latency demands and simplicity of selecting the type of AI technique to be used. Moreover, since most AI techniques require learning from big data sets and reasoning using a multitude of classification patterns, new simplified and collaborative solutions are now necessary more than ever. As such, the concept of introducing decentralized and distributed 'Plug and Play' (PnP) AI tools is now becoming more attractive given the vast numbers in edge devices, data volume and AI techniques. To this end, this article envisions a novel general AI solution that can be adapted to autonomously select the type of machine learning (ML) algorithm, the data set to be used, and provide reasoning in regards to data selection for optimal features extraction. Moreover, the solution performs the necessary training and all the necessary parameter fine-tunings to achieve the highest level of generality and simplicity for AI at the edge. We explore several aspects related to PnP-AI and its impact in the smart city ecosystem.

Introduction

Since the beginning of the early development of computer machines, both researchers and users have envisioned an era where intelligent machines will dominate and provide an intellect that surpasses the cognitive performance of humans. Today, such a vision is still prevalent and is coming closer to reality rather than fiction. Although intelligent systems have not yet outperformed human intelligence, such solutions are now becoming crucial to efficiently deliver the enormous number of user-specific and domain-specific complex service requests. AI solutions are being applied to solve uncertain, volatile and ambiguous problems. For instance, in the medical sector, a wide variety of AI solutions are used to effectively diagnose diseases rapidly and reduce the number of medical diagnosis errors [1]. In the transportation sector, AI tools are used to detect anomalies in traffic and offer opportunities for significant improvements in traffic management [2]. Such examples are countless nowadays and are considered crucial given the rapid transformation in city infrastructures and connected IoT devices. AI solutions will even advance further with the development of future-generation networks. The deployment of 5G and the research conducted on beyond 5G communication is becoming heavily reliant on AI to achieve reliable and efficient performance results [3].

Moreover, even though a significant amount of work has been performed in AI over the past few decades, most solutions are problem-specific and domain-specific. This requires significant processing and memory resources. As such, most centralized AI solutions (e.g., deployed in cloud datacenters) are no longer adequate given the time-sensitive nature of many smart city applications. Moreover, the volume of data has a significant impact on solution efficiency. A considerable number of user requested services do not require the full set of features and capabilities of AI which are provided through centralized datacenters. Rather, a sub-set of the intelligence capabilities is needed. Additionally, given the plethora of intelligent machines deployed in the environment, using such distributed capabilities (collaborative and cooperative) will result in the reduction of the dependence on the excessively operated cloud datacenters. Moreover, it will enhance AI services both in quantity and quality, which may not have been available on centralized entities in the first place. As such, using distributed cooperative AI techniques will enable delivery of complex and time-sensitive requests in an efficient and timely manner.

In addition to the processing and memory issues facing today's AI solutions, more important is the excessive amount of time needed to select a learning technique, test it, and then reconfigure different learning parameters. Such drawbacks make it repulsive for system designers to adapt intelligent solutions when developing IoT systems. The vision of a simplified and generalized learning solution that may be adapted to any problem and domain, namely plug-and-play, is one that may accelerate the technological advancements in AI. PnP-AI may be described as an AI solution that:

- Is applicable to a wide range of systems, networks and applications.

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Ismaeel Al Ridhawi is with Kuwait College of Science and Technology; Safa Otoum is with Zayed University; Moayad Aloqaily is with Al Ain University; Azzedine Boukerche is with University of Ottawa.

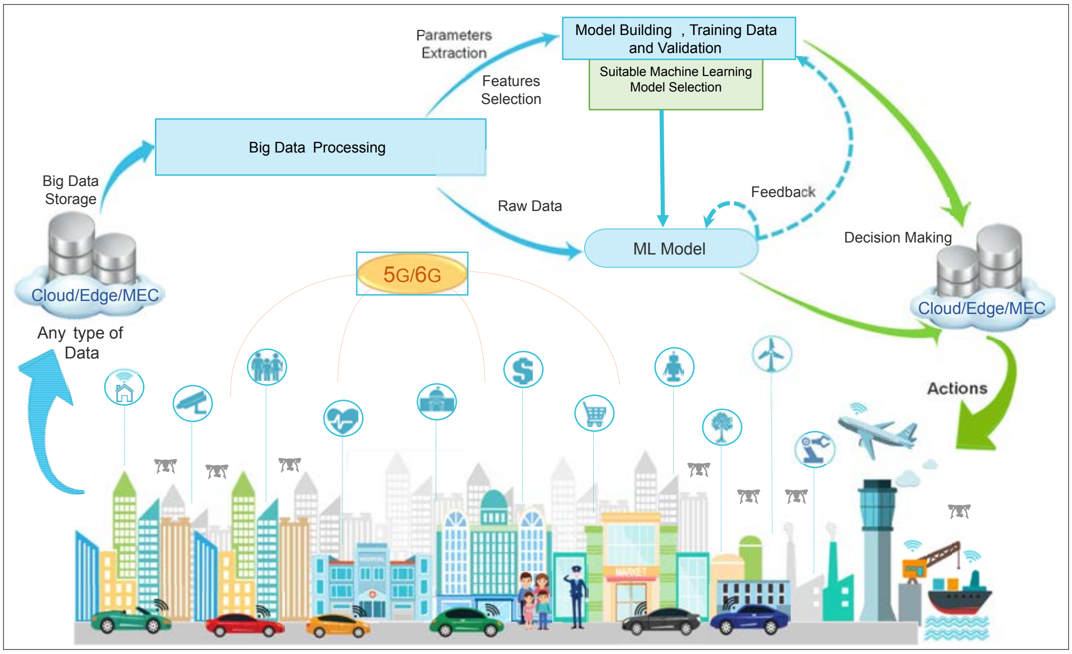

FIGURE 1. An Overview of an integrated PnP-AI solution for 5G and beyond networks in a connected intelligent IoT environment.

- Self-manageable, such that the type of problem at hand is self-determinable so that the correct learning technique is adapted.
- Self-configurable, in the sense that each device may perform data collection, filtering, learning, analysis, and decision making, either solely or collaboratively.
- Does not add another layer of complexity to the framework, in terms of excessive communication, computing and storage overhead. In essence, such a solution requires the learning process to be completely autonomous and self-configurable within an IoT ecosystem as shown in Fig. 1.

This article envisions the challenges and opportunities of generalizing AI. This vision requires a fully autonomous PnP-AI solution, such that the type of learning techniques (e.g., supervised learning, unsupervised learning, and so on), recognizing the data set (i.e., understanding the data type, cleaning and filtering, data reasoning, handling missing data, and so on), the configurations within each layer of the learning technique (e.g., the hidden layers of the Artificial Neural Network (ANN)), in addition to the actions taken, can all be performed autonomously without human intervention. Such a mechanism simplifies the process and provides a vast availability of distributed Machine Intelligence (MI) [4]. With that said, many challenges arise from such a technique, but at the same time it provides opportunities for a plethora of domains.

Understanding Artificial Intelligence

The intelligent learning methodology, namely artificial intelligence, was designed to make both hardware and software systems and applications capable of performing tasks that require a higher level of human intelligence, that rely on learning and reasoning. AI comprises a multitude of machine learning (ML) and deep learning (DL) techniques, in addition to other logical reasoning, search, statistical and behavioral approaches. AI has progressed over time as we became more aware of how our minds work and interact with the environment. In certain cases, AI has surpassed human performance, particularly in cases that require hundreds of inputs to analyze and decide upon an action. These capabilities of AI have introduced opportunities for a multitude of domains, resulting in enhanced decision-making, productivity improvement, cost reduction, and the availability of a plethora of simple and complex services.

Current Solutions

To achieve a PnP style of AI (ML to be more specific), it is important to understand the general concepts and classifications of learning algorithms. Moreover, AI solutions must become both interpretable and explainable to users for it to have the generality behavior [5]. The three main types of ML algorithms are: *supervised learning*, *unsupervised learning*, and *reinforcement learning*. Consider the ML system as a black box that results in an output given a set of inputs. Historical data of the outputs achieved given the set of input data leads to a supervised learning solution. The ML model can be trained in a guided manner achieve recognized classifications. Samples with class labels or samples with desired output values are required in order to achieve the supervised learning concept. In the unsupervised learning paradigm, labeled data or desired output values for the given inputs is not available. Thus, clustering mechanisms are used, where, given a set of inputs, the best matching cluster is selected to classify the output. As such, there is no knowledge to be learned from previous experiences. Reinforcement learning involves feedback from the environment to produce the desired behavior. It is neither classified as supervised nor unsupervised.

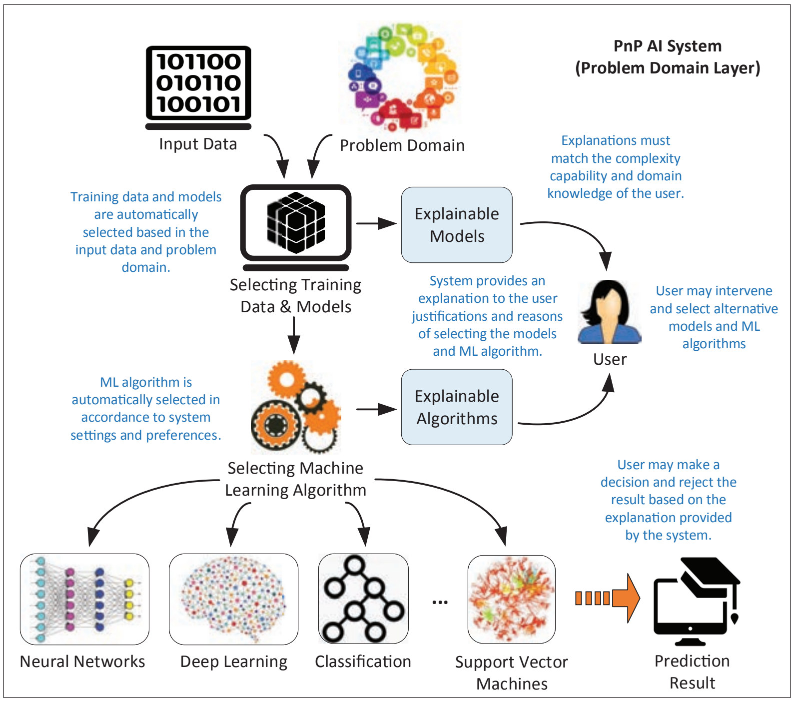

FIGURE 2. An Overview of a PnP-AI solution. The solution adapts an explainable AI approach where the user gets insight of each step in the learning process and may intervene in both configuration and decision making.

A plethora of data modeling techniques are used in ML, such as linear models, linear regression, regularized linear regression, generalized linear models, K-Nearest Neighbor (KNN) and much more [6]. Such modeling techniques are used to establish more robust classifications and achieve a better learning process. Artificial Neural Networks (ANNs) comprised of input, output and hidden layers are used to find patterns and label outputs. Backpropagation is used to correct errors and achieve higher classification success rates for future runs. Training ANNs is crucial for accuracy, where the weights of the network are learned given the labelled training data. The process begins with assigning default weight values to the network. Each input is transferred into an output in each layer of the ANN. Generated outputs are compared with the expected label or output. The differences in error between predictions and labels are used to update the weights. Increasing the number of hidden layers and their dimensionality makes the training process more complicated.

Decision trees represent a different approach toward ML, processing non-numerical data (e.g., categorical or string type). A tree-type structure is used, where a decision is performed at each node, at different hierarchical layers. Such a technique is of heuristic structure built upon a sequence of choices or comparisons. It can work with missing data and is scalable from linear to non-linear data without any change in the logic. Training decision trees begin with choosing the metric of choice (e.g., gini-index, cross-entropy, and so on) and the root node. The data is split into two parts repeatedly until all the leaf nodes are reached in all branches in accordance with a stop rule. To optimize the overall performance, robustness, and generality of the models, ensemble methods that rely on aggregation of multiple decision trees may be applied.

Another important pillar of ML is Support Vector Machine (SVM), which is used for building optimal classification and regression models. SVM tries to partition classes with maximal separation using the minimum number of data points. Although the training process is quite complex, once tuned, SVM models provide high accuracy and generalization capabilities. Probabilistic models are another important element of the AI study, where it tries to assign a belief probability to known variables and uncertainty to unknown variables. *Probabilistic models* may be classified into two types, namely, generative and discriminative. Generative models take a holistic approach toward data analysis by observing the input and output set and then assigning a joint probability. Changes in the output are modeled based on changes in the input and the state of the system, whereas discriminative models assign conditional probabilities, such that predicting changes in the output is modeled only on changes in the input set.

Reinforcement learning applies biological aspects of learning to solve more complex problems without reliance on the availability of labelled data beforehand. A considerable number of possible actions may arise at a given instance for a system. Furthermore, since there is no separation between the training and application phases, the system is said to be continuously learning as it is predicting. *Deep learning* was introduced to enhance the classical ANN model by adding more complexity to solve a plethora of problems from a given sufficient set of data. Moreover, the computation performance is improved by parallelizing the training optimization of deep networks. As such, the learning framework is not limited to a single type of ML technique, but rather both supervised and unsupervised problems can be tackled through deep learning.

Lessons Learned

A plethora and countless number of novel learning techniques and approaches have emerged over the decades. Most are application-oriented, but have shown promising results for different scenarios. Most AI solutions are complex and require excessive storage for raw data, time to filter and learn from the data, and have moderate prediction accuracy. Simple AI solutions may have minimal interaction between the user and the system, but lead to both inaccurate results and vagueness of the learning process from the user's side. To obtain accurate predictions, complex ML algorithms require continuous interaction between the user and the system, hence leading to a decline in usability and adaptation. On a similar note, Federated Learning (FL) has emerged as an enabling technology for collaborative and distributed learning. It aims to preserve personal data privacy and adapt with heterogeneous end-devices in cellular networks [7]. In FL, distributed end-devices use their local data to train ML models requested by centralized entities (e.g., cloud), such that only model updates are sent back to the central entity for aggregation rather than communicating raw data. Although such a solution is promising, challenges in terms of communication costs, resource

	Traditional AI (Limited Decentralization, Low FL)		PnP-AI (High FL, Autonomous, Self-Configurable, Explainable)	
Performance Aspect	Concerns	Outcome	Advantages	Outcome
Applications	Centralized solutions have limited data sets. Distributed solutions provide larger data sets but are still limited.	Limited to moderate personalization in services and application settings.	Continuously new and large data set, models and parameters	Highly personalized services and applications, higher intelligence level, higher autonomy.
Privacy	Raw data is usually stored and processed using centralized solutions. Distributed solutions still require model updates.	Learning is performed on centralized entities which might compromise user privacy.	Data is locally collected, stored and processed. Minimal interaction with centralized entities.	Most of data processing and learning is performed in a decentralized and federated manner. Fine-grained control and management of personal data.
Security	Security settings and control are defined strictly by the centralized entities.	No personalization, less effictive.	User-defined level of security and preferences.	Personalization, effectiveness, and high-level of integrity.
Control	Massive data stored either on the cloud or on distributed fog and edge devices. Load may not be balanced.	Current FL solutions require full control from centralized cloud to ensure fair load balance.	Massive distributed local data available on-time, and may be shared and distributed for balanced load.	Predictive local and decentralized control, efficient resource usage, flexible training.
Communication	Current FL solutions require excessive communication.	Complex solution.	Low to moderate communication.	Simplified layerd approach.

TABLE 1. Comparing current solutions in AI against the proposed plug-and-play AI that can be adapted for future generation networks.

allocation, privacy, and security are still large at scale. Moreover, FL does not solve the issue of simplicity and adaptability.

Some PnP ML solutions have emerged lately but are very limited to certain applications and scenarios. Such solutions do require some basic understanding of ML for it to provide successful results. For this reason, most AI systems fail due to the lack of user understanding, and as such require rejuvenated solutions to achieve simplicity. One such technique is called Explainable AI, which enables greater transparency for AI to be rolled out at a much faster pace in both industry and government [8]. Explainable AI is a new paradigm of defining, implementing and interpreting AI techniques aiming to improve users' trust in ML algorithms. The goal is to achieve ethical AI and produce systems that can explain why decisions were made by ML algorithms. Such explainable AI systems are described as more transparent in terms of how decisions are made. It provides such descriptions in a language that the user can understand. Any form of biasness should be avoided in ML models, either on the training data itself or the objective functions. Users should also be able to verify whether AI results are fair. Such techniques would ensure that AI systems are safe to use and have higher levels of reliability. Although such a solution is promising, adopting the methodology of explainability to current complex AI solutions will not result in pragmatic outcomes in terms of usability and generality.

Rejuvenating AI

With the deployment of the 5G communication infrastructure and the outlook into beyond 5G, namely, 6G, the concept of collaborative, distributed and decentralized learning will undoubtedly become a reality. To achieve such technological desire, simpler AI solutions must be developed, in terms of adaptability, explainability and ease of communicability. Figure 2 provides an overview of a PNP explainable AI system architecture. Such a system would detect the type of problem and the input data to be used. The training data set, labeling and models are selected and performed without any user intervention. Concurrently, explainable models matching the domain knowledge and complexity capability of the user are generated to describe the data labeling and model selection process. Such an approach would enable user intervention at an early stage to correct and re-configure the training process. ML algorithms are selected in accordance with the problem complexity, while taking into consideration time and accuracy preferences. Similarly, justification and reasons for the selection of a particular ML algorithm is provided to the user as part of avoiding a black-box solution style and enabling transparency. Results given by the system are presented to the user for acceptance or rejection, if intervention is preferred by the user.

A comparison of current trends and their shortcomings against a PnP-AI solution that may be adapted for future generation networks is summarized in Table 1.

Challenges and Issues

The plethora of complex AI-supported problem domains and applications, coupled with the wide variety of ML algorithms and their related supportive elements, make it nearly impractical to provide universal PnP general AI solutions. As such, AI-supported systems need to have the capability of understanding the context and environment in which they operate. Moreover, such systems need to be supported by underlying explanatory models that describe and characterize the state of the problem and the decisions taken by the system to allow for corrections and reconfigurations from users, in accordance with their domain knowledge. Many challenges and issues arise from such PnP explainable AI solutions in terms of self-configurability, reliability, and transparency.

Self-Configuring AI Solutions

The concept of achieving a self-configuring AI solution would in itself require another layer of learning. Imagine having two layers of ML systems, one targeting the problem domain and another targeting the management aspect of the ML system, as depicted in Fig. 3. Such a technique may be characterized as complex and resource consuming. The training and learning process would need to happen at two levels, one to solve the problem domain related tasks, and another that determines the type of problem at hand, the state of it, the type of learning methods required, and other management related issues. Different use case patterns need to be classified to determine the type of AI techniques and ML learning algorithms that can be adapted to

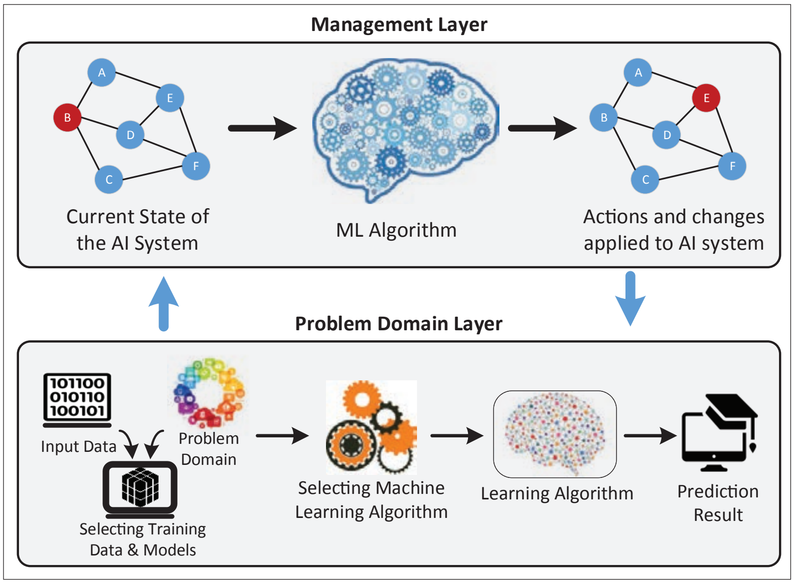

FIGURE 3. Self-configurability in PnP-AI systems through a multi-layered machine intelligence approach. The management layer focuses on accurate identification of the needed configurations and learning-related tasks for the use case application. The problem domain layer focuses on the intelligent learning aspect of the given problem.

such problem domains. For instance, a massive monitoring use case requires different data sets, models and learning algorithms than an autonomous machine use case. The management layer will consist mainly of architectural blueprints that include many different types of domains and its system components. Due to its excessive complexity, the management layer may need to be decentralized and distributed. IoT data collection occurs mainly at the edge, and thus, intelligence will likely require a degree of decentralization in terms of processing, storage, and management.

Decentralized and distributed data collection with the aid of fog and Mobile Edge Computing (MEC) [9] would provide the functionality of the intelligent framework to realize the use case application relevant to the problem domain, and execute management and control operations. Many challenges may arise, one of which is determining the extent of decentralization and distribution. In a fully distributed scenario, the centralized framework's simplicity might become diluted to address communication and synchronization effects. As such, any solution taken must consider a distributed machine intelligence ecosystem that enables fast and accurate intelligence orchestration among the management and problem domain layers, configured to the requested application scenario.

Reliability Issues of PnP-AI

One of the main issues that face PnP-AI is the reliability of the system. Intelligent machines require consistent and accurate selection of the input data set, training, and parameter configurability to achieve accurate results. Moreover, most ML algorithms are application-specific and require user involvement in the configurability aspect. Hence, a PnP solution can only be considered reliable based on the feedback of the user. Such user involvement decreases the level of system autonomy. As such, a trade-off occurs between less autonomy and more robustness on one hand, or more autonomy and less reliability on the other. To achieve high levels of reliability, the learning curve may require excessive numbers of exhaustive trials for a multitude of use cases and problem domains, hence, more time. This introduces a new training data set that needs to be managed and updated accordingly.

Moreover, a PnP-AI system must incorporate fault tolerance aspects to insure reliable operation. The system must have knowledge of the exploitable fault space in all problem domains and use cases. Similarly, such a large size of system fault space mandates the use of an automated strategy to overcome system faults. Some faults might result from attacks that may or may not be known in priori by both users nor the PnP-AI solution. Hence, privacy and intrusion detection solutions, in addition to techniques of overcoming cybersecurity attacks on ML policies, must be considered in the general AI scenario. Testing the effectiveness of any proposed PnP-AI solution is crucial and must undergo both governmental and industrial studies and policy making to ensure not only system reliability, but also people and environmental safety.

Explainable AI

To produce explainable AI models and algorithms for PnP-AI systems, user groups with interest in the explanation of AI systems and their motivations need to be addressed first. Such groups may be:

- The developers of the AI system, where such explanations may be useful for diagnosis and improvement purposes.
- End-users and decision makers that use the results and recommendations of the AI system, that may need explanations to reassure their trust and confidence of the system, in addition to improving the decisions of the AI system in the future through direct system intervention.
- Governmental agencies, which may need to overlook the automation and learning process to ensure it follows governed rules and policies to protect citizens' rights and safety.

Therefore, these explanations are needed to justify, control, improve, and discover the details and processes used and followed by the AI system.

A multitude of challenges arise from explainable AI solutions. For instance, most of today's modern AI models such as deep neural networks are not easy to understand, especially for end-users. Most techniques in AI are not simple algorithms, whereby giving a set of input would not result in a typical output. Additionally, some require regression models and heuristic search methods to produce an output. Moreover, most engineers will have a hard time tracing, reasoning and predicting results for some algorithms. As such, many of today's models are becoming more interpretable and allow for easy tracing by the developers through proper documentation. Such interpretation needs to be extended for different system users to achieve an explainable AI system. We believe that for any future AI solution, system engineers and developers need to have consistent contact with end-users to understand their learning capabilities of technical details. Additionally, the AI solution must be documented more toward the user rather than the developers.

Opportunities and Future Insights

With the advancements in today's fixed and mobile devices at the edge, and the deployment of the 5G network, came the opportunity to achieve intelligent solutions using distributed user and edge devices. Such advancements have opened new areas of smart services for a multitude of applications. For instance, unmanned aerial vehicles (UAVs) are being deployed in both rural and urban areas as a supportive technology to not only collect data, but also analyze and process intelligent algorithms using its computing and storage capabilities [10]. Swarm of drones in rough terrains are also being explored to provide environmental analysis and predictions using the drones' intelligent capabilities, with the support of advanced cooperative systems [11]. Therefore, to support such advancements, simple and general AI solutions must be adapted to a multitude set and variety of IoT devices, in a plug and play fashion. This will simplify the process of mass deployment of intelligent solutions to diversified problem domains and applications.

Researchers envision an intelligent and technological ecosystem for beyond 5G and 6G communication. Network softwarization seen in 5G will be taken to new levels of network intelligentization. The 'non-radio' aspect of 5G communication, namely, Software Defined Networking (SDN), Network Function Virtualization (NFV) and MEC has become more important. Similarly, in 6G, the learning and intelligence aspects will become crucial and must be integrated with the communication network for it to become smart, agile and adaptive, to both the changing network dynamics and application/user-specific requests. All things are to be connected to share their intelligence on and above the ground, under water and in space.

Collaborative, decentralized, and distributed AI can only become a reality when the following design constraints are considered within 5G and beyond networks, namely:

- Distribution of training data over all network participants, ranging from network base stations all the way to simple IoT devices such as sensors, where such training data is collected locally.
- All collaborating entities exchange their locally trained models, rather than exchanging raw private data, wherein training and inference are carried out both locally and collectively.
- Data abstraction, filtering, and reduction becomes necessary given the massive amount of monitored and collected data that would take a big portion of devices' repositories.
- Such a connected 6G intelligence scenario requires a generalized and explainable plug and play AI solution so that it can be adapted and used for a multitude of use cases and problem domains.

Figure 4 depicts a scenario where such a PnP-AI solution can be adapted to a beyond 5G network, at different ends of the communication spectrum. Different cooperative and collaborative entities share their resources in terms of processing power, storage, communication and most importantly intelligence, to provide complex user- and problem-specific services. Such services may not be available without a general and universal PnP-AI framework and the cooperative entities. Although no solutions exist yet in regards to such a general PnP-AI technique, a number of research and development trials are ongoing.

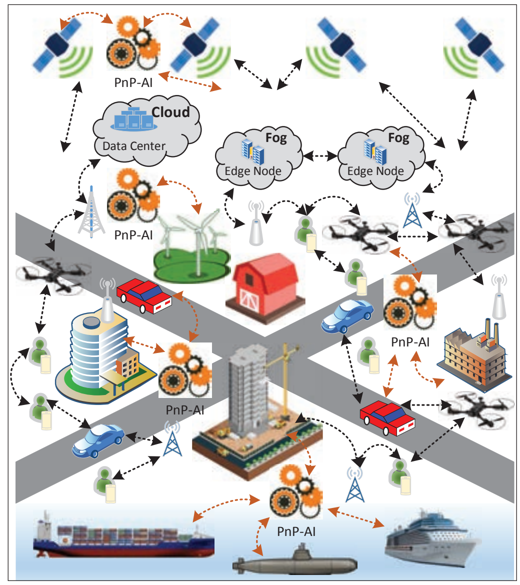

FIGURE 4. Integration of PnP-AI solutions within different beyond 5G use cases and problem domains to provide simpler and more general connected and distributed intelligence.

In late 2019, Amazon introduced PnP AI services designed to support business data sharing [12]. Amazon Kendra is an easy to use enterprise search service powered by ML algorithms. It is a PnP style tool that can be integrated within an enterprise's system to enable end users to find the information they need using natural language instead of just keywords. Search results become more accurate over time through reinforced learning methods and the sharing of distributed and updated training data available over Amazon's cloud. Although such a solution is not yet as general and self-configuring as envisioned, such techniques are promising and are setting the path toward true PnP-AI frameworks.

Furthermore, explainable AI solutions have been tackled in a number of studies and have shown promising results. In [13], the authors surveyed numerous interpretability strategies of AI, and have determined that the complexity of ML models is directly related to their interpretability, such that the more complex the models are, the more difficult it becomes to interpret and explain the solution to users. They noted that it would be easier to design AI and ML algorithms that are inherently and intrinsically interpretable. As such, decision trees, additive and sparse linear models provide convincing capabilities to gain domain experts' trust. They also noted that a reverse engineering approach without altering and knowing the details of the running algorithm is one approach that can be taken for complex models. Providing explainability to a single prediction is sometimes considered much more convenient

The automation and self-configuration process of AI is both transparent and explainable to the users. The integration of an explainable AI solution within the PnP-AI framework will enhance user trust for AI systems and accelerate the process of having a connected intelligence ecosystem.

than describing the entire model. Furthermore, it has been noted that creating a generalized description for agnostic models is something that may be useful to common ML algorithms. The work in regards to explainable AI is still premature and is expected to produce favorable results in the near future.

Distributed intelligence and learning have gained popularity recently, especially with the ever-increasing size of data samples and data sets. Traditional centralized in-cloud learning has begun to show its weaknesses and will eventually become even more clear with the increased volume of IoT devices and the produced and gathered data. As such, with soaring demands in bandwidth and data privacy concerns, on-device learning networks have gained popularity and are showing benefits in terms of storage and device processing improvements. A case study was conducted by Yue *et al*. [14] on decentralized learning using two scenarios, namely, decentralized disjoint datasets and decentralized overlapping datasets. Their results have shown that by applying Fountain codes, the advantages of using decentralized learning are achievable with reduced communication loads in large-scale networks.

User-specific composite service provisioning for smart city problem domains is one of the most use cases that will benefit from generalized and distributed PnP-AI solutions. In [15], we proposed a blockchain-based decentralized service composition solution for complex multimedia service delivery to end-users. The composition process is conducted through user device cooperation and relies on a reinforcement learning technique to compose and deliver complex services. The learning technique is adapted to fog and edge devices and thus is not completely decentralized. With the availability of distributed on-device PnP-AI solutions and beyond 5G communication, we believe that more complex services could be composed and delivered to a sparse spectrum of users and contextual domains. Benefits are not only seen in the QoS and QoE context, but also in terms of profit sharing, service provider resource usage reduction, and energy efficiency.

Conclusion

Mobile devices operating under water, on-ground, in the air and even in-space have powerful processing, storage and intelligence capabilities. Not using such capabilities to provide enhanced intelligent services signifies that resources are underutilized. More and more cooperative and decentralized intelligent solutions are being developed to provide composite domain-specific services. But with the wide availability and complexity of AI and ML algorithms, an excessive amount of time is needed to select the right ML algorithm, the dataset, train it, and configure specific parameters. This makes it repulsive for system designers to adapt intelligent solutions when developing IoT systems. In this article we envisioned a simplified and generalized learning solution, which we referred to as plug and play-AI, that can be seamlessly adapted to any problem and domain to simplify and generalize AI for users. The automation and self-configuration process of AI is both transparent and explainable to the users. The integration of an explainable AI solution within the PnP-AI framework will enhance user trust for AI systems and accelerate the process of having a connected intelligence ecosystem.

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Biographies

Ismaeel Al Ridhawi [M'09, SM'19] received his B.A.Sc., M.A.Sc., and Ph.D. degrees in electrical and computer engineering from the University of Ottawa, Canada, in 2007, 2009, and 2014, respectively. He is an assistant professor of computer engineering at Kuwait College of Science and Technology and a researcher in the field of wireless communications. He has also worked at the American University of the Middle East in Kuwait as an assistant professor from 2014 to 2019. He is a registered professional engineer in Ontario (P.Eng). He is a Senior Member of IEEE with many peer-reviewed publications in highly ranked magazines, journals and conference proceedings. He is an associate and guest editor in many journals and has organized a number of IEEE conferences over the years. He has also served as session chair for a number of symposiums and was part of the technical program committee for numerous journals and conferences. His current research interests include service delivery and provisioning in fog and cloud computing, quality of service monitoring for wireless networks, MEC network management, and service-specific overlay networks.

Safa Otoum [S'12, M'19] is an assistant professor of computer engineering in the College of Technological Innovation (CTI), Zayed University, United Arab Emirates, and a researcher in the field of communications and networks security. Prior to joining

CTI, she was a postdoctoral fellow at the University of Ottawa and has been a data scientist at Cheetah Networks Inc. Ottawa since 2019. She received her M.A.Sc. and Ph.D degrees in computer engineering from the University of Ottawa, Canada, in 2015 and 2019, respectively. Her research interests include network security issues, intrusion detection and prevention, wireless sensor networks, and blockchain solutions. She received several academic and research scholarships, including the NSERC Canada Graduate Scholarships-Doctoral and the NSERC FSS. She is an IEEE member and a Professional Engineer Ontario (P.Eng.).

Moayad Aloqaily (S'12, M'17) received the M.Sc. degree in electrical and computer engineering from Concordia University, Montreal, QC, Canada, in 2012, and the Ph.D. degree in electrical and computer engineering from the University of Ottawa, Ottawa, ON, in 2016. He was an instructor in the Systems and Computer Engineering Department at Carleton University, Ottawa, Canada, in 2017. He has been working with Gnowit Inc. as a senior researcher and data scientist since 2016. He is also the Managing Director of xAnalytics Inc., Ottawa, ON, Canada, 2019. Currently, he is with the Faculty of Engineering, Al Ain University, United Arab Emirates. His current research interests include the applications of AI and ML, connected and autonomous vehicles, blockchain solutions, and sustainable energy and data management. He has chaired and co-chaired many IEEE conferences and workshops including BCCA2020, AdHocNets2020, PEDISWESA-ISCC2020, ITCVT-NOMS2020, E2NIoT-IWCMC2020, ICCN-INFOCOM19, AICSSA19, and BAT-FMEC19-20. He has served as a guest editor for many journals including *IEEE Wireless Communications Magazine*, *IEEE Network*, *International Journal of Machine Learning and Cybernetics*, *Elsevier IPM Journal*, Springer JONS, *Springer Cluster Computer*, *Internet Technology Letters*, *Transaction on Telecommunications Technologies*, *Security and Privacy*, and *IEEE Access*. He is an associate editor with *Cluster Computing*, *Security and Privacy*, and *IEEE Access*. He is an IEEE member and a Professional Engineer Ontario (P.Eng.).

Azzedine Boukerche [F'15] is a Distinguished University Professor and holds a Canada Research Chair Tier-1 position at the University of Ottawa, Canada. He has received the C. Gotlieb Computer Medal Award, the Ontario Distinguished Researcher Award, the Premier of Ontario Research Excellence Award, the G. S. Glinski Award for Excellence in Research, the IEEE Computer Society Golden Core Award, the IEEE CS-Meritorious Award, the IEEE TCPP Technical Achievement and Leadership Award, the IEEE ComSoc ASHN Leadership and Contribution Award, and the University of Ottawa Award for Excellence in Research. He is a Fellow of the Engineering Institute of Canada, a Fellow of the Canadian Academy of Engineering, and a Fellow of the American Association for the Advancement of Science. His current research interests include sensor networks, autonomous and connected vehicles, distributed and mobile computing, wireless multimedia, IoT, blockchains and network security, and performance modeling and analysis of evaluation of large-scale distributed and mobile systems.