A Review of Cognitive Dynamic Systems and Cognitive IoT

Alessandro Giuliano
McMaster University
Hamilton, ON, Canada
giuliana@mcmaster.ca

Waleed Hilal
McMaster University
Hamilton, ON, Canada
hilalw@mcmaster.ca

Naseem Alsadi
McMaster University
Hamilton, ON, Canada
alsadin@mcmaster.ca

S. Andrew Gadsden
McMaster University
Hamilton, ON, Canada
gadsdesa@mcmaster.ca

John Yawney
Adastra Corporation
Toronto, ON, Canada
john.yawney@adastragrp.com

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***Abstract*— This review covers the topics of cognitive dynamic systems and their definition following Simon Haykin's work in the field as well as their application through cognitive radar, cognitive radio and cognitive control. Furthermore, the article presents the topic of cognitive IoT and discusses it under the lens of cognitive dynamic systems referencing research in the field. It also discusses the needs for interoperability between IoT architectures and the need to integrate cognitive radio with future IoT frameworks developments.**

Keywords—Cognitive Dynamic Systems, Cognitive IoT, Cognitive Radio

I. INTRODUCTION

The augmentation of physical objects with the power of the internet has become commonplace in the midst of the fourth industrial revolution. Many elements are becoming increasingly intertwined, including wearable technology, healthcare, home appliances, and transportation. The Internet of Things (IoT) has been characterised as a deeper integration of all physical objects with the digital realm, including the advancement from simple control systems sensing devices and effectors to more complex systems capable of exchanging data between devices connected to the internet for more timely and productive decision-making. The magnitude of today's IoT applications has posed several issues in terms of building a system-to-system interoperability framework. Developing IoT services that are intended to adapt to the circumstances and self-adjust in response to unforeseen situations through cooperation. These should also use the acquired data to extract semantic notations and optimize the system's effectiveness. In a general context, the IoT model has been defined as a globally connected network of uniquely addressable devices following established communication protocols. This term refers to a theoretical model of complex multidimensional systems made up of interconnected and interdependent items [6]. Smaller subsystems collaborate to achieve results in the most efficient way possible. Social network analysis is a study tool that is used to explain the network of relationships that exists among the numerous objects that make up the larger Internet of Things, as well as to investigate the effects on data processing, context extrapolation, and semantic derivation. This is especially beneficial in time varying IoT systems like smart cities.

In a point-of-view essay published in the Proceedings of the IEEE in 2006, Dr. Simon Haykin initially suggested the concept of a dynamic cognitive system (CDS) [3]. He went on to write "Cognitive Radio: Brain Enabled Wireless Communication" [2] and "Cognitive Radar: A Way of the Future" [3], both of which were hugely significant. The author of these defines CDS as systems that learn from repeated enduring interactions with the environment to develop norms of behaviour over time, allowing them to deal with environmental uncertainty. Following Fuster's work on cognition, Haykin refined this concept in [4], outlining the distinction between adaptation and cognition by outlining the norms by which a cognitive dynamic system is defined, the perception action cycle (PAC), memory, attention, language, and intelligence.

Novel cyber-physical systems (CPS) are continually being launched in this new era of greater connectivity, upgrading things with the ability to control the world around them, compute the data acquired, and share it through the internet. This transformation affects a wide range of sectors and services, prompting the development of novel IoT architectures targeted at efficiently capturing and processing data to improve process efficiency. The concept of cognitive IoT (CIoT) has been introduced as a way to enhance current IoT systems with cognitive capabilities in order to better leverage the vast volumes of data being collected and tackle scalability issues. To better examine variables that impact functionality and data gathering, semantic computing, cognitive computing, and perceptual computing can be used [5]. The goal of CIoT is to make IoT systems capable of understanding environmental elements and capable of contextual awareness. This new paradigm aims to apply the principles of human cognition to IoT dynamic systems. The process of learning, reasoning, and understanding the physical and social environments by embedding cognition processes into IoT seeks to build a new class of systems capable of operating with minimal human intervention [7]. Some present obstacles for a scalable and reliable IoT must

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also be faced and answered beforehand in order to build such systems. The existing constraints of wireless technology and mobile networks are the first major worry in terms of scalability of such systems. Regarding future large-scale IoT systems, the restricted range, data capacity, and spectrum availability are major concerns [8]. These difficulties will likely intensify in the coming years, given the rapid development of IoT.

Cognitive Radio (CR) and Cognitive Radio Networks (CRN) have sparked the interest of academic and business communities in recent years as a potential solution to many of these issues [8]. Spectrum sensing, spectrum decision, spectrum management, and spectrum mobility are the main processes of cognitive radio, with the goal of taking full advantage of licenced spectrum bands through the effective application of dynamic allocation to fill present spectrum gaps.

A further constraint in vast IoT network is the complexity of aggregating data from multiple sources. Since data collected in a multi-sensor IoT system can be heterogeneous, adaptive analytics approaches must be considered. Collecting such diverse datasets to get a holistic picture of the system can be difficult. The data collected can also be nonlinear, multidimensional, or partial, making its use for intelligent decision-making and services provisioning much more difficult [7][1]. This problem is addressed by Cognitive IoT, which adapts to the data type, situation, and setting, utilising techniques like association analysis, clustering analysis, and regression, for contextual data analysis. Big-data-driven applications, on the other hand, necessitate more intelligent decision-making to enable more efficient and flexible operations via cooperative self-organized and self-optimized behaviours. Moreover, for large-scale IoT systems, centralized data handling is a significant barrier. The challenges associated with central data processing include single-node failure, restricted scalability, and massive trade overhead [7].

II. RELATED WORK AND MOTIVATION

Because of the wide range of disciplines to which IoT may be applied, developments in architectural design for IoT systems have primarily been targeted to individual applications. As a result, cooperation amongst IoT systems is constrained, thereby restricting advancement toward a bridge architecture [9].

Although cognitive IoT is still a new topic, it is growing in prominence because of scientific research in cognitive dynamic system and cognitive control. This new paradigm could be used as a model for developing new IoT designs and as a framework for addressing specific IoT concerns. In principle, CIoT aspires to provide IoT systems with a cognition component that allows them to learn, reason, and comprehend both physical and social realms [7], bringing together a variety of professions and areas such as computer science, mathematics, cognitive science, neurology, and engineering. CIoT may improve the interconnection of diverse IoT networks and be applied beyond disciplines and sectors, spanning the physical and cyber worlds to improve smart distribution of resources, autonomous process controls, and intelligent service provisioning.

The Internet of Things can be viewed as a macro-level development of ubiquitous computing combined with CPS. At the moment, IoT can only use permitted spectral bands, which are presumably already being used, posing an impediment for large-scale IoT implementation. As trillions of objects become more interconnected in the near term, we can anticipate the issue to intensify [14]. In turn, by significantly increasing IoT data transmission using cognitive radio and incorporating machine learning, signal processing, and other technologies, effective distribution of data transmission within 4G and 5G licenced available spectrum could be an answer [13].

Cognitive Radio is a promising enabling communication technology for IoT, dealing with issues such as wireless access network conflict and severe congestion, as well as automaticity, scaling, dependability, energy consumption, and service quality [14]. The most immediate advantage of CR for IoT is that it allows for more efficient spectrum allocation and administration, which improves accessibility, usability, flexibility, and interconnectivity. Addressing efficient and flexible networks and addressing heterogeneity concerns are the two types of CR techniques, with flexible networking referring to the optimal use of available spectrum via spectrum aware optimization to enhance QoS. While addressing diversity, the aim is to strengthen environment discovery, self-organization, adaptability, and nodal cohabitation.

Devices in both centralised and decentralised networks will require routing in order to convey data to a predetermined destination. However, traditional single-hop and multi-hop routing algorithms are incompatible with cognitive radio systems because they lack additional functions like flexible spectrum allocation. CR mesh networks (semi-static) and CR ad hoc networks (adaptable and self-reconfiguring using P2P interactions) have both been discussed in the literature [14]. By accessing data about interference zones and relaying this to the underlying common infrastructure or cluster leader, spectrum knowledge would be readily available to all nodes in centralised networks. Delay, hop count, energy usage, bandwidth, and route stability will be among the network parameters which will be collaboratively optimised. Simultaneously, single-hop, D2D networking will most likely be used in centralised networks provided that the transmitter's range is not surpassed.

A. Cognitive Dynamic Systems and Cognitive Control

Dr. Simon Haykin was the first to propose the concept of a cognitive dynamic system as an answer to the radio spectrum's utilisation inefficiencies. Prospective bandwidth users' capacity for using non - utilized bandwidths is constrained due to government organisations' control of electromagnetic bands in the nature of licences [2]. Cognitive radio was created to maximise the usage of existing radio frequencies by taking advantage of spectral gaps. The study describes it as a smart wireless communication technology that learns from the surroundings and adjusts its settings in real-time using the approach learning by building.

By assessing the electromagnetic environment, finding channels, and transmitting data through dynamic bandwidth control, cognitive radio seeks to maintain high reliability in connectivity utilising the radio spectrum efficiently. The radio scene analysis is performed by the receiver, which surveys the surroundings to detect spectrum holes and calculates the interference temperature. Dynamic beamforming is used for inference control in this passive activity, which requires interpreting non - stationarity temporal signals to accommodate for the spatial characteristics of radiofrequency inputs. This strategy relies on constant spectrum observation and the computation of alternate paths to recognised spectrum holes since it offers resilience whenever a main user requires the spectrum for its own purpose.

Difficulties in the channel estimation problem are solved by adopting semi-blind receiver training, resulting in a receiver with two modes: supervised learning and tracking. The first option acquires and estimates the channel value using a quick training cycle. The other, on the other hand, is intended to be used in operating condition and repeatedly evaluates the channel state. The computations are performed using a state-space model of the channel parameters, with the premise of linearity, utilising the process equation and measurement equation. Choosing an effective monitoring approach and filter choice addresses AR coefficients, dynamic noise, and measurement noise.

Cognitive radio might have to function in a distributed mode via a cooperative system that accomplishes collaboration among nearest neighbors in constant interaction, widening the reach of its application and making it easier for multiple users to adopt and implement the technology to existing networks. The challenge of transmit-power regulation for different users can indeed be viewed as a game-theoretic problem. The author suggested Nash equilibrium and water-filling procedures as remedies. The transmit-power regulation problem affects the dynamic spectrum management system in a similar fashion. The transmitter handles each of these components of the operation, thus it employs the very same methods to address it.

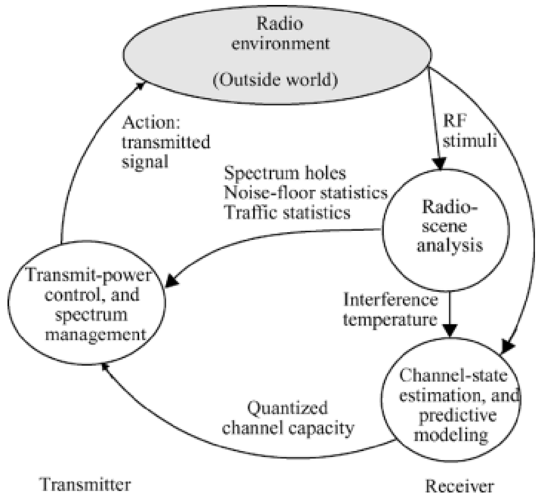

Figure 1: Cognitive Radio operational representation. [2]

In [15] authors considerations are raised regarding modulation techniques and traffic control, with a focus on OFDM. Orthogonal frequency-division multiplexing (OFDM) is a powerful modulation approach for cognitive radio and a cost-effective way to enable dynamic bandwidth allocation. Co-channel interference must be avoided when using an OFMD, which necessitates the inclusion of a traffic control system in the dynamic spectrum management algorithm. This system will be able to anticipate the length of time the spectrum gap would be empty, as well as predicting traffic patterns, based on previous data. More information regarding routing protocol, gateways and more can be found in [16]-[19]

Following the new paradigm outlined by the five principles of cognition, a system is deemed cognitive if it can perform the five basic cognitive processes: perception-action cycle (PAC), memory, attention, language, and intelligence. The perception-action 's cycle concept ties to feedback loops, using sensing devices to extract data regarding the system's condition and functioning, which is then used to trigger predetermined events that affect the environment and the system itself within the context of the Internet of Things. To reach intelligent decision-making, this approach employs advanced data analytics and the other components of cognitive dynamic systems. Expanding on the PAC, by using relevant stored information about the surroundings, the system, and past behavior, which are stored in order to improve the system's reaction to hypothetical situations. perceptual, executive, and working memory are the three types of memory.

The PAC and memory elements of CDS are responsible for attention. This refers to the cognitive system's ability to comprehend data and properly optimise all preceding operations. In a cognitive dynamic system, attention is the systematic method for prioritising the distribution of computational capabilities to alleviate the problem of information overload. As a result, dynamically filtering processed data by significance to aid learning and cognitive controller enhancement are employed. In CDS, attention is not defined by a physical state, but rather by an artificial process that shows itself within system. Network protocols used by devices to interact and send information to other systems represent speech in engineering systems. To share data, cognitive systems should be able to adjust to any communication protocol. Nevertheless, initiatives to standardise such protocols in the IoT are aimed at finding an easier solution. Intelligence is built on the preceding four cognitive operations and incorporates them into an analytical process capable of choosing the best decisions. Intelligence can carry out an assessment and develop appropriate action in the face of unanticipated conditions and uncertainty to then learn from it.

This innovative feature to Haykin's realisations sparked the special necessity to incorporate cognitive control further into conceptual frameworks of cognitive dynamic systems [10]. Fatemi et al. present a fresh perspective on cognitive control in this study, concentrating on two key components: training and planning, both of which are based on two basic ideas. Firstly, the global perception-action cycle, which in this case refers to a cyclic controlled stream of environmental information and is the basic premise of cognition. Secondly the two-state model is composed of the target state, or target of interest, and the current entropic state of the preceptor, which can be viewed as a measure of the lack of sufficient data in the cyclic flow of information from the global PAC. Mathematically it is represented by a state-space model of the environment defined by a process equation and a measurement equation. The target state, or target of concern, is made up of the goal state and the entropic state of the preceptor, which again can be thought of as a gauge of the insufficient data in the cyclical flow of information from the global PAC. A state-space model of the environment characterised by a process equation and a measurement equation is used to describe it analytically.

The purpose of cognitive control is to optimise cognitive strategy, which is defined as the probability density function of cognitive activities, such as the impact of past behaviour on present state, via learning and scheduling. The current state of the preceptor is described using Shannon's entropy notion, which quantifies the disturbance existing as a probability distribution depending on acquired data. The system attempts to estimate future entropic state of the system and apply it in the planning stage of the cycle through gradual variations, formalised by an automatic rewarding mechanism at the end of every iteration [10]. The core of the cognitive controller capabilities is the cognitive control algorithm, which is described in the article as a method to converge towards the optimal policy. This is defined and proved as a special example of dynamic programming that inherits the fundamental traits of convergence and optimality.

The authors explain a combined strategy of pure exploration and pure exploitation dubbed the $\epsilon - greedy$ strategy, which they adapted from Powell et al. [11], to accelerate the learning and convergence of the algorithm to optimized parameters. This balance among exploitation (selecting activities based on the highest value criterion) and exploration (purposeful sampling actions arbitrarily) could be considered as an attentiveness enhancer. Assigning computing resources to sustain developing awareness of the environment while avoiding local sub-optimal solutions [10]. Figure 2 depicts the global feedback loop as well as the interconnections between both the cognitive perceptor and the cognitive controller. The implementation of cognitive control studied in [10] uses this novel cognitive controller idea to solve a radar surveillance challenge. The cognitive controller adjusts the parameters in the system to enhance the prediction of the object's potion, velocity, and ballistic coefficients. When contrasted to a static waveform radar, dynamically modifying the waveform led to a four-order-of-magnitude enhancement in performance.

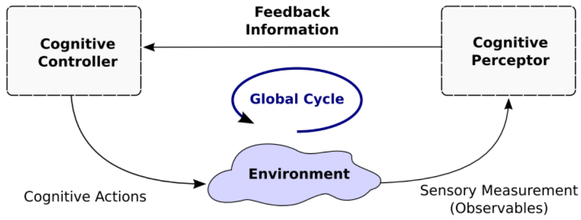

Figure 2: Cognitive Control flow diagram. [10]

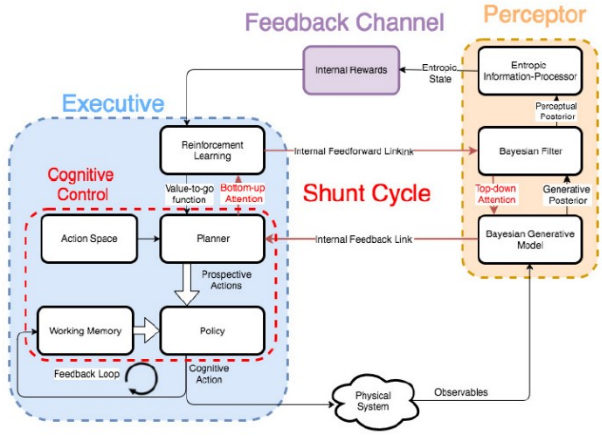

Figure 3: Architectural composition of CDS inclusive of Cognitive Risk Control mechanisms. [12]

In the face of future unforeseen uncertainty, cognitive control, as previously established, misses a strategy for anticipating undesirable outcomes or impediments, often known as risk. The researchers in [12] go even farther, recognising the necessity for a component able of interfacing with multiple parts of CDS, like the preceptor, working memory, and executive memory, in order to predictably adjust the system to the new unpredictable environment. To drive CDS via timely risk-avoidance actions, this redefined subsystem employs a Bayesian filter algorithm and a Bayes generative model [12]. Figure 3 depicts the perceptor's engagement with the Bayesian-based subsystem. The posterior is calculated on the latest state derived from previous iterations in this generative model, with the caveat that each PAC cycle may have multiple repetitions.

The article's Bayesian filtering is the sub-optimal Kalman filter, which is applied under premise of a linear model. For nonlinear applications, the cubical Kalman filter is recommended. The screening phase' goal is to gather up valuable information from the generative model and discard useless details, all while refining the important information given to the entropic information processor in a top-down attention process. In addition, a shunt cycle is established to transfer bottom-up attention from the scheduler to that same reinforcement learning algorithm, culminating in localized feedback between the systems. The entropic state computation flows through into internal rewarding mechanism, which feeds into the executive for reinforcement learning and task switch control. This has two key qualities that let it distinguish between different scenarios: internal rewards are always positive in the absence of uncertainty and persistently negative in the presence of uncertainties. The reinforcement learning mechanism computes and transforms them into a value-to-go function, which is used as input to the cognitive controller. The action space (which contains all theorised activities), internal incentives, discount factor (a weight provided to progressively discount prior actions), and policy, all impact this.

The cognitive controller is made up of the planner and the policy, as defined earlier in this section (the function that leads to decision making) and of a classifier involved in decision-making, selecting risk-sensitive cognitive actions when there is ambiguity. The classifier assigns a specific posterior to prior disrupted cognitive activities stored in executive memory based on N past events. Moreover, a task switching mechanism is provided to avoid the disrupted cognitive operations from impacting executive memory; this directly connects with the internal reward systems' dual composition. Pre-adaptation is accomplished by correctly identifying events that took place in hazardous uncertain situations versus those that did not. In the CDS framework, a set of gates are employed to divert the flow of data to other regions, necessitating additional investigation if disruptive cognitive actions are required [12]. The implementation of effective policy decision is of major relevance in the administration of these systems, hence cognitive control is highly pertinent in the IoT field.

The following Section will discuss some attempts to apply the CDS framework to the IoT and more general trials to bring cognition into these systems.

B. Cognitive IoT

Incorporating a cognitive element to the Internet of Things advances existing studies in the areas, which is focused on enabling generic objects to detect their surroundings and share their findings with a central administrator. According to Wu et al. [7], simply being connected is insufficient. IoT systems should be able to learn,

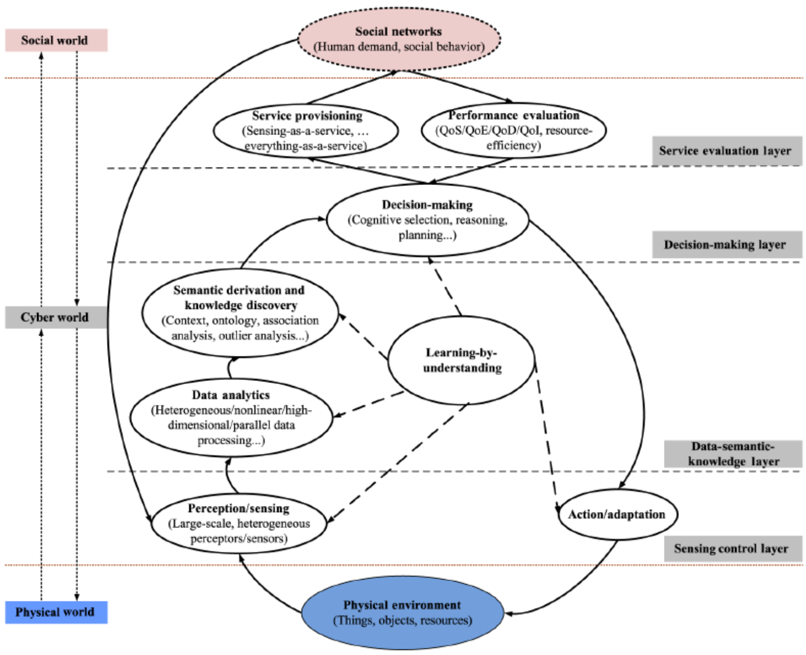

Figure 3: Cognitive Control flow diagram. [7]

think, and comprehend the physical and social world on their own, giving them "high-level intelligence" [7]. Based on past work by Haykin and Fuster, the study proposes a new concept, the Cognitive Internet of Things (CIoT). It presents a new implementation strategy based on interactions between five basic cognitive tasks: the perception-action cycle, large data analysis, semantic extraction, knowledge extraction, intelligent decision-making, as well as on demand resource provisioning [7].

By bridging the tangible, virtual, and social worlds and enabling smart distribution of resources, active network operation, and smart service provisioning, the researchers introduce a new network framework wherein physical/virtual objects are interconnected and act as autonomous agents with minimal intervention. The structure can be separated into layers. Through processing incoming inputs and feedback data, the sensory control layer, which is linked to the global PAC cycle, directly interacts with the surroundings. The semantic knowledge layer, which is concerned with semantic and ontological derivations, further analyses the input in order to provide context awareness. The decision-making layer reasoned, planned, and selected the best appropriate action for the interacting parts to take to use the information extracted from the preceding layer. The service evaluation layer evaluates the services provided and the feedback, using innovative social world-related performance measures.

Planning and choosing are the two aspects of decision-making generally. The article refers to the process of selecting an action from a range of options based on gathered data and deduced knowledge in Cognitive Radio Networks (CRN), which is driven by their learning capabilities. The ability to cognitively modify based on previous and present data is known as cognitive selection. The research highlights three types of cognitive selection: Markovian decision processes, multibandit armed problems, and multiagent learning. Since a distributed IoT architecture is likely to have a high number of decision-makers, the authors focus on the last described method, modelling it using game theory and studying the learning approach with ambiguous, volatile, and incomplete data [7].

Noncooperative game theories, which characterise exchanges between individual decision whereby each player optimises its utility function, are indeed a good fit for the challenge. The development of this systems is primarily concerned with constructing a utility function and achieving acceptable stable solutions. Local relationships amongst actors and spatial game models present additional hurdles in sizable CIoT systems. While global information exchange is impossible in a traditional large-scale IoT system, local interactions between agents can be achieved via regional collaboration, resulting in near-optimal solutions. The paper does not address whether blockchain may be a plausible solution for the worldwide flow of information in an IoT ecosystem and could be a future topic for research in this field.

In CIoT, evaluating the overall system performance is a difficult operation that is reduced by classifying the data into two dimensions: cost and profit. Three primary measures are presented in the profitability dimension. The quality of data (QoD) is the initial parameter, which assesses the data gathering procedure as well as the reliability of sensed data. Furthermore, the QoD ought to be able to measure data completeness, veracity, and timeliness. The next indicator is quality of information (QoI), which reflects the amount of useful data obtained over a certain task based on precision, accuracy recall, and volume by the decision-maker. These specifics define the quality of the information presented. Finally, the profit dimension's quality of experience (QoE) indicator assesses customer experience relating to access, steady operation, speed, and requirements. Device usage performance, computational complexity, energy efficiency, and storage efficiency, on the other hand, are the cost aspect measures provided in the study.

Home automation provide an ideal platform for analysing the prospects of CIoT as a people centric IoT that enhances the quality of life by dynamically modifying the living spaces in the context of linking the cyber-physical and social worlds, as described in [21]. Additionally, the growing presence of intelligent sensors in households makes it feasible to introduce intelligence to today's smart homes, buildings, automobiles, and, eventually, cities.

In a larger sense, CIoT could be deployed to smart cities in a variety of ways. Feng et al. detail a test case employing the CDS concept towards the Internet of Vehicles (IoV) in smart cities in [22], claiming that modernising the transport network has the potential to decrease traffic, vehicle crashes, and commuting expenses. CAVs (connected autonomous vehicles) are ideal for this since they can change their activities in response to perceived environmental data. To keep up with recent advancements in the use of electric automobiles, the article expands this description to RACE vehicles. The adoption of vast CAV networks could help both commercial and public mobility but would also expose them to cyber-attacks. While delving into the CDS framework for smart vehicles, the authors explain the cyber dangers that such networks may face and recommend countermeasures to maintain the system's resilience, security, and privacy. This study looks at active attacks like jamming, binding, and FDI attacks, as well as passive attacks such eavesdropping and stalking [22]. Due to complex, variable, and hostile environment in which CAV function, adding CDS as a proactive supervisor of all components existing in a car is desired to improve risk management reduction via joint interoperability and adaptability. Relying on the context extrapolation features of CRC, operational sensors like LIDAR, video cameras, radio receivers, and radar receivers might be dynamically modified to the scenario, increasing their functionality. The authors offer an improved CRC framework that is based on a Bayesian generative model and entropic information processing, which uses a task switch method of control to change mode of operation situationally. The reinforcement learning and scheduler, action library, policy, classifier, working memory, and executive memory all make up the executive element of CDS, that would estimate the optimum cognitive action or policy based on the adaptive and filtered feedback information. Further studies in the application of CIoT to smart cities, smart manufacturing and smart energy grids can be found in [23]-[25].

III. Conclusion

This article provides an overview of Cognitive Dynamic Systems and how they can be used in the Internet of Things. The standardisation initiatives aimed at expediting the creation of new IoT designs were also discussed in order to highlight the current issues with interoperability in IoT architectures, which is required to develop larger scale and comprehensive IoT and CIoT architectures. In addition, based on current research, the usage of Cognitive Radio for IoT was examined. Finally, IoT was used to improve cognitive policy selection and how CIoT is approached.

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