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Cognitive Dynamic Systems: A Review of Theory, Applications, and Recent Advances

This article reviews the current state of research literature published on cognitive dynamic systems and their applications.

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ABSTRACT | The field of cognitive dynamic systems (CDSs) is an emerging area of research, whereby engineering learns from neuroscience. Under this framework, engineering systems are configured in a manner that mimics the human brain and improves the utility and performance of traditional systems. In essence, a CDS builds on Fuster's paradigm of cognition and is fulfilled with the presence of five cognitive processes: the perception-action cycle, memory, attention, intelligence, and language. When augmented with these processes, a system can be classified as a CDS and is afforded the capabilities of processing information and learning from experience through continued interactions with the environment. Tremendous benefit from adopting the CDS framework has been observed in the literature, especially in the fields of cognitive radio and cognitive radar. More recently, the framework has been extended to other areas, such as control theory, risk control, and the Internet of Things; where the potential for drastic performance improvements has been evident in the literature. This comprehensive article presents a thorough background and exposition of the CDS framework and each field where it has been applied. In addition, we provide a comprehensive review of the recent advancements and related works in each domain by summarizing the key facts relating to the methodologies, findings, and limitations of the surveyed papers. Our novel contributions involve being the first source of centralized information on this topic and forming the foundation for future research efforts by presenting suggestions regarding worthwhile avenues for further investigation.

KEYWORDS | Cognitive control (CC); cognitive dynamic systems (CDSs); cognitive Internet of Things (CIoT); cognitive physical systems; cognitive radar; cognitive radio; cognitive risk control (CRC); engineering; stimation theory; machine learning (ML); natural language processing (NLP); reinforcement learning (RL).

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NOMENCLATURE

5G	Fifth-generation.
ANN	Artificial neural network.
ATSC	Advanced Television Systems Committee.
BDI	Bad data injection.
BP	Basis pursuit.
BUCB	Bayesian upper confidence bound.
DL	Deep learning.
CAF	Cyclic autocorrelation function.
CAV	Connected autonomous vehicle.
CBTC	Communication-based train control.
CC	Cognitive control.
C-CRC	Coordinated cognitive risk control.
CDS	Cognitive dynamic system.
CIoT	Cognitive Internet of Things.
CKF	Cubature Kalman filter.
CM-CNN	Covariance matrix-aware convolutional neural network.
CNN	Convolutional neural network.
CPS	Cyber–physical system.

CRC	Cognitive risk control.
CREW	Cognitive radar engineering workspace.
CS	Compressed sensing.
CSI	Channel-state information.
CUSUM	Cumulative sum.
CVR	Cognitive vehicular radar.
DBN	Dynamic Bayesian network.
dc	Direct current.
DRM	Demand response management.
DSM	Dynamic spectrum manager.
FAR	Fore-active radar.
FCC	Federal Communications Commission.
FDI	False data injection.
GFDM	Generalized frequency division multiplexing.
GMM	Gaussian mixture model.
HMM	Hidden Markov model.
IoT	Internet of Things.
IR	Infrared.
IWFA	Iterative water-filling algorithm.
KF	Kalman filter.
kNNs	k-nearest neighbors.
LFM	Linear frequency-modulated.
LiDAR	Light detection and ranging.
LMR	Land-mobile radio.
LTE-M	Long-term evolution for metro.
M2M	Machine-to-machine.
MAB	Multiarmed bandit.
MCC	Microgrid control center.
MES	Manufacturing execution system.
MIMO	Multiple-input multiple-output.
ML	Machine learning.
MSE	Mean square error.
MTM	Multitaper method.
NFC	Near-field communication.
OFDM	Orthogonal frequency-division multiplexing.
OMP	Orthogonal matching pursuit.
PAC	Perception-action cycle.
PCRLB	Posterior Cramér–Rao lower bound.
pdf	Probability density function.
PRM	Probabilistic reasoning machine.
RFID	Radio frequency identification.
RKRL	Radio knowledge representation language.
RL	Reinforcement learning.
RMSE	Root mean square error.
SCAN	Stopband cyclic algorithm new.
SCF	Spectrum correlation function.
SIF	Sliding innovation filter.
SMDP	Semi-Markov decision process.
SNR	Signal-to-noise ratio.
SVM	Support vector machine.
T2T	Train-to-train.
T2W	Train-to-wayside.
TAR	Traditional active radar.
TPC	Transmit-power controller.
TR	Time-reversal.
TSC	Task-switch control.
UAV	Unmanned aerial vehicle.
UCB	Upper confidence bound.
UWB	Ultrawideband.
UWB-PPM	Ultrawideband pulse position modulation.
V2V	Vehicle-to-vehicle.
VMM	Virtual measurement vector.
VRE	Virtual representation of the environment.
WeSCAN	New weighted stopband cyclic algorithm.
WLAN	Wireless local area network.
WSN	Wireless sensor network.

I. INTRODUCTION

CDSs have emerged as a new integrative field of physical systems heavily inspired by ideas drawn from neuroscience and cognition in the human brain. Viewing human cognition as a form of unique neural computation, the study of CDS combines knowledge from various fields, including neuroscience, cognitive science, computer science, mathematics, physics, and engineering [1]. With this combined knowledge, CDS aims to advance and improve current dynamic physical systems by instilling them with a sense of cognition.

A dynamic system operating in the environment is deemed cognitive when capable of five fundamental processes essential to human cognition: the PAC, memory, attention, intelligence, and language [1]. When designed and implemented with the processes mentioned, a system is classified as a CDS, which will be equipped to perceive and interact with the environment, while it stores and learns from past experiences to adapt its operation, improving its efficiency, effectiveness, and robustness. It is important to note that, occasionally, a CDS may simply be referred to as a cognitive system, as cognition is inherently dynamic.

Motivating the growth of interest in CDS research is the seminal work by Haykin on cognitive radio in 2005 [2] and cognitive radar in 2006 [3], which have seen exponential growth from the literature, more so in the former than the latter. Cognitive radio has been proposed for solving the problems associated with the underutilization and scarcity of the electromagnetic spectrum, while cognitive radar was proposed for improved performance in terms of accuracy and reliability in remote sensing applications [2], [3], [4].

In 2012, CC was proposed and described by Haykin et al. [5] as one of the two special functions of CDS to overcome the limitations of current adaptive controllers and neurocontrollers when faced with unmodeled dynamics and unstructured environments. The CC paradigm is additive in nature to current system designs and introduces a new state known as the entropic state based on the notion of an information gap to be controlled instead of the state-space model. A CIoT framework was first described in 2014 by Wu et al. [6] to improve on and exploit the interconnectivity of smart devices by empowering them with the ability to learn and understand from collected data and adapt to changes by resource-efficient decision-making mechanisms. Namely, the CIoT framework tackles issues associated with the heterogeneity of data collected from various sources in a network. Finally, and most recently, CRC was proposed as the second special function of the CDS by Haykin [7] and Haykin et al. [8]. The objective of CRC is to expand on the CC architecture to account for and bring under control the risks associated with uncertainties faced by a system, such as security threats frequently encountered by physical systems like cyberattacks on smart grids or jammers acting on radar systems.

The idea that engineering can be inspired by nature or humans can be traced back extensively throughout history. Biomimicry and biomimetics are concepts, whereby engineering learns from the physical or behavioral functionality of humans, animals, or anything else found in nature. One such example of these concepts includes the design of towers based on the structure of the human femur and its bone fibers, which are woven in a lattice arrangement [9]. Another example is based on the human knee, which consists of two bones and two ligaments that allow the knee to act like a four-bar hinge mechanism, which engineers study when designing humanoid robots [10]. If further rotation is required in the design of joints, engineers study the gibbon's wrist joint, which permits the human hand to rotate in a complete circle [11]. Thus, the idea that engineering can learn from human cognition and the brain's computational power in the design of existing or new physical systems is not without its merits.

This point is further justified in this article, as it will be shown that the CDS framework can instill existing systems with new functionality, such as cognitive radio's ability to find and exploit unused parts of the electromagnetic spectrum or cognitive radar's ability to adapt its transmitted waveform to avoid reserved frequency bands or narrowband interferences. Such abilities are beneficial in incrementally increasing the autonomy of these systems and decreasing their reliance on human operators. Otherwise, the CDS framework can result in various performance improvements when augmented into existing systems. For instance, it will be demonstrated that CC, when integrated with cognitive radar, can lead to improved tracking performance of single or multiple targets, even in multipath scenarios. Furthermore, CC can function as the supervisor of smart grid networks and CBTC systems, by managing their sensors, meters, and communications to ensure that the systems' resultant control actions are accurately informed and effectively delivered, even in the face of disruptions or uncertainties. Consequently, when augmented with CC, such systems have exhibited improvements in terms of state estimation accuracy, control performance, energy expenditures, reliability, and more. Finally, it will be demonstrated that the CRC architecture can extend upon CC by accounting for extended types of risky, uncertain, or unstructured environments in existing systems. An example of such includes the CRC's ability to detect and neutralize the effects of malicious acts from external actors, including jammers in cognitive radar applications, and FDI or intrusion attempts in smart grid networks.

It is important to consider, compare, and make a clear distinction between the mission of CDS and that of other cognitive frameworks. Cognitive architectures, for instance, are chiefly concerned with the study of the human mind and its structure, and the creation of models that are capable of human-level artificial intelligence [12]. Surveys in the field of cognitive architectures define cognitive architectures as proposals about mental representations and computational procedures, which operate on those representations to enable a range of intelligent behaviors [13], [14]. On the other hand, cognitive robotics has been defined as a field that combines insight from several fields, such as cognitive and biological sciences and artificial intelligence, to the application of robotics [15]. The goal of cognitive robotics is to create robots that embody human intelligence and to evaluate and investigate hypotheses about human cognition and neuroscience [15]. The mission of CDS bears more resemblance to that of cognitive robotics than it does with cognitive architectures, in the sense that CDS combines knowledge from cognitive science and neuroscience to define human cognition and instill physical systems with the elements that comprise human cognition. CDS achieves this by integrating various techniques and ideas from the fields of engineering, computer science, mathematics, and physics. The goal of CDS is to equip systems with a sense of autonomy and the ability to learn from their surrounding environment through experience over time based on the five fundamental principles of Fuster's paradigm of human cognition [16], [17].

The purpose of this article is to review and provide a comprehensive and structured overview of the current state of research literature published on CDS and its applications. By presenting the methodologies, key findings, and limitations of the surveyed literature, this work aims to provide a complete guide to the most recent contributions, advancements, and experimental results in the field. Furthermore, this work will serve as the foundation for future research efforts by sharing insight into the most promising areas for future research efforts for all the surveyed applications of CDS. The timeline of the major milestones and achievements in the field of CDS, as surveyed and discussed in the remainder of this article, are summarized in Fig. 1.

Based on our understanding, this is the first article to survey the entire field of CDS, which will hopefully accelerate growth in this relatively young field further. Other survey papers exist; however, their scopes are usually much more limited and usually focus on a single application of a CDS or a specific aspect of an application. For example, two survey papers were published recently in 2019 focusing on cognitive radio, where, in [18], the discussion was geared solely toward the related works in spectrum sensing, while Wang et al. [19] focused on spectrum allocation techniques based on RL algorithms. A survey of research

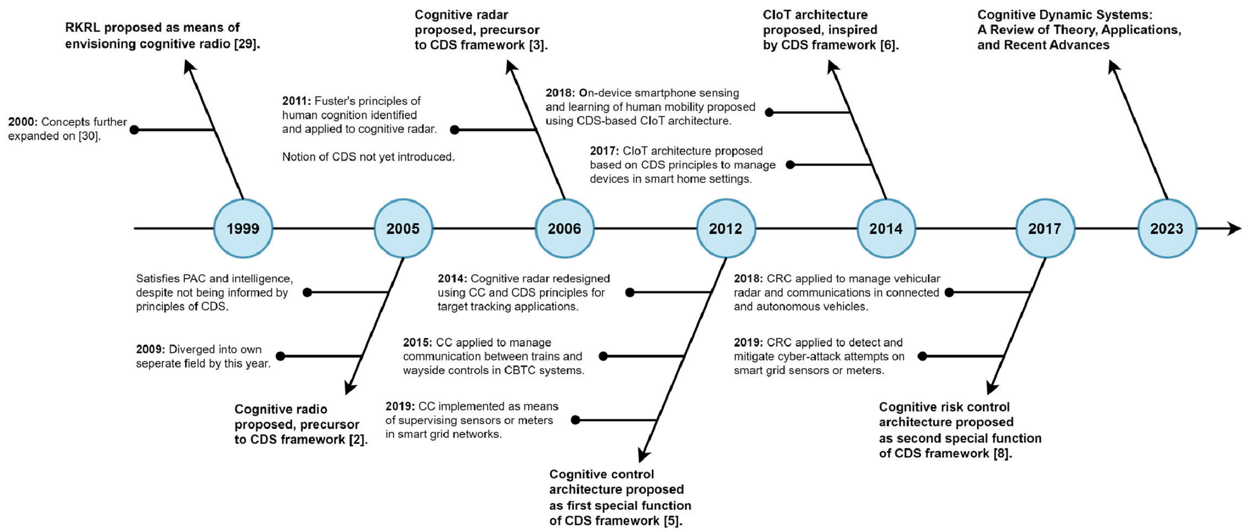

Fig. 1. ***Timeline of the major milestones and advancements of the field of CDS, as surveyed in this article.***

trends on cognitive radar, also published in 2019, can be seen in [20], where an overview of the applications and techniques is detailed with a discussion on future technical and practical challenges. The need for cognitive radio and standardization efforts in IoT technology, an issue related to but not fully encompassing CIoT, has been surveyed extensively in [21]. More survey papers exist for each of the mentioned topics, and are mentioned and discussed in their relevant sections throughout this work. However, the areas of CC, CRC, and CIoT have yet to be the subject of a comprehensive survey or literature review. Therefore, this survey provides a universal overview and study of CDSs, which provides a foundation for future research and industrial applications.

This article is organized as follows. Section II provides background on CDS and an exposition of the theory of the framework's architecture. Section III describes the first CDS, cognitive radio, and a review of recent works in the field, followed by the same procedure in Section IV for cognitive radar. Other frameworks relating to the special functions of the CDS, such as CC and CRC, are introduced alongside their related works and applications in Sections V and VI, respectively. Section VII describes CIoT and reviews the recent advances in the literature. Next, a discussion of the key findings of this article and suggestions for future research are presented in Section VIII. Finally, Section IX concludes this article.

II. COGNITIVE DYNAMIC SYSTEMS

Any system can be defined as a dynamic system if its variables or input–output behavior are time-dependent. CDSs are a new class of dynamic systems first envisioned in 2006 [22] and formally described theoretically in 2012 [1], [4], [23] by Dr. Simon Haykin. These types of systems are inspired by neuroscience and human cognition with the viewpoint that the latter is a form of computation. The CDS framework relies on a model for cognition proposed by Fuster et al. [16], henceforth referred to as Fuster's paradigm of cognition, which is based on five fundamental principles or building blocks: PAC, memory, attention, intelligence, and language. Once equipped with these fundamental principles or, as will be commonly referred to as cognitive process throughout the rest of this article, only then a system can be considered cognitive and classified as a CDS. However, as will be discussed later in this section, language has often been considered beyond the scope of consideration by CDS. Building on Fuster's paradigm, the functional structure of a CDS is illustrated and described in Fig. 2, as depicted in [17], whereby the role of each cognitive process can be summarized in the following.

A. Perception-Action Cycle

Within any CDS, there exists a perceptual part and an executive part. The perceptual part or perceptor resides on the right-hand side of Fig. 2, while the executive or cognitive controller is situated on the left-hand side [17]. The perceptor is responsible for directly observing the system and the environment using appropriate sensors, depending on the application of the CDS. For example, an estimation method or algorithm might be used during perception, which extracts relevant information from what is perceived by computing posterior estimates of the environment or system's states in each PAC. A feedback link delivers the extracted relevant information about the environment and system from the perceptor to the executive. The executive is then tasked with performing cognitive actions on the environment or the system per this information [17].

The purpose of the cognitive actions performed by the executive is to continually enhance the information extracted by the perceptor in subsequent cycles. Thus, the

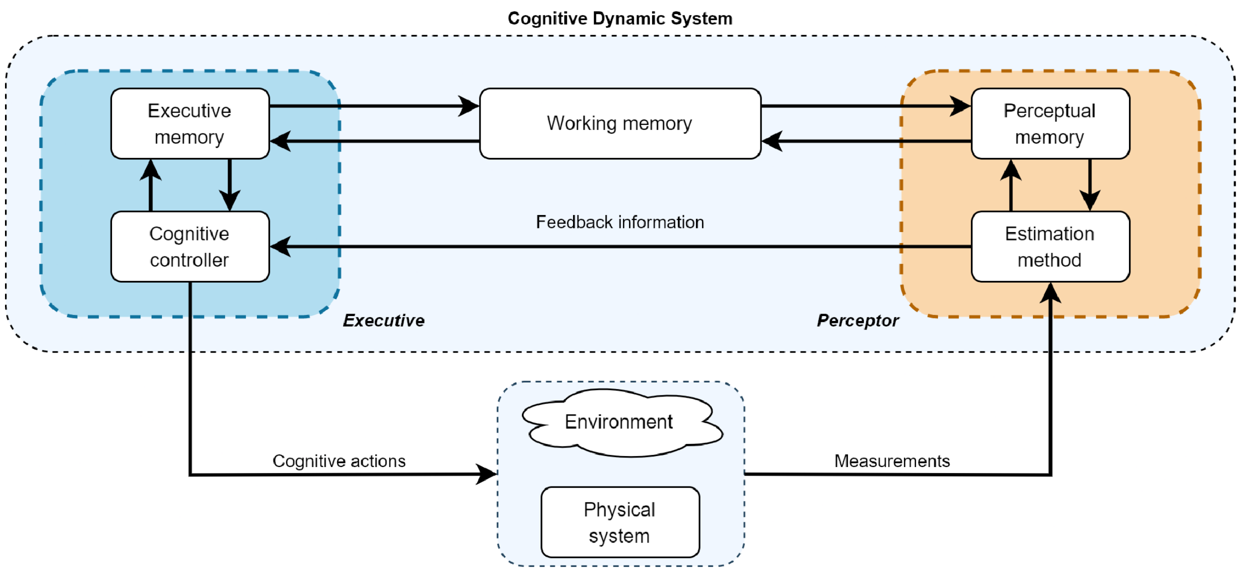

Fig. 2. ***General block diagram of a standard CDS architecture.***

executive indirectly perceives the environment through the perceptor and acts according to the information extracted, forming a global feedback loop that completes the PAC. Cognitive actions are usually applied to the environment to indirectly affect the system's perception, such as by adjusting the lighting in a dark room [5]. In this scenario, the physical state includes the positions of objects, and a cognitive action, such as turning on a light, does not affect the state of the objects but instead reduces their uncertainty. Other types of cognitive actions may be applied to adjust the system itself, such as reconfiguring its own sensors or actuators. An example of this is the adaptation of a transmitted waveform in a cognitive radar system, as will be discussed in Section IV. In addition, cognitive actions may also be applied to influence state-control actions by introducing another term, known as the entropic state, to the cost function of the state controller [5].

The cognitive controller is responsible for the decision-making behind the described cognitive actions in the executive, as can be seen in Fig. 2, based on feedback information from the perceptor [24]. However, it is not always the case that all the different types of cognitive actions exist in a particular problem. For example, a cognitive radar system performs cognitive actions only on its actuators and the environment. In doing so, cognitive radar systems can estimate a target's state without being able to control the target physically [5]. Regardless, the mechanism behind the decision-making in the executive often, but not always, involves the implementation of RL for the cognitive controller. Other methods such as Q-learning, for example, may be used. Further details regarding the cognitive controller and the implementation of RL in the framework are discussed in Section V, which focuses on CC as the overarching function of a CDS [5].

B. Memory

Building on the PAC, the cognitive process of memory occupies its own physical place in a CDS in three forms, as illustrated in Fig. 2: perceptual, executive, and working memory. The specific function and responsibility of both memory types slightly differ; however, the overall goal of equipping a CDS with memory is to allow for the capture and storage of long- and short-term information [4]. With access to this information, a CDS can learn from its past experiences in terms of action and perception, resulting in improved performance and robustness.

According to the CDS framework, the structure of perceptual memory is desirably hierarchical and consists of several layers [17]. With this configuration, the motivation is to perform perceptual abstraction of incoming stimuli or measurements to represent the essence of an object, event, or experience. The abstraction of incoming measurements is then stored internally within the perceptual memory. This is similar to and motivated by the human memory system. This approach enables long-term memory in the perceptual part of the CDS, as relevant information is retained, while irrelevant information is discarded [25]. The executive memory performs the dual function of perceptual memory in response to feedback information from the perceptor. Cognitive actions performed by the cognitive controller based on the information from the perceptor are stored long term in the executive memory. Thus, the executive memory associates a cognitive action to each incoming measurement from the perceptor, which can be used as a reference for future cognitive actions. By introducing the output of the executive memory to the cognitive controller and combining it into future policies, a new policy considering both long- and short-term experiences is achieved [24]. The executive memory essentially maintains, in a probabilistic manner, the knowledge of the action space of the cognitive controller. This action space is also associated with in measurement space of the perceptual memory.

The role of the working memory is to reciprocally couple the executive and perceptual memories, thereby acting as an interface for short-term memory between the two within the CDS [3]. With this integration, the cognitive controller can carry out its actions in a synchronous fashion, specifically when it comes to storing the predicted rewards of planned cognitive actions in short-term memory in every PAC. The concept of learning and planning is the subject of discussion later on in Section V. Otherwise, in summary, it can be said that the general role of memory is to continuously learn from and model the behavior of the environment, the measurement space, and the action space of the CDS [24].

C. Attention

Unlike the PAC and memory, which occupy their own physical places in the CDS, the cognitive process of attention manifests itself within the framework through algorithmic mechanisms. It exists as two, perceptual and executive attention in the perceptor and the executive, respectively, and both rely on localized cycles and feedback links in their respective parts of the CDS [5]. Working closely with and driven primarily by the presence of memory, their responsibilities include the prioritization of efforts and efficient allocation of resources. This is achieved in the perceptor through various techniques that can be used for filtering irrelevant information with help from past characterizations of the environment stored in memory. On the executive side, attention also exploits the well-known explore–exploit tradeoff to facilitate strategies for the learning and planning of cognitive actions for future cycles. Specifically, the explore–exploit strategy mainly serves to reduce the action space of future cognitive actions for consideration by the learning mechanism (e.g., RL) depending on the relevance to the perceived information in the current cycle [3], [24]. The explore–exploit process described is illustrated in Fig. 3, whereby the darkest point represents the learned action in the action space from the preceding PAC. The other eight, surrounding, lighter colored points are the relevant cluster of possible actions to be passed to the controller for planning in the current PAC.

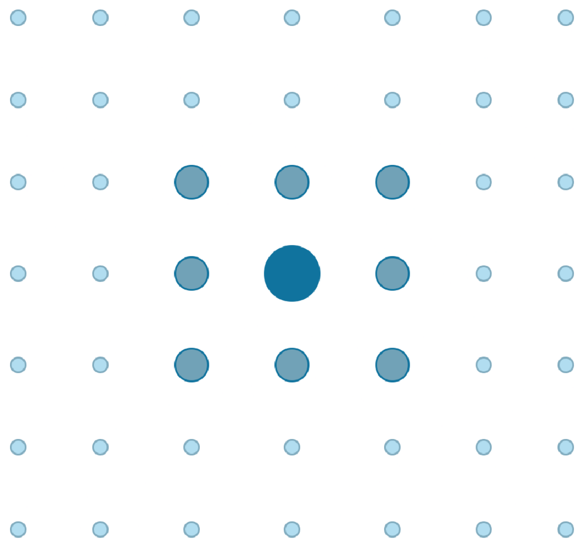

Fig. 3. ***Illustration of the explore–exploit strategy that represents one of the manifestations of the cognitive process of attention, as described in Section II-C.***

D. Intelligence

Like attention, intelligence does not occupy its own physical place in a CDS. However, it builds on all the previous cognitive processes, such as memory and attention, and utilizes them in an integrated fashion with the PAC to facilitate computational intelligence through efficient decision-making [4], [22]. The influence of intelligence is distributed throughout the entirety of a CDS, whereby its power and effectiveness in information processing are derived from exploiting all the system's feedback loops, both global and local. Quantifying the level of intelligence of a system is a challenging task. However, computational efficiency and overall system efficiency are typically used as metrics to help measure intelligence for comparative purposes. For example, if a system is computationally complex yet highly efficient, it is said to be more intelligent compared with a less-efficient system. Intelligence in the CDS framework has the key role of optimal decision-making in terms of the actions taken by the controller on the system or environment of interest [17]. As such, the choice of algorithm for the cognitive controller in a system is one of the major factors contributing to the arguments of whether or not the process of intelligence is satisfied.

E. Language

Language, the fifth principle of CDS, is primarily concerned with providing the means for effective and efficient communications between different constituents of a CDS, or between external parties, such as other systems or CDS. This final principle of cognition has generally been considered outside the framework's scope, as repeatedly stated in most of Haykin's literature [4], [23]. In addition, it has been mentioned to be deferred for future research by Haykin and Fuster [17]. Consequently, this article generally considers language to be outside the primary scope of the study. This can also be mainly attributed to the fact that the cognitive process of language has yet to be the subject of detailed examination or research in the CDS framework, which we have deduced from our survey of the existing literature. However, this provides a significant opportunity for future research work, particularly in the areas of natural language processing (NLP) and explainable artificial intelligence (xAI). These rapidly growing areas of research are critical for our understanding of CDS behavior and will assist with user uptake as the public becomes more comfortable with these types of systems as they become more embedded in our society.

It is also important to note that language in a CDS is highly dependent on its application area. Furthermore, often, language is inherently already accounted for in the application of interest. For example, Marinho and Monteiro [26] mention that the basics of cognitive radio's communication protocol are limited to physical and medium access control (MAC) layers and extensively review the works done in those areas. Similarly, in most radar applications, the communication protocols are standardized according to the IEEE 802.11 standard and the improved IEEE 802.11p standard for communication in vehicular environments, which are limited to channels of 10-MHz bandwidth in the 5.9-GHz band of the spectrum [27], [28]. The heavily regulated nature of communication protocols is among the main reasons behind rendering language beyond the scope of consideration in this article.

However, it is noteworthy to introduce and briefly discuss the concept of RKRL proposed by Mitola and Maguire [29]. The term cognitive radio was coined by Mitola [30] and expanded on in his thesis in the subsequent year as a means of enhancing the flexibility of personal services and devices. Specifically, this is achieved through RKRL, which is a declarative language for representing knowledge about the radio environment. RKRL consists of sets of rules that define relationships between aspects of the radio environment to allow for knowledge reasoning. This knowledge includes information about the spectrum, radio wave propagation, modulation schemes, and other factors, which can affect radio communications. In terms of radio etiquette, RKRL also encompasses knowledge of devices, software modules, networks, user needs, and much more. The goal of RKRL is to provide a language framework for software-defined radios in which data exchanges can be dynamically defined [31]. Furthermore, representing knowledge in this formal framework allows software-defined radios to share information about the radio environment with other users, as well as other parts of larger systems or networks. As a result, more efficient use of the radio spectrum and better coordination amongst software-defined radio users can be realized. It should be noted, however, that, based on a quick review of the literature on a software-defined radio, RKRL has not been widely adopted or implemented in the academic community or industry. A severe dearth of literature exists on the topic, and RKRL has yet to see any significant adoption or use in real-world systems. Despite this, these efforts demonstrate the first and only efforts in the field of CDS to approach the cognitive process of language. Furthermore, as will be discussed in Section III of this survey article, this work is one of the inspirations behind Haykin's work on cognitive radio in [2]. Regardless, RKRL and cognitive radio are considered precursors to the CDS framework, in which they were proposed prior to the proposal of the CDS framework. This matter is the subject of many detailed discussions and explanations throughout the remaining sections of this survey.

Finally, considering the rapid advancement of technology, the issue of cybersecurity is of paramount importance when it comes to the context of language as a cognitive process. Although cybersecurity in language may not have been previously mentioned in the literature, we consider it to be a matter that in all future research and practical applications as the field of CDS evolves. This will help minimize the possible dangers that any CDS may encounter. Other future research activities in the area of language are considered in Section VIII.

III. COGNITIVE RADIO: A PRECURSOR TO CDS

Cognitive radio has been defined as an intelligent wireless communication system, which is aware of its environment and utilizes the methodology of understanding-by-building to learn from the environment and adapt to statistical variations in the input stimuli [2]. However, the concept of cognitive radio first appeared in the literature in 2005, six years before the introduction of the CDS framework in [4]. Thus, in this section, it will be made readily apparent that cognitive radio does not strictly adhere to or even use the CDS framework. Despite being inspired by the idea of human cognition, cognitive radio has diverged and evolved into its own respective area of study. As such, cognitive radio is regarded as a precursor and motivation to the development of the CDS framework.

Even though cognitive radio does not strictly fall under the classification of a CDS, this section of this article serves to highlight the similarities and differences between cognitive radio and the CDS framework. Furthermore, this section aims to provide further insight into the timeline and development of the field of CDS over time, which has been graphically summarized in Fig. 1. This will be achieved by introducing and discussing the architecture of cognitive radio and whether any of the five pillars of cognition are satisfied even though they have not been a guiding principle in its development. A review of the main aspects and research areas of cognitive radio will follow, whereby further parallels between the two paradigms will be examined. In addition, a summary of all the surveyed works in the field of cognitive radio is presented and can be found at the end of the Section in Table 1.

A. Background and Motivation

Radio technology applications operate by using transmitters and receivers that utilize the electromagnetic radio spectrum. The radio spectrum is a precious natural resource by which governmental bodies license the use of and regulate. The traditional procedures adopted by the FCC to issue licenses and allocate bands exclusively to single entities have seen increased criticism in recent years. The exclusive licensure of these bands prohibits other

Table 1 Summary of Published Works on Cognitive Radio

Year	Authors	Reference	Research Application	P	M	A	I	Comments
2005	Simon Haykin	[2]	Original architecture	✓	×	×	✓	Proposal of original cognitive radio architecture.
2009	Haykin *et al.*	[44]	Spectrum sensing	✓	×	×	✓	MTM for spectrum hole detection; high spectral-resolution and can estimate average power in subbands as well as directions of interfering signals.
2013	Thilina *et al.*	[45]	Spectrum sensing	✓	×	×	✓	Comparative study of popular ML methods for spectrum hole detection: k-means clustering, *k*NN, GMM and SVM.
2019	Lee *et al.*	[46]	Spectrum sensing	✓	×	×	✓	Cooperative spectrum sensing employing a CNN to learn how to fuse individual sensing results of secondary users for increased sensing accuracy.
2019	Liu *et al.*	[47]	Spectrum sensing	✓	×	×	✓	CM-CNN for online spectrum sensing and detection for increased accuracy, robustness to SNR and scalability.
2007	Rashad *et al.*	[51]	Channel-state estimation	✓	×	×	×	OFDM for cognitive radio, computationally efficient and flexible.
2012	Datta *et al.*	[52]	Channel-state estimation	✓	×	×	×	GFDM proposed to address issues with OFDM such as spectral leakage, however, shown to cause increased interference.
2012	Datta *et al.*	[53]	Channel-state estimation	✓	×	×	×	Interference cancellation scheme proposed for GFDM in cognitive radio.
2018	Ye *et al.*	[54]	Channel-state estimation	✓	×	×	✓	DL-based CSI estimation in OFDM systems demonstrates robustness over traditional approaches and can address channel distortion problem.
2019	Soltani *et al.*	[55]	Channel-state estimation	✓	×	×	✓	DL-based for OFDM systems approach using deep image processing techniques to process input when considered as a 2D image.
2020	Luo *et al.*	[56]	Channel-state estimation	✓	×	×	✓	CNN and LSTM-based online CSI prediction scheme for 5G wireless communications to address computational complexity issues. ML for 5g wireless comms. Channel state information prediction.
2009	Setoodeh and Haykin	[58]	Spectrum access	✓	×	×	✓	Robust IWFA proposed for spectrum resource allocation based on permissible interference power level criterion in noncooperative networks.
2015	Ahmad *et al.*	[59]	Spectrum access	✓	×	×	×	Survey on resource allocation in cognitive radio sensor networks, classifying approaches as centralized, cluster-based or distributed.
2015	Xu *et al.*	[61]	Spectrum access	✓	×	×	×	Survey on robust power control and beamforming algorithms.
2016	Ahmed *et al.*	[60]	Spectrum access	✓	×	×	×	Survey on channel assignment algorithms in cognitive radio networks.
2018	Li *et al.*	[62]	Spectrum access	✓	×	×	✓	RL-based method proposed for power control in cognitive radio networks, demonstrates robustness to random variation in state observations.
2019	Wang *et al.*	[19]	Spectrum access	✓	×	×	✓	Survey on RL-based spectrum allocation methods in cognitive radio networks.

* P represents the PAC, M represents memory, A represents attention, I represents intelligence, ✓ represents the presence of cognitive process, and × represents the absence of cognitive process.

entities or devices from transmitting significant amounts of power within them. The FCC has also designated a few unlicensed bands known as the industrial, scientific, and medical radio bands over which popular Wi-Fi devices transmit. However, these ISM bands are being occupied rather quickly.

The significant underutilization of the radio spectrum was made apparent in a 2002 report prepared and published by the FCC; the aim was to improve the management of this precious resource within the United States' jurisdiction [32]. The task force responsible for the report consisted of top-level FCC professionals whose expertise spanned multiple disciplines and industries. In terms of spectrum utilization, the main findings of the report detail that, if portions of the radio spectrum were to be scanned, many of the legally licensed and owned frequency bands would be vastly underutilized by the *primary* users. As such, this leads to the following definition by Haykin for *spectrum holes* [33]:

"A spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user."

In recent years, researchers have recommended allowing secondary users, who are not otherwise serviced, access to spectrum holes unoccupied by primary users given the appropriate spatial and temporal conditions to achieve improved spectral efficiency [2], [34]. Cognitive radio is a term coined by Mitola and Maguire [30] and built on the novel idea of software-defined radio and expanded in Mitola's Ph.D. thesis. Furthermore, as mentioned in Section II-E, Mitola's cognitive radio was based on the concept of RKRL, a language framework to facilitate knowledge reasoning and exchange between devices. Cognitive radio has been suggested as a novel way of solving the spectrum underutilization problem by exploiting the presence of spectrum holes [2], [30]. This technology facilitates the coexistence of the incumbent primary users with the secondary users by dynamically adapting its transmissions to search for unutilized frequency subbands. This is carried out while minimizing interference and providing the means for accessing those subbands [33]. Spectrum holes pose technical challenges in their identification and exploitation, rooted in the stochastic nature of how they appear and disappear.

B. Overview of Cognitive Radio

Cognitive radio consists of three functional blocks or cognitive tasks that form a cognitive cycle: radio scene analysis and channel identification, carried out by the receiver, and radio scene actuation, by the transmitter. The processes involved in a cognitive radio are represented in a flow diagram in Fig. 4. Radio scene analysis is conducted through an environmental scene analyzer within the receiver, which senses the radio environment to discover spectrum holes and their locations in time and space [4]. Another critical function of the environmental scene analyzer is identifying the location of interferers in time and space, and estimating a metric known as the interference temperature. Effectively, spectrum holes and interferences can be regarded as the spatiotemporal state of a radio's environment from the cognitive radio's frame of reference. Channel identification is also carried out in the receiver and encompasses the estimation of CSI and the prediction of channel capacity for use by the transmitter based on the interference temperature. This results in the formation of a local feedback loop [2]. A new metric known as the interference temperature is proposed to measure the radio frequency power available at a receiver. This metric reflects the power generated by noise sources and other entities. Furthermore, the new metric makes it possible to enforce a maximum amount of tolerable interference for a given frequency band at a particular location, thus characterizing the worst case environment in which a receiver would be expected to operate [32].

As mentioned previously, information about the presence and location of spectrum holes, predicted CSI, and capacity in the transmitter is relayed from the receiver. Given this feedback information from the receiver, a TPC is utilized to allocate limited battery power among competing secondary or cognitive radio users with this information [2]. Furthermore, the DSM is responsible for distributing the available spectrum among the competing secondary users. Following the processes carried out by TPC and the DSM, the radio scene actuator is responsible for transmitting a signal, closing the global feedback loop.

Despite the lack of guidance from and reference to Fuster's paradigm of cognition, several observations can be made about cognitive radio. First, the presence of the PAC in cognitive radio is considered to be fulfilled by having a receiver perceive the environment and a transmitter acting in response to that receiver's perception of the environment through a global feedback loop. As for memory, there is no mention throughout the cognitive radio literature

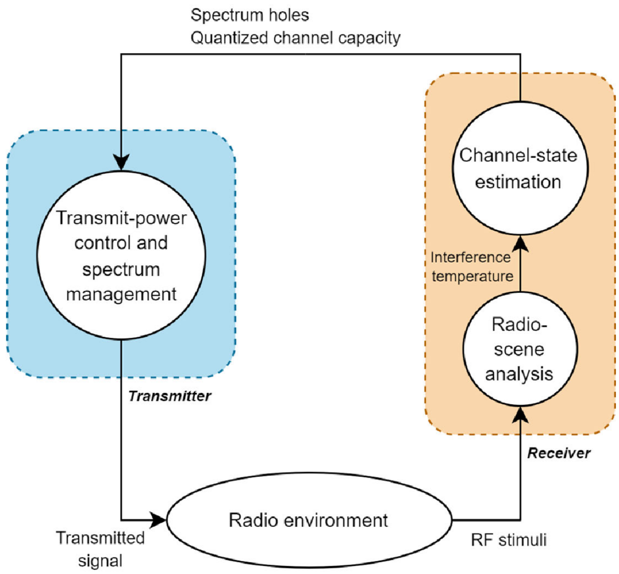

Fig. 4. ***Overview of a basic cycle in a cognitive radio system and the three fundamental tasks involved (adapted from [2]).***

regarding the need for storage or retrieval of any past data or experience. Consequently, it is determined that the cognitive process of memory is absent in the cognitive radio architecture. In the case of the cognitive process of attention, an argument can be made that attention is present only due to the nature of the TPC algorithm described in the literature [2]. Specifically, an IWFA is described for this task, which is equipped with the ability to adjust the power allocation among several users depending on their data transmission rate. If a user's data-transmission rate is greater than a target value, the transmit power is reduced. On the other hand, if the rate is below the target, the transmit power is increased while keeping in mind that the interference temperature must not be violated. Although this implementation of the mechanism of attention does not strictly adhere to that described earlier in Section II-C, it can still be argued to be another form or degree of the manifestation of attention. It must be emphasized again that it is due to the IWFA that cognitive radio exhibits some degree of the process of attention; however, certainly not to the full extent that one would expect from a typical CDS. Finally, when it comes to the cognitive process of intelligence, there is evidence of its existence in cognitive radio. This is mainly due to the ability of cognitive radio systems to exploit the feedback information from the receiver in the transmitter and enable effective decision-making with the TPC through the use of game-theoretic and statistical learning-based approaches [2].

C. Related Works on Cognitive Radio

1) Spectrum Sensing: Among the many fundamental processes involved in cognitive radio, the most exhaustively researched is the task of spectrum sensing, which is embodied by radio-scene analysis. As briefly mentioned, spectrum sensing is responsible for locating spectrum holes and monitoring the appearance and disappearance of primary users. The purpose of this is to minimize the interference that the cognitive radio users may cause to the primary users. Spectrum sensing also entails determining the resolution of each spectrum hole, the estimation of spatial directions of any incoming interferers, and the classification of signals. In the last decade, there have been significant efforts to study and improve spectrum sensing techniques and performances, and in this section, the most prominent techniques and approaches will be highlighted. For a more comprehensive review of this topic, we refer the reader to [18].

Energy detection is considered the most straightforward approach to spectrum sensing, providing reasonable performance levels without much computational complexity [35], [36]. This approach requires no a priori knowledge of the primary signal, making it robust to statistical variations of the signal, and can detect the presence or absence of the primary signal [37]. The RF energy in the channel is measured to determine if a channel is idle or not, and the input signal is subsequently filtered using a bandpass filter to select bandwidths of interest. Then, the signal is squared, and the integral is taken over the observation interval and then compared to a predetermined threshold to determine the presence or lack of the primary user signal [38]. However, there are disadvantages and drawbacks to the energy detection approach; the first is that it performs poorly under low SNR conditions. A low SNR means that the noise's variance is not known with enough accuracy, and thus, the uncertainty of the noise renders the energy detection approach useless [39]. Furthermore, energy detection techniques cannot distinguish other cognitive users with whom a channel is shared from primary users requiring the channel to be vacated [40]. The minor errors resulting from noise power estimation may result in a significant performance loss due to the dependence of the threshold used in energy detection on the noise variance.

Alternatively, the cyclostationary detection approach to spectrum sensing is more robust to noise uncertainty than energy detection techniques. In general, signals that are human-made are nonstationary, and many of these signals are often cyclostationary. A signal is characterized by the property of cyclostationarity if its statistics exhibit periodicity, often caused by the modulation format and coding, or it may be produced in such a way intentionally to assist in channel estimation and synchronization [37]. It is possible to exploit this periodic nature to detect random signals with specific modulation types in a noisy background with other modulated signals, otherwise known as cyclostationary detection. The detection of these signals is achieved by first computing the CAF of an observed signal and then taking its discrete Fourier transform to observe its 2-D SCF [41]. The importance of the SCF is due to the correlation between widely separated frequency components due to the spectrum redundancy caused by the modulated signal's periodicity. From the SCF's-plane analysis, detection is achieved by finding the unique cyclic frequency that corresponds to the peak in the plane [42]. The robustness of this approach to noise and interference from other signals lies in the fact that the noise only has a peak in the SCF at a cyclic frequency of zero, and the various other modulated signals have unique cyclic frequencies. Therefore, it is possible to detect the signal of a primary user from cognitive user signals over a frequency band. A limitation of the cyclostationary detection approach is the increase in implementation complexity compared to energy detection [43]. Another major limitation of this approach is its requirement of a priori knowledge of the primary user signal properties, such as the modulation format.

Due to the unreliable nature of wireless communications, which are further compounded by the uncertainties of accessing those spectrum holes, it is often preferred that a nonparametric approach to spectrum sensing is undertaken. Using a nonparametric approach, modeling the system under study can be avoided, and instead, it is possible to deal directly with the stochastic process under study. Energy detection is one such approach; however, it is affected by significant limitations discussed earlier in this section. The MTM was proposed by Haykin et al. [44] to address these issues by reliably and accurately estimating the power spectrum of RF stimuli as a function of frequency and subsequently identifying locations of spectrum holes within the spectrum. This nonparametric approach uses multiple tapers (or windows) to reduce the bias of the power spectrum estimate of a stochastic signal. With the use of multiple tapers, the increase in the estimate's variance resulting from loss of information due to the truncation of time-domain windowing that is usually accompanied by using a single taper is mitigated.

In addition to locating spectrum holes and estimating power contents, a sense of direction is required when analyzing the radio scene in the neighborhood of a local receiver to listen to any inbound interfering signals from unknown bearings. In other words, a sensing technique must be equipped with space–time processing capabilities, which the MTM naturally lends itself to. This is due to an effective tool known as singular value decomposition [44]. The studies expand on the MTM by embracing the Loève transform and, thus, enabling time–frequency analysis to be performed by cognitive radios. This feature allows for the MTM to find properties of cyclostationarity in signals. Furthermore, the authors perform experimental simulations and apply the MTM to perform wideband spectrum sensing in ATSC and LMR signals. From the results of the experimentation, the literature concludes that the proposed MTM with time, space, and frequency analysis capabilities is a robust spectral estimator, which resolves the bias–variance dilemma. Furthermore, it is shown that the MTM is feasible for real-time computation, has the capability of multidirectional listening, and characterizes the property of cyclostationarity in the receiver's input [44].

In more recent years, there have been increased efforts in the literature focusing on applying ML and DL techniques for spectrum sensing in cognitive radio. ML approaches can effectively extract the features of various environments in a data-driven methodology and have been proven to provide superior performance in many different applications. Thilina et al. [45] proposed several ML models, such as k-means clustering, SVM, kNNs, and GMMs as classification and clustering techniques to determine the availability of spectrum holes from incoming signals. The authors showed that the model's performances are rather impressive and exceed existing techniques. However, a limitation of some of these models is their reliance on information from the primary user about the spectrum occupancy of incoming energy vectors during their training phase. As a result, these models are often more challenging to implement. Lee et al. [46] also proposed a cooperative spectrum sensing scheme, where a CNN is trained with simulated data to autonomously learn strategies for combining individual sensing results of cognitive users to detect a primary user instead of explicit mathematical modeling. The proposed CNN model was shown to have greater sensing accuracy than conventional approaches and lower computational overhead. Liu et al. [47] suggest that a more practical approach is required and proposed a CNN that relies on its input from a sample covariance matrix due to its versatility as a test statistic. The proposed CM-CNN takes advantage of the input's 2-D structure to extract discriminative features. The CM-CNN was demonstrated to perform similar to other conventional approaches through experimentations while being robust to SNR conditions and not depending on a priori information from primary users.

2) Channel-State Estimation: The CSI in communication systems contains knowledge about the properties of a channel in a communication link. Channel-state estimation is a feature needed in a receiver of cognitive radio for coherent detection of transmitted signals to acquire CSI to describe the nature of the propagation of signals from the transmitter to a receiver [2]. The information describing how a signal propagates represents the combined effects of scattering, fading, and power decay over distance. The CSI is also used to compute a channel's capacity and is required for the transmitter to carry out transmit-power control, which is the focus of discussion in Section III-C2. Despite the practical significance of channel-state estimation in improving the reliability of spectrum sensing in cognitive radio, research on novel methods and advancements in this field has been relatively scarce compared to other areas of cognitive radio systems.

Generally, the channel-state estimation problem is dealt with using training-based strategies, which often requires a pilot signal [48], or blind strategies that use the statistics of incoming data and eliminate the need for a pilot signal [49]. The training-based approaches can achieve significantly better accuracy than blind estimators but are often imprudent in managing channel bandwidth and transmit power. The reasoning behind this is that channel estimation can be impaired by pilot signals transmitted by other users, which renders the addition of transmit power ineffective [50]. This effect is known as the pilot contamination effect. Furthermore, when it pertains to channel-state estimation techniques, most of the published literature on the topic assumes systems based on the OFDM modulation strategy [51]. Inherent features of OFDM allow them to be computationally efficient and flexible, and commend themselves to cognitive radio. Building on this success, GFDM has been proposed to address weaknesses in OFDM, such as spectral leakage to adjacent frequency bands resulting from rectangular pulse shaping [52]. However, interference is introduced in this approach, which degrades GFDM systems' performances due to using a root-raised cosine filter. Owing to the subsequent work of Datta et al. [53], it has been shown that, by using a successive interference canceller, the degradation in performance can be mitigated.

We observe, interestingly, that, in recent years, there has been a proliferation of literature investigating the use of ML-based channel-state estimation techniques for legacy communication systems. For example, in [54], an ML-based model using ANNs in OFDM systems is proposed, and similarly, Soltani et al. [55] proposed a framework for channel estimation in OFDM using CNNs, with both approaches demonstrating superior performances compared to traditional approaches. In [56], a hybrid CNN and LSTM model is used to estimate CSI in 5G communications. As such, we postulate that further investigation into applying ML techniques for channel-state estimation in cognitive radio networks may serve as a worthwhile avenue of consideration for future research efforts.

3) Spectrum Access: With the ability to now identify the location of spectrum holes using spectrum sensing techniques and the estimation of CSI to determine a channel capacity, a cognitive radio's transmitter is then responsible for spectrum access [57]. In Fig. 5, the concept of locating spectrum holes in time and space and estimating channel capacity is illustrated. From this figure, it can be seen that a third component must be factored into consideration in cognitive radio systems to facilitate spectrum access: the power of a secondary user's transmitted signal. The TPC, located in the transmitter, is responsible for allocating and distributing transmit power to secondary users to maximize their transmission rates while ensuring that interference on primary users is below prescribed thresholds [2]. Subsequently, the DSM, also in the transmitter, is responsible for devising a decentralized dynamic spectrum management policy to utilize spectrum holes effectively and efficiently among competing secondary users in a manner that ensures reliable communication across the

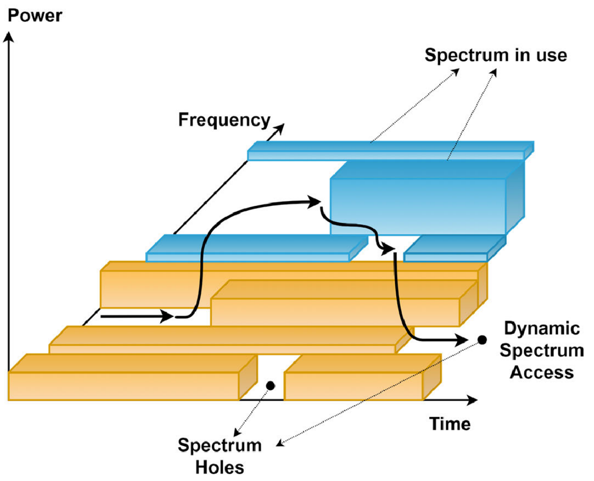

Fig. 5. ***Illustration of the concept of locating and accessing spectrum holes in cognitive radio. Each color of the occupied spectrum represents a different primary user (adapted from [57]).***

channel [2]. The operation of the TPC in a transmitter is generally performed cooperatively with the DSM. As such, the focus of the discussion in this section will be on both components.

Among the most notable literature contributions to spectrum access is a robust IWFA proposed by Setoodeh and Haykin [58], which is a formulation of the classic IWFA from [2]. The authors describe the IWFA as a viable candidate for resource allocation in cognitive radio networks, citing their low complexity, fast convergence, distributed nature, and convexity. The robust IWFA, which is implemented in a decentralized manner, takes the form of a Nash-equilibrium game, utilizing the effects of propagation in its formulation through interference gains [58]. The main motivation behind the robust IWFA formulation is to address the problems of the appearance and disappearance of spectrum holes and other cognitive users with the cost of the compromise of optimality. However, the robust formulation guarantees an acceptable level of performance even under worst case conditions and, through experimental simulations, was demonstrated to maintain stability and consistently converge to equilibrium solutions [58].

In the above examples, we discuss an approach assuming a decentralized cognitive radio network spectrum-sharing structure. However, two other structures exist, which are distributed networks and hybrid networks. Centralized network approaches are similar to traditional communications in which there must be a base station to function as a central controller. The central controller is responsible for allocating the available spectrum among secondary users and optimizing operations by enforcing adjustments in the transmit power of the users. In hybrid networks, multiple base stations exist, each serving a cell that covers multiple secondary users. The spectrum access transmit-power allocation within a cell is controlled by its respective base station in a centralized model form, and the access among each of the base stations then takes the form of a distributed network.

Within each spectrum-sharing framework, a vast number of different considerations must be factored in, including an increasing variety of algorithms to choose from, as studied in the literature. Thus, in fairness to the significance of spectrum sharing and its advances, we warrant the topic beyond this survey's scope due to space constraints. In place, we suggest the reader refer to a review of spectrum resource allocation techniques in [59] and [60], and a detailed review and discussion of robust transmit-power techniques in [61]. We make one important final observation regarding the advancements of spectrum access in cognitive radio, which is the increased attention directed toward implementing and applying RL algorithms for this task. As such, we refer the reader to [19] and [62] for surveys on the topic of RL-based spectrum access.

IV. COGNITIVE RADAR: A PRECURSOR TO CDS

Cognitive radar was proposed in 2006 [3], a year after cognitive radio but similar in the sense that it is a discipline that was proposed prior to the introduction of the CDS framework. Cognitive radar can be considered another precursor to the CDS framework, which has also diverged and evolved into its own area of study but provides insight into the evolution of the CDS theory over time. Despite not abiding by the principles of Fuster's paradigm of cognition, cognitive radar is, nonetheless, motivated by the ideas of cognition and intelligence. Specifically, it will be shown in Section IV-A that the cognitive abilities of a bat in its adaptation of its transmitted signals based on the target's state and characteristics is one of the main sources of inspiration for cognitive radar. More interestingly so, cognitive radar is the first application that has been revisited by its original authors after the proposal of the CDS framework and subsequently adapted to adhere to it, as will be examined in Section V.

This section will present and examine the theory behind cognitive radar to provide insight into and context over the development of the CDS framework. Furthermore, we will investigate whether any of the pillars of cognition is satisfied despite not being guided by them, as well as review the most significant related works in the field. Finally, pertinent details and summaries of the surveyed work on the cognitive radar are presented in Table 2.

A. Background and Motivation

Radar technology is used in tracking and detection systems and operates similar to radio in the sense that it makes use of both a receiver and a transmitter. The applications of radar span both military and civilian uses in surveillance, tracking, imaging, and detecting weather formations. The radar consists of two critical subcomponents known as the receiver and the transmitter. TAR

Table 2 Summary of Published Works on Cognitive Radar

Year	Authors	Reference	Research Application	P	M	A	I	Comments
2006	Simon Haykin	[3]	Original architecture	✓	✗	✗	✓	Proposal of original cognitive radar architecture.
2008	Haykin *et al.*	[68]	Waveform design	✓	✗	✗	✗	Waveform design algorithm proposed to provide smooth trade-off of SNR and mutual information between Gaussian ensemble of target and received signal.
2010	He *et al.*	[70]	Waveform design	✓	✗	✗	✗	SCAN algorithm proposed for unimodular sequence design to address transmit-waveform hardware constraints.
2012	Nijsure *et al.*	[72]	Waveform design	✓	✗	✗	✓	Single waveform design optimization solution using UWB for tracking, detection, as well as communication between multiple cognitive radar nodes in a network.
2010	Haykin *et al.*	[74]	Single-target tracking	✓	✗	✗	✓	First experimental simulations applying cognitive radar on a target tracking problem. Dynamic programming used for waveform selection from prescribed library.
2011	Haykin *et al.*	[75]	Single-target tracking	✓	✗	✗	✓	Results from previous paper and experiment expanded upon, further highlighting the need for memory and attention to realize a fully cognitive radar.
2012	Haykin *et al.*	[77]	Single-target tracking	✓	✓	✓	✓	First paper referring to CDS principles, experimental simulations on aircraft trajectory tracking problem. Improved accuracy over FAR and fixed waveform radar.
2015	Bell *et al.*	[78]	Single-target tracking	✓	✗	✗	✓	Generalized mathematical cognitive radar framework for single-target tracking. However, exhibits shortcomings in terms of presence of cognitive processes.
2012	Chavali and Nehorai	[81]	Multi-target tracking	✓	✗	✗	✓	Cognitive radar network proposed for state estimation of multiple targets, employing approximate greedy programming for antenna selection and power allocation.
2016	Chen and Wu	[82]	Multi-target tracking	✓	✗	✗	✓	Waveform design method for multiple extended targets proposed, with a joint waveform optimization method for separated and close targets.
2017	Chen *et al.*	[83]	Multi-target tracking	✓	✗	✗	✓	State estimation of multiple extended targets with novel CS-based model, whereby novel two-step mutual coherence method used to optimize transmit waveform.
2018	Wang *et al.*	[86]	Multi-target tracking	✓	✗	✗	✓	Multi-target detection and adaptive waveform design method proposed for MIMO cognitive radar.
2010	Chavali and Nehorai	[91]	Multipath scenarios	✓	✗	✗	✓	VMM proposed to exploit and deal with multipath environments in OFDM systems. Adaptive waveform design by minimizing PCRB of targets' state estimates.
2013	Witrisal *et al.*	[93]	Multipath scenarios	✓	✓	✗	✓	Localization of large numbers of RFID transponders in indoor environments. Study refers to CDS principles, proposing TR for waveform adaptation to exploit multipath components through learned models of environment.

* P represents the PAC, M represents memory, A represents attention, I represents intelligence, ✓ represents the presence of cognitive process, and ✗ represents the absence of cognitive process.

systems operate by illuminating the electromagnetic environment using a transmitter, which produces returns or echoes by reflecting off unknown targets within the environment. A radar's receiver is then tasked with receiving and processing the radar return to determine the target's properties, and as such, a TAR is considered a feedforward information processing system [1]. FAR systems are another class of radar intended to manage the allocation of available resources for control in an online adaptive manner. Examples of such resources that may reside in the transmitter include, for example, libraries of transmit waveforms for target tracking or sets of scan times for environmental surveillance [1]. An FAR system is essentially a closed-loop feedback control system, as feedback information from the receiver to the transmitter is required to facilitate control of the receiver by the transmitter.

Upon initializing a traditional radar system, an electromagnetic link is formed between the system and its surrounding environment, strongly influencing the radar returns or echoes. A radar system's knowledge of its environment is developed from each scan to the next, and the radar receiver eventually determines the locations of unknown targets once the targets desired for surveillance are declared. The need to keep a record of all past data for the radar is eliminated by adopting a state-space model of the environment and updating, recursively, the state vector representing estimates of parameters relating to the environment [3]. The nonstationary nature of the environment, which is explained by statistical variations in the weather and unknown targets at unknown locations, requires recursive updating of estimates of the environmental state. This process of recursive updating is also known as adaptivity and is a feature that is generally confined to the receiver in current radar system designs.

In 2006, Haykin [3] described cognitive radar for the first time, highlighting it as a new generation of radar systems with tracking capabilities and reliability that will exceed the reach of traditional radar systems. The echolocation ability of the bat using sonar waves, which provides bats with information about the range, relative velocity, size features, azimuth, and elevation of a target, is the inspiration behind cognitive radar [63]. The ability to extract this useful information lies in the complex neural computations performed within, as Haykin quotes, the

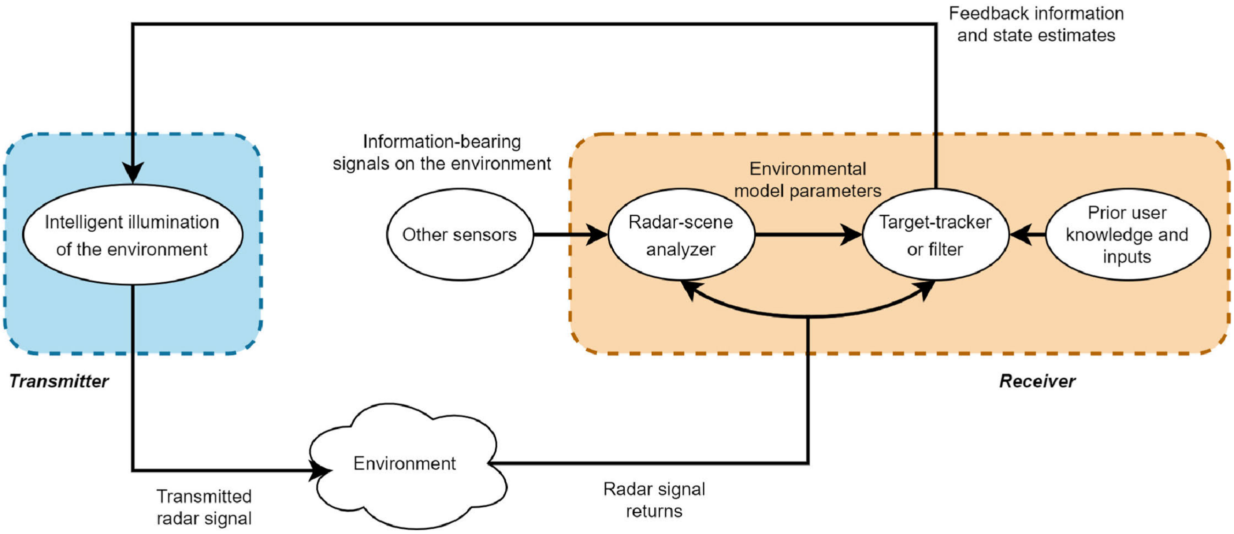

Fig. 6. ***Block diagram of a dynamic closed-loop feedback system for cognitive radar (adapted from [3]).***

"size of a plum" [1]. Using echolocation, the bat can pursue and capture targets with aptitude and accuracy that would far exceed any radar engineer's capabilities. The answer behind how they are equipped with these skills lies in the fact that, shortly after birth, bats use their innate hard-wired brains to construct rules of behaviors through a mechanism we refer to as experience [64]. With the knowledge and experience acquired over time, bats learn to adapt their transmitted signals based on the parameters and state of their targets of interest to extract more accurate and reliable information about their states [65]. This knowledge of a bat's echolocation system and the potential breakthroughs that can be realized through biomimicry is the motivation behind Haykin's pioneering work in cognitive radar [1].

Specifically, the ability of a bat to extract information about the target of interest is emulated in the receiver of cognitive radar systems, as can be seen in Fig. 6. In each cycle, the storage of knowledge and experience gained from the perceived information is also carried out in the receiver—just as the bat learns from experience over time. This information is subsequently relayed to the transmitter, which is responsible for intelligently deciding on the adaptation of the transmit waveform based on the feedback information from the receiver.

Thus, the task of the transmitter is similar to that of the bat's brain, in which they are both responsible for deciding how to adapt their transmitted waveform based on perceived information and past experiences. It will be demonstrated further in this section that this is possible in cognitive radar through advanced algorithms responsible for decision-making. The ultimate result is more effective illumination of the target and the environment, which leads to improved tracking accuracy of targets by the bat and cognitive radar.

B. Overview of Cognitive Radar

There are three fundamental parts in cognitive radar systems: the receiver, transmitter, and the environment, as shown in Fig. 6. The radar-scene analyzer is one of the elements in the receiver and is responsible for providing information about the environment in response to the radar returns or other relevant information on the environment such as temperature, humidity, pressure, and more, which is gathered by sensors other than the radar itself [3]. Another element in the receiver is the target tracker or filter, which makes decisions on the possible presence of targets based on information from the radar-scene analyzer. We start with a state-space model in tracking applications, generally treated as state-estimation problems under the Bayesian framework. Within the state-space model exists a pair of equations, the first of which is the system equation, which describes the evolution of the state across time with system noise as a driving force, and the second is the measurement equation that describes the dependence of the measurements on the state corrupted by measurement noise. Due to the typically nonlinear nature of the state-space model, an approximation of the optimal Bayesian filter is required. From there, the approximated Bayesian filter is used as a means of perception of the target/environment based on incoming measurements [3]. A feedback link is required from the receiver and is responsible for relaying information about the radar environment and target from the radar-scene analyzer and the target tracker for action by the transmitter.

The function of a transmitter in a cognitive radar is to indirectly control the receiver by illuminating the environment based on feedback information received. Specifically, the transmitter is responsible for adjusting its transmitted waveform effectively and robustly by considering the size, range, and velocity of its target and other environmental factors. Within the transmitter's first component, dynamic programming is resorted to as a means of optimal control of the transmitter actuation, given the feedback received from the receiver. In the literature, Bellman's dynamic programming is the method of choice. However, when the dimensionality of either the state, measurement, or action spaces is high, one must resort to approximate dynamic programming [3], [23]. Cognitive radar extends adaptability, which is generally confined to the receiver in traditional radar systems, to the transmitter. In doing so, cognitive radar can learn from experience how to deal with different targets at varying ranges of any size effectively and robustly.

Although discussion of Fuster's principles of cognition is not present within the literature on cognitive radio, it can be identified that the first pillar of cognition, the PAC, is satisfied in cognitive radar due to the presence of a receiver to perceive the target and environment and a transmitter to act in response to perceived information, all in the presence of a global feedback loop. The presence of this process in cognitive radar can be attributed to the motivation in emulating the bat's ability to perceive and adapts its transmission based on the information received, as discussed in Section IV-A, and coincidentally satisfying the PAC. Intelligence is also identified to be accounted for due to the global and local feedback loops, which enhances the controller's information-processing power and the algorithmic mechanisms throughout the system. The function of intelligence is to enable the transmitter's decision-making capabilities to pick a transmit-waveform vector to exercise control over the receiver to perform with effectiveness and robustness, just as the bat does in deciding how to adapt its transmitted signal based on its target's states.

However, after extensive study and examination of the literature on cognitive radar, we note that there has been neither consideration nor implementation of the cognitive processes of memory and attention. Despite Haykin's discussion on the bat's ability to learn from experience and construct rules of behavior over time, there is no physical or direct approach to facilitate the cognitive processes of memory and attention, which are core to such behavior. It may be argued that the use of dynamic programming to select the optimal waveform based on learned rewards may somewhat resemble the act of learning from experience over time; however, this is only true for a very limited number of possible scenarios or action-space size. Without the presence of a true form of memory to facilitate learning of a wide and nonfinite range of experiences, dynamic programming falls burden to the problems of high dimensionality and is consequently rendered too computationally expensive and infeasible.

C. Related Works on Cognitive Radar

1) Waveform Design: One of the most critical processes of cognitive radar systems is adapting the transmitted waveform to the environment through which it propagates in response to information about that environment. Waveform design is a topic of research that has received considerable interest in the past years. Traditionally, the approach to optimal design of waveforms for radar systems has been dependent on the task. For instance, when detecting a specific target, the SNR of the output signal is usually maximized, and the energy of the waveform is distributed to the corresponding target's largest mode [66]. Another example is when the task is to estimate the parameters of a single target from a given ensemble; the transmitted waveform must distribute the energy to several target modes in a matter, which maximizes the mutual information of the received signal and target ensemble [66], [67]. However, cognitive radar systems require an approach to waveform design that allows for more flexibility to optimize and account for various competing design criteria.

Haykin et al. [68] proposed a waveform design framework to synthesize waveforms providing a smooth tradeoff between different detection and estimation criteria and accommodating various constraints imposed on the transmitted spectrum. In their approach, the authors seek to maximize the mutual information of the target ensemble and received signal, subject to lower bounds on the specified target's SNR, bandwidth constraints, and energy normalization [68]. Despite showing that the formulation of this problem is not convex and challenging to solve, the authors prove that it can be transformed into a convex problem in the waveform's autocorrelation. A customized interior-point algorithm is developed in the study and demonstrated to solve the problem efficiently through numerical examples. The model developed assumed that estimates of the target and spectral density of the Gaussian ensemble were known precisely with a radio scene analyzer; however, the authors comment that, in practice, these terms may not be known with such precision. Therefore, the authors state that insight from [67] and [69] will serve as motivation for future efforts to develop waveform design techniques providing more robust performance in the presence of imperfect estimates [68].

He et al. [70] proposed a stopband cyclic algorithm for unimodular transmit sequence design. The algorithm was implemented to adapt to the need to avoid reserved frequency bands and narrowband interference, and improve the correlation properties of the transmit waveform as desired for specific applications. A feature of the proposed SCAN is its ability to design discrete sequences whose spectrum can be suppressed in arbitrary bands [70]. Such sequence designs can be used for active sensing and spreading sequences for spread spectrum applications, such as code division multiple access systems [71]. Starting from random initializations, SCAN can generate many similar sequences with desirable properties and, through numerical examples, was demonstrated to handle very long sequence designs efficiently. The authors extend on SCAN by introducing weighted terms in the penalty function, and the WeSCAN algorithm was able to generate sequences with improved frequency stopband suppression but at the cost of increased computational complexity and a decrease in correlation [70].

Generally, radar and radio communications have been independent research entities in the research literature. In response to this, an approach to combine radar and communication capabilities within a single waveform design for cognitive radar-radio networks was proposed by Nijsure et al. [72]. UWB signals are used for their high spatial resolution and immunity to path fading to address existing issues with the coexistence of radar and radio in mission-critical systems, where information from multiple radars functioning in tandem with one another must be integrated as one. A joint wireless communication and radar technology system is postulated as a cost-efficient alternative solution for intelligent surveillance, which requires sensing the environment and establishing ad hoc communication links [72], [73]. In their work, the authors use a UWB-PPM technique to obtain a unified waveform design solution for radar and communications. A mutual information minimization approach is used to design the UWB transmission sequences and then embed them with communication data using the PPM scheme. An analysis of the proposed methodology is provided in the study, highlighting the improved target impulse response and range resolution and the high data rate performance over short ranges from a communication perspective [72]. A unified system such as the one proposed by the authors, which ensures maximum information extraction from the radar scene and better discrimination capability, may constitute a future unique and cost-efficient platform for applications in intelligent surveillance. These statements hold especially true in applications where both environmental sensing and ad hoc communication links are essential [72].

2) Single-Target Tracking: In the surveyed literature, the application of cognitive radar for single-target tracking is among the first to receive attention. However, our survey found that the first experimental study confirming cognitive radar's superior performance was not published until six years after the application was proposed. During those six years, however, there have been studies carried out by Haykin et al. [74], [75], by which the theoretical validity of cognitive radar is justified and substantiated. In those studies, numerical simulations using an FAR were carried out, emphasizing the CKF [76] for filtering in the receiver and the introduction of a cognitive waveform selection algorithm in the transmitter based on approximate dynamic programming principles and global feedback to embody a PAC. The purpose of the waveform selection algorithm is to select the optimal waveform parameters from a prescribed library of possible waveforms arranged as points in a grid while minimizing a measure of tracking error formulated as an optimization problem in the literature [74].

As a reminder to the reader, memory and attention were considered beyond the scope of the studies presented in [74] and [75], but the studies demonstrated and validated the superior tracking performance exhibited over traditional TAR due to the ability to adapt transmitted waveforms to the target and environment. However, agile jumps were observed of the action points in the grid of possible waveform parameters. The authors attribute this effect to the absence of memory and attention. As such, the system has no notion of utilizing and exploiting previous actions to learn the landscape of all actions and build local neighborhoods of search spaces for future actions. Due to this limitation of the cognitive waveform selection algorithm, the approach has been, therefore, noted to be very computationally expensive by Haykin et al. [75].

Motivated by their previously discussed findings, Haykin et al. [77] continued their research by simulating and experimenting with fully cognitive radar and providing a comparative analysis against a TAR and FAR. In the receiver, a continuous-discrete CKF is used to perceive the environment, the performance of which is assessed using the PCRLB, which represents the lowest possible mse for deterministic parameter estimates [77]. An LFM waveform pulse with Gaussian amplitude modulation is used to formulate the transmitted waveform. The control of the transmitter is governed by a formulation of Bellman's dynamic programming, whereby the practical problem of requiring a Markovian environment and perfect knowledge of the state is overcome by introducing an information state vector, resolving this to an imperfect state-information problem.

The novelty of this work, however, lies in the fact that the authors acknowledge Fuster's principles of cognition for the first time in any of their works. Specifically, the authors describe a guideline for the design of memory coinciding with the description provided in Section II-B and of a hierarchical nature to perform feature abstraction, such as the autoencoder network. Perceptual memory exists in the receiver, which is tasked with associating the measurement space to a grid point in the system-model library. Each preprescribed point in the system-model library represents a different set of values of the nonlinearity (responsible for the transition from one state to another) and covariance of the system noise [77]. Executive memory is situated within the transmitter and is similar to perceptual memory in structure and operation, with the difference that its input is the feedback information from the receiver, which it must match to a transmit-waveform library. The transmit-waveform library's grid points are preprescribed and represent a different combination of two parameters of the transmit-waveform vector. The working memory is reciprocally coupled to the perceptual and executive memory and, unlike them, is short term in nature. The working memory acts to correct the actions of the perceptual memory should they pick a grid point that is incorrectly matched to the input. Similarly, the process of attention is accounted for through the implementation of the explore–exploit strategy, as mentioned in Section II-C, to reduce the global search to a local one in the perceptual and executive memory by determining a subset of

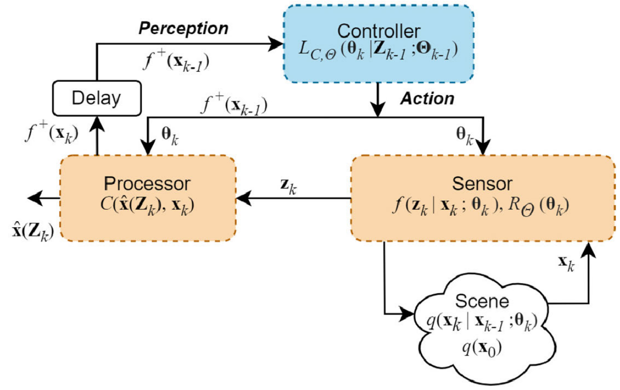

Fig. 7. ***Mathematical model of a generalized framework proposed for a cognitive radar system (adapted from [78]).***

grid points lying in the immediate neighborhood of the preceding PAC's selected grid points [77]. Finally, the last cognitive process, intelligence, is considered to manifest as the algorithmic mechanism that facilitates decision-making while accounting for and anticipating future actions and outcomes with the knowledge gained from the perceptor and stored in memory.

Experimental simulations involving tracking a single target with a coordinated turn, described by a 7-D state vector, demonstrated that the cognitive radar achieved the most accurate tracking performance and lowest RMSE in its state estimates, demonstrating an RMSE reduction of 98% and 78% over the TAR and FAR, respectively [77]. Furthermore, it was shown that, with cognitive radar, the lower bound on the PCRLB was pushed lower. The standard deviation of the estimation error over time for range and range rate estimates achieved was lower than the square root of the PCRLB of TAR, indicating that cognitive radar has been able to exceed TAR's theoretical limits of accuracy [77]. Further analysis showed that attention and memory helped the temporal stability of the transmitted waveform's time rate of change, allowing for much smoother transitions in exchange for a slight sacrifice in optimality and savings in computational resources.

In the pursuit of generalizing and formalizing the concept of cognitive radar for the specific task of single-target tracking, a mathematical framework was proposed by Bell et al. [78]. In their framework, the authors' goal is to separate the general principles from the specific application and implementation details. A mathematical model of the proposed framework is illustrated in Fig. 7, which depicts a scene, a sensor, a processor, and a controller. The scene represents the environment and target, while the sensor refers to a radar system's receiver and transmitter. A processor is tasked with perceiving data observed by the sensor and relaying that perception to the controller, which is responsible for deciding the sensor's actions [78].

In the author's framework, the target state at time t_k is denoted as $\mathbf{x}_k$. The measurement vector produced by the receiver is $\mathbf{z}_k$ and depends on the target state and the parameters of the transmitter, $\boldsymbol{\theta}_k$. Assuming the estimate of a target at a timestep to be a function of the observations up to that timestep, which, in turn, are also dependent on the sensor parameters up to that timestep, then the observations and parameters can be denoted as $\mathbf{Z}_k \equiv \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k\}$ and $\boldsymbol{\Theta}_k \equiv \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, \ldots, \boldsymbol{\theta}_k\}$, respectively. A Markov motion model is assumed with an initial target state pdf of $q(\mathbf{x}_0)$ and transition pdf of $q(\mathbf{x}_k|\mathbf{x}_{k-1};\boldsymbol{\theta}_k)$. The sensor's measurement model is described by a likelihood function $f(\mathbf{z}_k|\mathbf{x}_k;\boldsymbol{\theta}_k)$. The costs associated with an observation and parameter constraints in the sensor are modeled by a cost function $R_\Theta(\boldsymbol{\theta}_k)$. From the measurement vector, the processor outputs a target state estimate $\hat{\mathbf{x}}_k(\mathbf{Z}_k)$ by the minimization of its cost function $C(\hat{\mathbf{x}}_k(\mathbf{Z}_k), \mathbf{x}_k)$. The controller is responsible for optimizing the next value of parameters by minimizing the loss function $L_{C,\Theta}(\cdot)$ to balance the performances of the processor and the sensor through their cost functions. The authors further introduce a novel predicted conditional Cramér–Rao lower bound, which differs from the PCRLB in which it characterizes the performance conditioned on actual data received [78]. The proposed framework is suggested to work exceptionally well in distributed radar systems over traditional radar systems, as demonstrated through experimental simulations for target detection and tracking applications.

An example application of this framework can be found in [79], where a transmit subaperturing frequency diverse array radar was proposed using the framework from [78] for moving target tracking via joint angle-range-Doppler estimation. Furthermore, a CREW was proposed in [80] based on the same framework discussed in [78]. The CREW, which is shown in Fig. 8, is an experimental, purpose-built cognitive radar designed to facilitate research into the practical and hardware aspects of cognitive radar for target tracking and demonstrate the viability of the performance of such systems over conventional radars [80].

However, we must bring to the attention of the reader the concerns regarding whether the proposed mathematical framework adheres to the CDS framework and Fuster's pillars of cognition. It is simple to identify that the presence of a PAC is satisfied by the controller's need for feedback information from the sensor and processor to adapt the transmitted waveform. Similarly, intelligence is deemed to be present through the decision-making capabilities of the optimization algorithm outlined for selecting the optimal waveform based on the perceived information. The concerns lie in the belief that the cognitive processes of memory and attention are not truly fulfilled while claimed otherwise by the literature. We note that, in the framework, memory is justified to be satisfied by the posterior density's recollection of all past data and attention as a result of optimal parameter selection of the transmitted waveform [78]. Otherwise, no further discussion exists on either memory or attention. However, we do not consider the statements made in this article to be a sufficient

Fig. 8. ***Apparatus involved in the CREW setup, as shown in [80]. A radar RF module with a single transmitter and receiver is shown on the left-hand side, and the waveform generators, digitizers, and other signal processing equipment mounted on a standard rack are shown on the right-hand side.***

justification for the presence of memory as per the guidelines described in Section II-B.

Specifically, the authors state that the perception process of their proposed system is responsible for converting sensor data to the posterior density, which inherently remembers all the past data collected [78]. There are issues with this justification, however. The posterior density described is a conditional probability, which occurs as a result of an update in the prior probability using information summarized by a likelihood function. The prior probability represents how likely a hypothesis is prior to observing the data, and the likelihood function is the probability of the data being correct given the hypothesis. In turn, the posterior density represents the updated belief of the correctness of the hypothesis based on the incoming data. While the posterior density represents the update in belief over time, it does not explicitly store the incoming data in a way that allows for the retrieval of that data in future cycles. As such, the cognitive actions decided by the controller in past cycles are not associated with their respective past measurements. This is contrary to the claims made in the authors' work. The main implication of this lack of associative memory is that the controller will have no notion of what cognitive actions were taken for each past observation or circumstance. Accordingly, the controller has no way of shortlisting a subset of potential cognitive actions to be taken in the current cycle based on similarity to cognitive actions taken due to observations from previous cycles. Instead, it only relies on the updated belief of the perceptor through the posterior density of the current cycle. As a result, the role of attention is also rendered unclear in the author's proposed work due to the lack of a mechanism to facilitate any learning or planning of future cognitive actions.

Essentially, the function and role of the posterior density in Bell et al.'s [78] work is equivalent to that of a filter or state estimator. Regardless, this work constitutes a significant contribution and the first step toward a complete generalized mathematical framework for state-estimation and tracking problems in cognitive radar. Further work is still required to develop a mathematical model for cognitive radar, which satisfies all pillars of cognition of a CDS, a task that has now been made easier with the introduction of this first foundation.

3) Multitarget Tracking: The problems associated with multiple-target tracking have been of significant interest to researchers and industry, especially for commercial, military, and defense applications. This tracking task is made much more challenging when the targets are undergoing movement in dense urban environments. Among the first works to apply cognitive radar to address these issues and apply cognitive radar for multiple-target tracking were by Chavali and Nehorai [81]. In their studies, the authors propose a centralized network of cognitive radars to jointly estimate the states of multiple targets and the channel state to extract information on the propagation conditions of an urban transmission channel. A hybrid Bayesian filter, the multiple Rao–Blackwell particle filter, is proposed to be employed at the receiver, which is a combination of a multiple-particle filter and a Rao–Blackwell particle filter to overcome the high dimensionality of the problem at hand and partition the state space to smaller subspaces, thereby reducing the computational complexity [81]. Approximate greedy programming is employed to determine the most suitable subset of antennas in the network for each tracking interval while optimizing the power transmitted by each system. The power allocation and antenna selection or scheduling optimization tasks are facilitated using the PCRLB as the criterion computed on target and channel state estimates. The proposed model was explicitly considered for multipath environments characterized by delays and Doppler spread and, through numerical simulations, was shown to be superior to fixed scheduling and allocation approaches and reduced computational costs [81]. We note a lack of discussion on the waveform optimization techniques involved, which may result in a limitation of the proposed approach and is an issue stated to be an avenue for possible further research by the authors. Furthermore, when the number of antennas used in the network grows large, computation of the PCRLB may become cumbersome [81]. As such, it is postulated in the study that it may also be worthwhile for future efforts to research and develop alternative optimization criteria to address this.

In the surveyed literature, there have also been efforts to study the issue tracking of multiple extended targets, which are targets that may generate multiple measurements per timestep. This situation may occur for reasons such as when targets are large enough to occupy more than one resolution cell [66]. There are specific challenges associated with these targets since they violate typical critical assumptions in a system's measurement models. Chen and Wu [82] addressed the waveform design issue for this problem. The authors proposed an approach based on the KF to exploit temporal correlations of the target scattering coefficients from the Fourier transform of the target impulse response [82]. Their study devised a novel optimization procedure to design transmitted waveforms by minimizing the mse of the KF-estimated targeted scattering coefficients at each iteration. A weighted vector is also introduced to allow for flexibility in achieving the desired tradeoff among the detection of different targets of interest. The optimization problem was shown to be nonconvex and challenging to solve efficiently but could be converted to a convex one through a proposed two-step method motivated by semidefinite programming [82].

Another similar study conducted on tracking multiple extended targets was proposed in [83] based on a CS cognitive radar system. A novel CS-based model is devised to extract parameters of extended targets by exploiting their sparsity in the delay-Doppler plane. Rather than using the dictionary matrix of a traditional CS system that consists of only the delays and Doppler shifts of the originally transmitted waveform at a singular point, a new overcomplete dictionary matrix is defined for each extended target. This new dictionary matrix is established by collecting all echo waveforms of the different delays and Doppler frequencies, rather than just for the single point [83]. Thus, incoming signals first undergo a transformation to obtain a compressed signal. After exploiting the sparsity of this compressed signal through the construction of the new dictionary matrices, a sparse vector is reconstructed in which the nonzero terms represent scattering coefficients, and the respective nonzero entry's index corresponds to a pair of target delay and Doppler frequency [83]. Mutual coherence is adopted as a metric for the reconstruction performance by the authors since, according to Elad [84] and Tropp [85], it is more reliable in ensuring that a sparse vector can be reconstructed from a measurement signal with a given dictionary matrix.

Furthermore, a two-step method is proposed to improve the reconstruction performance of the measured signal by optimizing the transmitted waveform and minimizing the mutual coherence of the dictionary matrix. The first step involves the individual optimization of waveforms for each extended target with an iterative algorithm. Moreover, the second step is concerned with optimizing the weight vector so that the waveforms from the previous step can be combined into a single transmission [83]. The proposed model's performance was evaluated through numerical simulations using two classical CS algorithms for the reconstruction of the sparse vector: OMP and BP [85], [85]. Results showed that the proposed model, using either the OMP or BP algorithms to estimate the range and velocity of seven targets, achieved improved results compared to other static waveforms [83]. The study provides further analysis of the effect of the tradeoff between the number of measurements required and the number of targets to be tracked on the system's accuracy. With the motivation of furthering progress in the field, it is stated that the author's future efforts will be concentrated on extending this model to account for the presence of environmental clutter.

Most recently, Wang et al. [86] conducted a study proposing a cognitive, MIMO radar for multitarget tracking. In MIMO radar systems, colocated or widely separated transceiver antennas transmit mutually orthogonal signals, which are then extracted by sets of matched filters, resulting in finer spatial resolution than traditional tracking radars [87], [88]. The diversity brought by the waveforms in an MIMO radar system provides additional degrees of freedom; as such, Wang et al. [86] proposed a novel adaptive waveform design algorithm to extend the capabilities of these systems further. A multitarget detection task is first modeled as a multihypothesis testing problem, which is investigated based on sequentially received signals. Then, the waveforms are designed using relative entropy, more precisely the maximum likelihood Kullback–Leibler divergence criterion between the distributions involved in the hypotheses [89]. A semidefinite relaxation technique is adopted from [90] due to the nonconvexity of this optimization problem, and numerical simulations demonstrated by the authors showed that the proposed method resulted in higher detection probabilities than orthogonal waveforms and shaped beam waveforms [86]. It is noted that the waveform designs can cognize the dynamic environment to concentrate power on angular grids where targets exist, even if the number of targets and their locations change over time [86]. The authors conclude by mentioning the computational burden of the proposed algorithm, especially when dealing with increasing numbers of targets due to the optimization problem, and suggest its applications to be more suitable for multitarget tracking applications in small, local airspaces [86]. Finally, the authors state that, although this model does not account for clutter, it is worth exploring extending to do so with further studies.

4) Multipath Scenarios: When operating in urban environments, radars often suffer from interference due to the presence of multipath reflections. Returns received by radars in such environments will be a linear combination of delayed, attenuated, and Doppler-shifted versions of the transmitted signal joining from various paths. Chavali and Nehorai [91] proposed a cognitive radar in response to the issues associated with multipath scenarios, in which the spatial diversity offered by multipath propagation is exploited. In their work, the system uses the knowledge acquired by the radar to separate the signals arriving from the various paths. A VMM is constructed by coherently combining the delayed versions of the separated signals, and then, the delays are estimated by discretizing the delay Doppler plane into several grid points and solving a sparse reconstruction problem [91]. Subsequently, after using the VMM for target tracking under the Bayesian inference framework, OFDM signaling is employed at the transmitter to predict the PCRLB on the mse of the target state estimate. A particle filter is employed to estimate the target state at each interval [92]. The predicted values of the PCRLB are then minimized to obtain the optimal specifications for transmission in the next pulse repetition interval. Through numerical simulations, the performance of the proposed model is shown to be significantly better than that of standard radar systems.

The accurate localization of passive radio transponders is a highly desired feature for RFID, and as such, Witrisal et al. [93] proposed employing cognitive radar as a solution to this issue. The authors tackle tracking, identifying, and high-definition localization of large numbers of passive radio transponders in indoor environments. Deterministic multipath components are exploited within the proposed model to overcome robustness issues in operating in non-line-of-sight situations. In the study, the radar's transmitter and receiver learn their own respective models of the environment through adaptive illumination using TR processing for waveform adaptation (from [94]) to overcome degenerate pinhole channels of radio systems [93]. The authors verify the performance of the TR processing technique and overall proposed approach through experimental tracking simulations, which show that the model can significantly reduce signal bandwidths and improve processing and response times once the target and environment models are learned.

It is interesting to note that this study stands out from others as it recognizes and considers the CDS framework and Fuster's principles of cognition in its methodology. The authors refer to the previously discussed work of Haykin et al. [77] as the motivation behind their adoption of the CDS principles. However, we note similar issues in this work in this regard to those identified in a previously surveyed work by Bell et al. [78]. Specifically, we refer to the fact that the cognitive process of memory in the work of Witrisal et al. is justified to be satisfied due to the computation of a posterior density, which stores knowledge of previous data through the update of belief over time—with no further explanation otherwise. As already encountered with Bell et al.'s work in [78] and discussed earlier in Section III-C2, this justification is arguably not sufficient to completely satisfy the presence of memory. Briefly summarizing our earlier discussion, the posterior density represents an update in belief over time in response to incoming data. However, the posterior density does not explicitly store the incoming data of each cycle in a manner that enables the controller to retrieve them in future cycles. Therefore, the controller cannot associate past or future cognitive actions with any measurements, nor will the controller be able to compare current observations to past ones. As a result, the controller will not be able to select and consider a subset of past cognitive actions, which may have been taken due to past measurements that are similar to the current cycle's measurements. Ultimately, this means that the cognitive controller's actions are only informed by the current cycle's posterior density.

Regardless, unlike other works surveyed in this field, this work explicitly describes and accounts for an incomplete form of short-term memory in the state space tracking for the target's states and as environmental memory for the states of RFID tags and environmental parameters. There is also a lack of justification in the case of the process of attention, which is stated to be responsible for fast and accurate responses to changes within the environment and the assignment of additional resources to moving targets [93]. This is described to be achieved through manipulating the bandwidth of the adaptive signal, where a lower bandwidth implies lower accuracy in return for a lower resolution of the search space. This is explained to benefit the PAC's convergence when relocalizing targets exhibiting sudden movements in scenarios with high numbers of targets [93]. Regardless, the literature does not go beyond this mere description and provides no information about how this is implemented. This deficiency is also consistent in terms of the cognitive process of intelligence, which is attributed to the proposed TR-based waveform adaptation approach. However, there is no discussion or justification as to how exactly the TR yields itself to facilitate intelligence. Instead, it is merely stated that TR depends on feedback information from the receiver to focus the power of the transmitted waveform to target locations. This is considered to be a weak justification of intelligence enabled through the PAC.

V. COGNITIVE CONTROL

In Sections III and IV regarding cognitive radio and cognitive radar, it was emphasized to the reader in both cases that the applications were proposed before the formal introduction of the CDS framework. Instead, research into the development of cognitive radio and cognitive radar, despite being motivated by the principles of human and animal cognition, was not informed by Fuster's principles of human cognition: the PAC, memory, attention, and intelligence. Upon surveying the literature on cognitive radio and cognitive radar, this was further corroborated by the fact that there was neither mention nor consideration of those principles of human cognition in many of the surveyed works. Regardless, examination of both fields' architectures reveals that, despite having no intent of doing so, the PAC and intelligence are two principals of CDS that has been observed to exist and be satisfied. The aforementioned points, along with the fact that cognitive radio and cognitive radar have gained significant attention and diverged into their own respective fields of study, are the reason why they cannot be classified as CDS. Instead, they are considered to be precursors to the CDS framework.

Section V is concerned with the concept of CC, which was proposed by Haykin et al. [5] as the first example of an architecture fully adhering to the CDS framework. Unlike cognitive radio and cognitive radar, CC is guided by the principles of Fuster's cognition and the CDS framework that were formally introduced by Haykin shortly before CC's introduction [1], [4], [23]. As will be discussed in Section V-B, CC is an additive architecture to existing systems and is comprised of multiple elements or components, including a cognitive controller. CC and the cognitive controller are two separate entities, in which the former is the architectural framework, and the latter is a component within that framework. In other words, systems over a wide range of applications, when augmented with all elements of CC, will be classified as a CDS. Toward the end of this section, an overview of all the works surveyed along with key findings is presented in Table 3.

A. Background and Motivation

The design of control systems can often be complicated due to a well-known problem encountered during the process: the tradeoff between optimality and robustness. It is also often desirable to have a controller equipped with the ability to modify its behavior in the face of uncertain circumstances. A plethora of literature has been published in recent years dedicated to studying and proposing techniques and algorithms to address these issues, the most prominent being adaptive controllers and neurocontrollers. Adaptive controllers are equipped with an adaptation mechanism that facilitates updating of their parameters. These updates are in response to the varying or uncertain dynamics of the system that they are controlling or the presence of environmental disturbances [95], [96].

Unlike adaptive controllers that are mainly based on parameterized mechanistic modeling, neurocontrollers are based on black-box modeling. When it is simple to find mechanistic models for parts of a system but too complex for other parts, it is also possible to combine mechanistic and black-box models to result in a hybrid model. Neurocontrollers can utilize neural networks in several ways; one such way is by implementing the controller itself using a neural network [97]. Alternatively, instead of being a neural network itself, the controller could rely on a neural network that models the system under study [98].

Adaptive controllers and neurocontrollers typically perform well in known, structured environments and the specified conditions that they are designed for operation within. However, their performances are generally compromised when there may be unmodeled dynamics in the system of interest. As such, the presence of a human operator in the control loop is often necessary for critical tasks or when functioning in uncertain and unstructured environments. The performance issues in these controllers arise due to their inability to collect sufficient information required to achieve their goals or to act in a self-organized fashion [95]. Based on the knowledge available on CC in the psychology and neuroscience literature, researchers have suggested that reducing human intervention in a control loop requires that the processes of cognition be built into the control system [99].

B. Overview of Cognitive Control

The paradigm of CC should not be thought of as a replacement system design paradigm, but rather one that is additive in nature [5]. When augmented with state-control paradigms, such as adaptive control and neurocontrol, CC can improve the performance of systems. It does so by allowing them to process information, store knowledge, and learn from experience over time through continuous interaction with the environment. Moreover, it will be shown that CC equips systems with the means for effective decision-making through the concepts of learning and planning, often resulting in improved utilization of computational resources [5]. This is all due to the fact that CC can be considered the first overarching function of a CDS, which prescribes the procedures to implement and satisfy Fuster's pillars of cognition [100].

First, the notion of the information gap must be introduced, which is related to the risk associated with an action or decision policy. Having the aim of reducing the information gap, it is then possible to define the overall goal of CC as follows [5].

1) Measurements affected by noise contain available information, which is extracted and transformed from the measurement space to the information space.

Table 3 Summary of Published Works on CC

Year	Authors	Reference	Research Application	P	M	A	I	Comments
2012	Haykin *et al.*	[5]	Original architecture	✓	✓	✓	✓	Proposal of original cognitive control architecture.
2014	Fatemi and Haykin	[25]	Cognitive tracking radar	✓	✓	✓	✓	First fully cognitive application proposed. Cognitive radar equipped with CC and Q-learning for transmit-waveform selection for improved target tracking.
2015	Wang *et al.*	[107]	Communication-based train control	✓	✓	×	✓	CC proposed as supervisor of communications in CBTC systems by addressing transmission delays and packet drop issues in WLAN, yielding improved train control accuracy, smoothness, handoff latency and failure rate.
2017	Sun *et al.*	[109]	Communication-based train control	✓	✓	×	✓	Previous studied extended to CBTC in smart grids to account for regenerative braking. Based on experimental simulations, CC demonstrated further improvements in cost efficiency by integrating financial cost into entropic state.
2019	Wang *et al.*	[110]	Communication-based train control	✓	×	×	✓	LTE-M proposed for T2T communications in CBTC, with CC as supervisor of power and resource allocation. Less unplanned traction and brake times, improved system resilience and smoother acceleration noted with proposed method than T2W and WLAN approaches.
2019	Fang *et al.*	[114]	Smart grid control	✓	×	×	✓	Entropic state is formulated based on data packet drops, and CC proposed to decide whether to retransmit or switch channels in such instances. Addresses issues with unstable communications and increases total social welfare.
2019	Oozeer and Haykin	[115]	Smart grid control	✓	✓	✓	✓	Entropic state proposed as a supervisor of SG sensors. Upon sensor malfunction or error, CC reconfigures weights of each sensor in SG to maintain or improve estimate of system's DC states.
2016	Mazzù *et al.*	[118]	Object detection and tracking	✓	✓	✓	✓	DBN architecture of several independent KFs to take advantage of varying dimensions objects present themselves at. CC is proposed to exploit the cooperation of the filters to understand object movement and improve tracking performance in far infrared sequences.
2017	Fatemi *et al.*	[123]	Observability of complex networks	✓	✓	✓	✓	CC proposed as a supervisor of complex stochastic networks to increase their observability by reconfiguring and optimizing the sensory nodes in the network.

* P represents the PAC, M represents memory, A represents attention, I represents intelligence, ✓ represents the presence of cognitive process, and × represents the absence of cognitive process.

2) Depending on the task at hand, available information can be partitioned into relevant and redundant information.
3) Sufficient information is the information required to perform the task at hand while minimizing risk; relevant information is the intersection between available information and sufficient information.
4) The difference between sufficient information and relevant information is what constitutes the information gap.
5) The goal of CC is to adapt the directed flow of information from the perceptual to the executive part, so as to reduce the information gap.

Quantifying and reducing the information gap require a suitable task-specific metric—this idea notions to a new state that must be controlled. A dynamic system's state represents the minimal information defining the conditions of the system at a point in time, and by similar thought, the state trajectory or change in state over time represents the system's behavior. The state, however, is only accessible through noisy measurements, which, in turn, requires a perception process for obtaining a posterior distribution of the state using an estimation method or filter. The difference between the posterior distribution's maximal useful information and the sufficient statistics for a given task is the information gap. This quantity is also defined as the entropic state, whose name comes from Shannon's entropy, as it is a firsthand candidate for this metric [5], [101].

As such, the mentioning of both states naturally leads to thinking in terms of a two-state model in CC. First, there is the state-space model describing the evolution of the system state over time and then the entropic state model that quantifies the information gap given the posterior computed by perception. Both models may vary from one cycle to the next according to statistical variations in the environment. Thus, the role of the perceptual part in CC involves estimating the perceptual posterior of the system and environment, from which the entropic state of the perceptor can be determined using Shannon's entropy. It is also worth noting that the feedback information passed on to the executive part of CC is simply the entropic state, as can be seen in Fig. 9, and as such, CC is merely the paradigm of reducing the entropic state [5].

In the executive of CC, as shown in Fig. 9, the cognitive controller is responsible for ensuring that the entropic state is decreased after each cognitive cycle and finding a policy facilitated only by rewards in each environment [24]. The entropic rewards are defined as the decrements of the entropic state after each subsequent cycle, which can be predicted with the estimation method employed in the perceptor through the use of local feedback loops. RL has

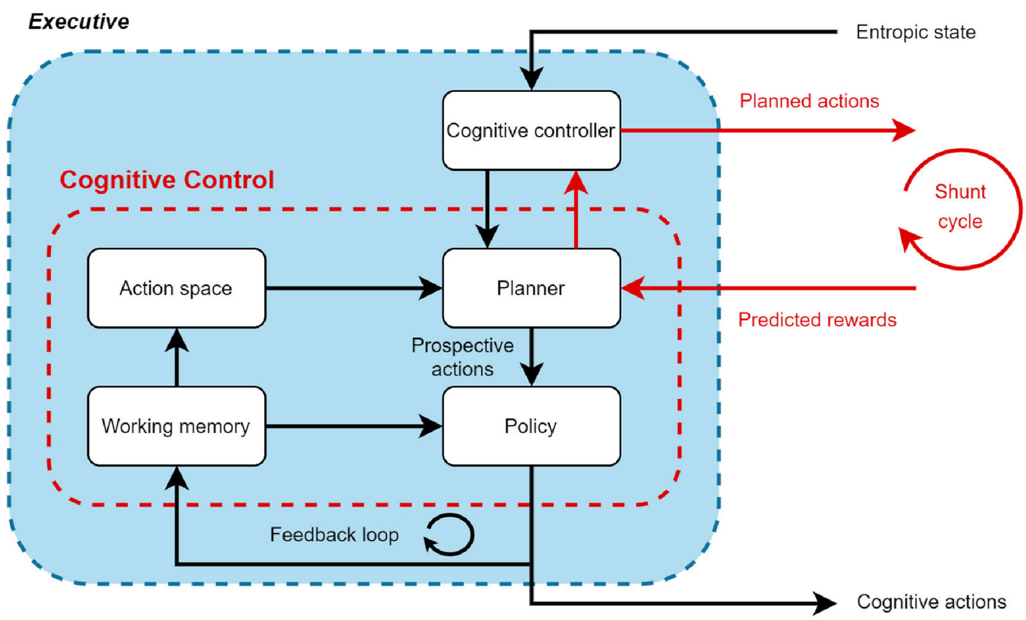

Fig. 9. ***Functional block diagram of the executive part of a CDS that is equipped with CC.***

been presented as the natural tool for the cognitive controller in the executive part of CC based on its practice in mammalian brains, as evidenced by the neuroscience and computational neuroscience literature [102], [103]. The discovery of a key RL signal in the brain that is understood as the temporal-difference reward-prediction error is one of the most critical findings proving the existence of RL in mammalian brains, with the dopaminergic neurons in the midbrain now evidently known as the means behind RL in the brain [103], [104]. RL is a mathematical paradigm concerned with learning the best possible actions solely based on positive and negative reinforcement or rewards. It is for this reason that RL demonstrates itself as a natural tool for the cognitive controller in the executive part of CC. In reality, the choice of cognitive controller to be adopted is not restricted to RL, and in fact, other possible but less effective choices include Bellman's dynamic programming or any sequential decision-making algorithm. One of the main advantages of the RL framework, however, is its ability to ensure that decreasing the entropic state not only occurs in the immediate cycle but also in the look-ahead horizon.

There are two distinct concepts introduced in CC, which are employed by the cognitive controller: learning and planning, in which the former uses actual values of the entropic reward for a given cognitive action, and the latter uses predicted values of entropic reward [24], [105]. During planning, it is first necessary for the planner to determine the choice of planned actions from the action space with the help of the working memory, whose entropic rewards must then be predicted. Due to local feedback links between the executive and the perceptor, the planned cognitive actions can be relayed from the former to the latter. The entropic state for each planned cognitive action is then predicted by using the estimation method or filter employed in the perceptor under the assumption that the noise distribution and state-space model are known [5]. It is important to note that these planned actions are not actually carried out by the CDS on the environment or system and instead are only used in the perceptor to simulate and predict the value of future entropic rewards. The predicted entropic state values are then relayed back to the cognitive controller through the local feedback links, and the predicted entropic reward is then determined from the entropic state of each planned action. Based on the results of the planning stage, the cognitive controller is responsible for deciding on which cognitive actions to actually execute by updating the policy in a manner to reduce the cost of the predefined value-to-go function and, consequently, the entropic state. The feedback links that facilitate the carrying out of learning and planning in CC constitute what is known as the shunt cycle in CC, as shown in Fig. 9.

Learning is responsible for updating the executive memory with the cognitive action and its associated feedback information and actual entropic reward for future reference. Thus, it is important to note that learning in CC can only be done once for the selected cognitive action of each PAC; however, the cognitive controller can perform planning for any number of simulated future cycles and any number of cognitive actions [5]. The limitation for how many actions can occur during planning depends on factors such as computational effort and expense, and time constraints that require the planning to be completed before the time it takes for a single PAC to conclude.

The presence of memory in CC is mainly to facilitate the storage and recollection of entropic rewards. In the executive, cognitive actions and their corresponding entropic state and rewards are stored as long-term memory in the action space after being updated by the learning stage once every PAC. This long-term memory represents the knowledge and experience gained by the system over time in a probabilistic manner. Furthermore, it describes the likelihood of each stored action to be selected in the course of all the interactions the cognitive controller has ever had with the environment [24]. The working memory is short-term in nature, existing only for the duration of each PAC before being reset, and is used to aid the planner in searching through the action space and facilitating planning [5]. Specifically, working memory stores knowledge about the previous cycle's entropic state, chosen cognitive actions, and their cognitive rewards, which is then used by the planner to improve its effectiveness in searching through the action space for candidates for planned actions in the current cycle. The coordination of planning from memory by the cognitive controller is facilitated by the presence of global and local feedback loops. This mechanism describes the essence of the PAC, which also facilitates learning over time by the system.

The manifestation of attention within a CDS can be attributed to two main factors: first, the algorithmic mechanisms responsible for both learning and planning; second, the use of the explore–exploit strategy to select the most relevant cognitive actions to plan for from memory while simultaneously predicting their entropic rewards [24]. The justification behind satisfying the process of attention with these mechanisms is reasoned to be due to the resultant reduction of the action space. Consequently, this results in reduced computational costs for the cognitive controller and improved allocation of resources. Finally, intelligence, such as attention, does not occupy a physical space within the framework but as the distributed algorithmic mechanisms throughout the system, namely, facilitating the cohesive integration and operation of all entities that play a vital role in decision-making for action to be taken on the environment by the cognitive controller [24]. As previously mentioned, the paradigm of CC is additive to existing systems and, when augmented to them, results in the classification of the systems into the CDS framework.

C. Related Works in Cognitive Control

1) Tracking Radar: With the introduction of the CC architecture following the development of the CDS framework, cognitive radar was among the first applications to receive attention and be augmented with CC. It has already been introduced in Section IV that Haykin et al. [77] recognized Fuster's paradigm of cognition for the first time during their work on cognitive radar. However, this work was still carried out prior to the official proposal of the CDS framework, and despite demonstrating a significant step toward a more complete form of cognition, the potential to achieve more was recognized in subsequent studies. Consequently, cognitive radar has been revisited by Fatemi and Haykin [25], whereby the authors implement the principles of CC and build upon their previous work and experimental simulations from [77].

In their work, the authors conceptually design and simulate cognitive radar according to the same benchmark example from their previous work in [77] and augment it with the capabilities of CC as described earlier in this section and based on Fig. 9 [25]. The CKF is employed to estimate the state covariance matrix in the perceptor in each cycle, and its output is subsequently used to formulate and determine the entropic state. The system is described to have 382 possible cognitive actions stored in the executive memory, representing the number of different transmit-waveform parameter combinations possible. The measurement noise covariance matrix is formulated in a manner such that it is a function of the waveform parameters decided by the cognitive controller for each cycle [25]. As such, each cognitive action taken after the conclusion of a cycle of the PAC results in the measurement noise covariance matrix and, consequently, the output of the perceptor being affected. Otherwise, guidelines for short-term memory storage of entropic rewards for the cognitive controller are also described in the study, serving the function of working memory.

In the first experiment, three distinct scenarios are studied. The first is the absence of CC on the system (fixed radar waveform). The second scenario, which is practically the approach implemented from [77] but with RL instead of dynamic programming, involves the cognitive controller with learning and no planning; the algorithm knows only the values of entropic rewards from the previous step. The third and final scenario introduces planning and implementing an explore-only approach in the planning phase, meaning that no regard is given to the cost function in the learning algorithm, and the algorithm is repeated for three different cases: the exploration of only one, two, or three random cognitive actions in each cycle of the PAC. It can be argued that, although planning occurs, the fact that the chosen cognitive actions are all random due to the explore-only approach casts doubt upon whether the cognitive process of attention is truly fulfilled.

In the author's experimental simulations, 50 cycles were conducted over one thousand Monte Carlo runs to minimize the effects of randomness [25]. In the scenario with no planning and only learning, performance in entropic state reduction is negligibly better than in the fixed waveform and is reasoned to be due to the total number of cycles being much less than the number of possible cognitive actions (50 versus 382) [25]. However, in the scenario with different numbers of planned cognitive actions per cycle, it was observed that, even with just one random cognitive action in the planning phase, which is much less than the total number of possible cognitive actions, it is enough to demonstrate a considerable improvement of four orders of magnitude in entropic state reduction [25]. Furthermore, the cases of two or three random cognitive actions displayed the same reduction in the entropic state but with faster convergence. Overall, the planning process in CC was demonstrated to significantly enhance the entropic state of the model compared to traditional fixed waveform methods regardless of the random selection of the planned cognitive actions. We postulate that future studies to explore effective mechanisms to select relevant candidates for planned actions may yield further potential improvements in the system and an opportunity for future researchers. One issue that we must bring to the reader's attention is that, although the entropic state is technically a measure of the perceptor's accuracy, no other indicators or measures of performance are provided or described in this study. This is a concern because it is crucial for research in the field of CDS to ensure that the advantages of their applications are clearly articulated and presented in the literature, especially when it comes to interpretable performance measures. The importance of being able to objectively compare the performance of proposed CDS models with that of previously proposed methods for similar applications, and thus serving as benchmarks, is crucial. This is especially true when it comes to further attracting future research interest toward advancing the state of CDS.

Further experimental simulations conducted in the study aimed to observe the performance of three different algorithms as the cognitive controller in CC, such as dynamic optimization, Q-learning, which is an RL algorithm, and a newly proposed algorithm by the authors, which incorporates Q-learning combined with the learning and planning mechanisms The proposed algorithm, which was set to plan for three cognitive actions, outperformed both Q-learning and dynamic optimization in reducing the entropic state and had the advantage of having a smaller computational load [25]. In a trial of 250 cycles to allow for convergence to optimality, the proposed algorithm reached an entropic state value of $10^{0.4}$ compared to approximately $10^{0.7}$ by both Q-learning and dynamic optimization [25]. To conclude, the authors state that, although the Q-learning algorithm offers a computationally tractable solution, it can be inefficient in performance [25]. As such, it may be worthwhile for future research to be directed toward the formulation of algorithms tailored specifically for the role of the cognitive controller in such applications where planning is a critical task.

2) Communication-Based Train Control: CBTC systems are automated train control systems that use bidirectional train-ground or T2W wireless communications to ensure rail vehicles' safe and efficient operation. These systems help to improve the utilization of railway network infrastructure while enhancing the service provided to customers. However, there are also challenges associated with both train-ground communications and train control, which are generally addressed as separate issues in the literature. CBTC systems generally use WLAN as the medium for information transmission between train and wayside equipment. However, transmission errors and MAC layer handoffs have been widely recognized to be inevitable since most of the current IEEE 802.11-based WLAN standards are not designed for high-mobility environments [106]. As such, information exchanged between trains and wayside equipment is commonly affected by packet delays and drops in train-wayside communications. Consequently, uncertainties in the information regarding the train's state are increased, leading to imperfect control commands and substantial energy expenditures during the compensatory traction process to return to the train's optimal state.

Studies have been proposed in [107], which lump the aforementioned issues into one problem and attempt to solve the challenges in a CC-inspired approach. In their work, the authors use the entropic state to describe the packet delay and drop of information exchanged between the train-ground communication and the train control center, and quantitatively describe the former's effects on the latter's performance [107]. WLAN is adopted as the medium for train-ground communication as commonly used in urban rail transit systems worldwide [108]. The linear-quadratic cost is used as the performance measure for the train control's performance, and Q-learning is then used to obtain the optimal policy based on this measure and the entropic state. The wireless channels are modeled as finite-state Markov chains with multiple state transition probability matrices to characterize high-speed railway and Rayleigh fading. The CC model is responsible for ensuring reliable and uninterrupted wireless communications and handoffs to ensure that the current train obtains accurate information about the front train. As such, the authors postulate that, with improved communication between the train and control center using CC, the resultant improved flow of information will allow for more robust control of CBTC systems in terms of acceleration, deceleration, speed, distance, and emergency braking profiles [107].

Through experimental trials with measurements extracted from antennas on a train from the Yizhuang Line of the Beijing Subway, as shown in Fig. 10, and subsequent MATLAB simulations, more stable velocity control was demonstrated between the system's front and back trains with the proposed approach [107]. With CC, wholly smooth and much safer behavior was observed, compared to other control policies, such as the SMDP and greedy policies, which exhibited slight perturbations in the difference in velocities of front and back trains. Further results showed that the handoff delay was significantly reduced with CC to 0.2 s, half of the train response time parameter, compared to handoff delays of 1 s by the SMDP and greedy policies [107]. Finally, when observing the failure rate of the CBTC system under different policies, it is clear that the CC method proposed is most effective

Fig. 10. ***Experimental setup used to collect data from for the study in [107]. (a) Tunnel where measurements were taken and recorded. (b) Shark-fin antenna located on the measurement vehicle. (c) Yagi antenna. (d) Access point in a section of the tunnel installed on the wall.***

due to having the highest availability of 99.78%. This value equates to unavailability rates of the magnitude of 10^{-3} using CC compared to the SMDP policy with 10^{-2} and the greedy policy with 10^{-1} [107]. Overall, the effectiveness of the proposed approach was proven through these results; however, the authors suggest that further research effort is necessary to investigate more advanced train-ground communication technologies, such as relaying, to improve the performance of CBTC systems further.

The studies performed in [107] were extended to CBTC systems in smart grids by Sun et al. [109]. In this work, the authors implement regenerative braking to restore energy to the smart grid and analyze the cost-aware power management problem of CBTC systems in such networks. Furthermore, a more practical performance measure is adopted, involving the total financial cost of the system's energy consumption. Ultimately, when applied to simulations of a subway line in Beijing, the proposed CC approach achieved energy consumption and financial cost reductions of approximately 17% and 22%, respectively, over conventional CBTC control schemes [109].

Conducting very similar studies and extending further in the field of CC-based CBTC systems, the literature in [110] proposes and implements a T2T communication system based on the improved reliability and latency from using LTE-M. The LTE-M protocol is proposed as the wireless communication system for next-generation urban rail transit but is associated with shortages associated with handoff schemes that result in long-time interruptions between trains and wayside equipment [111]. The CC T2T approach for CBTC systems aims to solve the handoff and interruption issues and further improve the system's quality of service through a newly proposed quantitative resilience measure based on the entropic state [110]. The proposed approach was demonstrated to be superior to traditional WLAN and T2W approaches in terms of velocity stability, smoother acceleration, and reduced handoff delay. Future works discussed involve including more parameters in the resilience measure, such as the throughput, train speed, and effects of sensing and actuation delays. Moreover, the investigation of more advanced wireless technologies, such as MIMO and millimeter-wave techniques, is postulated to show potential in reducing communication times and overall system performance even further [110].

We note that the methodologies claim to adhere to the CC framework in the three studies discussed. Upon closer examination of the literature, however, it is evident that the implementation of memory as a cognitive process is neglected, and its presence is barely justified. In general, the methodology outlined in the literature for CBTC applications requires more careful consideration of the CDS principles. This deficiency poses an opportunity to further support and justify the validity of the surveyed studies in implementing the CC model as per the CDS framework. As such, further research efforts in this regard may aid in further driving interest in this application and the entire field of CDS.

3) Smart Grid Control: The smart grid is considered a new paradigm for integrating advanced technologies, such as sensing and measurement, information communication, control and decision-making, and energy and power with grid infrastructure [112]. Autonomous energy management systems are a crucial component of smart grids that combine power suppliers, consumers, distributed energy resources, and energy storage units. Comprised of these elements is the microgrid, which facilitates interaction between power suppliers and electricity users to motivate users to participate in energy management. These interactions lead to the concept of DRM, which is tasked with balancing energy supply and demand and maintaining the stable operation of the microgrid. However, the performance of DRM in a microgrid depends on stable wireless communications, and in general, there are still challenges that exist in this regard [113].

A CC approach for optimizing the performance of microgrids is proposed by Fang et al. [114], in which the authors aim to specifically address the issues relating to unstable wireless communications affecting the DRM scheme. Expressly, the authors acknowledge and address the complicated wireless environments that are often difficult to obtain precise models. The proposed distributed CC model framework is embedded in both the user agents

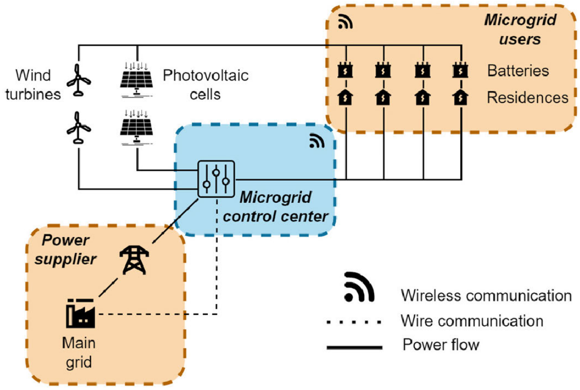

Fig. 11. ***Diagram representing an example system model of a residential district microgrid.***

and the MCC. The entropic state describes the expectation of purchase demand deviation in the user agents and the difference between the estimate and actual purchase demands in the MCC. A graphical illustration of an example microgrid system model can be seen in Fig. 11. Entropic state functions are formulated to represent the entropic states, as just mentioned, which are then used to decide the cognitive actions to be taken by the user agents or the MCC. The cognitive actions of the user agents involve switching to different wireless channels, while the MCC involves the adaptation of the demand deviation [114]. Furthermore, real-time pricing strategies are proposed to maximize the global benefit of all subscribers and indicate the DRM performance. Finally, Q-learning is introduced as the means for the cognitive controller and learning to generate optimal policies that maximize rewards by perceiving the system through the agents and performing cognitive actions based on learned experiences.

The performance of the author's proposed integrated CC scheme was compared against the performance of a traditional control scheme, a CC scheme only in the MCC agent, and a CC scheme only in the user agents [114]. Overall, the proposed integrated model demonstrated the lowest entropic state of all other approaches with a mean value and a standard deviation of 2.217 and 1.432, respectively, compared to 3.678 and 2.614 in the absence of CC, representing an improvement by a margin of approximately 60% and 54% in mean and standard deviation, respectively. Furthermore, the author's proposed scheme can achieve an increased benefit for social users of up to 22% throughout the day, which is also a measure of the DRM's performance in keeping up with supply and demand in a more stable, efficient, and generally improved manner [114]. Although the literature acknowledges the need for attention as a cognitive process to satisfy a CDS, no mention of how this is implemented or satisfied in the proposed system is provided. As such, future research efforts directed toward extending the work in [114] to implement attention, either through a planning mechanism similar to that in [25] or any other approach, may realize even further improvements, validating the viability of CC as a state-of-the-art approach in this application.

A CDS is proposed as a supervisor for smart grid networks using a CC approach by Oozeer and Haykin [115], as depicted in Fig. 12. In their work, the authors introduce a new way of calculating the entropic state tailored to the smart grid application and utilize it in implementing a control-sensing mechanism to identify and detect bad data from sensor measurements in the grid network. The bad measurements resulting from erroneous readings, faulty hardware components, or disturbances in power systems often result in a series of domino effects that hinder the state estimation process and can be detrimental to the performance of typical control systems [115].

In the author's proposed framework, the dc state estimator, being considered the recipient of measurements in the network, is regarded as the environment in which the CDS acts. A generative model based on the CUSUM is employed to classify the observables from the environment and accumulate knowledge of the states for a fixed window of time. Then, a KF is employed to filter the states and output updated estimates for future cycles. The cognitive controller is then responsible for learning and planning, which is made possible by the shunt cycles, as shown in Fig. 12, and for providing the network with the means to prioritize and disregard specific measurements for optimal state estimation by configuring the weights assigned to each sensor or meter. The shunt cycles facilitate planning by operating through local feedback links between the perceptor and executive to simulate the entropic reward values of planned cognitive actions in each PAC, with the help of the memory mechanism in the perceptual and executive parts [115]. RL through the BUCB algorithm is used to optimize the newly tailored entropic state of the system based on the results of the planning stage and provide a means for the cognitive controller to learn the best policy of cognitive actions. In this case, the cognitive actions consist of discrete weights attributed to sensors or meters [115]. The working memory then stores knowledge of the chosen actions applied to the system after each PAC, which forms the basis for planning in subsequent cycles through the mechanism of attention.

The proposed CC approach is evaluated with experimental simulations on a four-bus network to observe its performance in detecting and correcting bad data by reconfiguring measurement weights of various meters in the network. With CC, the system was demonstrated to act dynamically and choose the best set of meters simultaneously to obtain readings from and effectively assign the best weight to each measurement for optimal state estimation [115]. Upon a meter malfunction, only a couple of PACs are necessary to learn from the situation and adapt by decreasing the weight of that malfunctioning meter. It is also shown that the cognitive controller's assignment of weights to the different measurements is done in a

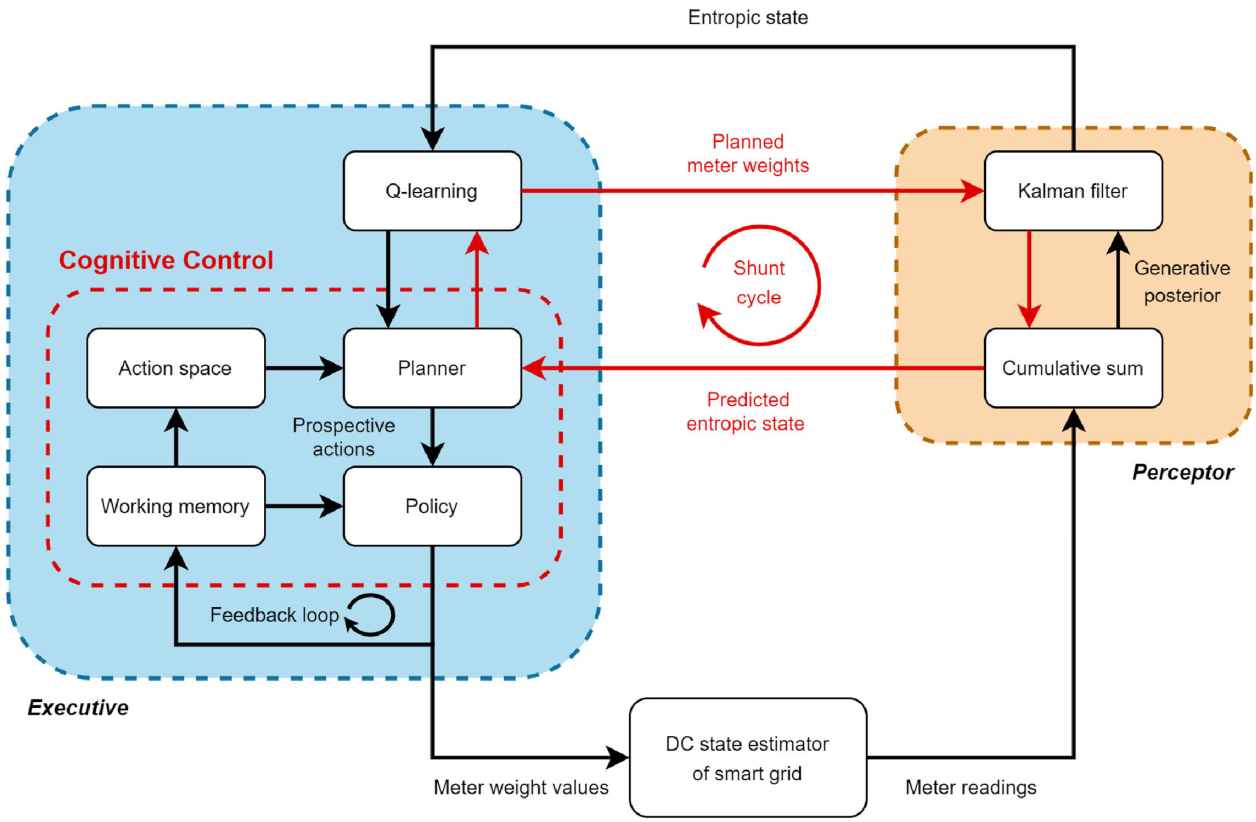

Fig. 12. ***Architectural structure of a CDS framework presented in [115] with CC applied as the supervisor of a smart grid network.***

manner to adapt to the probabilistic characteristics of noisy signals, and the mse of the estimates achieved with the cognitive controller is much lower than without the use of CC [115]. Furthermore, the authors show that, when faced with cyberattacks known as FDI attacks, it is also possible to use the entropic state as a metric to detect such cyberattacks. However, it is stated that the model must expand its structure to include CRC to actually deal with and eliminate the risk associated with these types of attacks, which the authors address in later studies [116] that we focus our discussion on in Section VI.

Otherwise, a limitation of the proposed framework in dealing with bad measurement data is that it is not practically scalable to real smart grid networks, which usually have thousands of meters. The reason given for this is due to the computationally costly requirement of an inverse calculation during state estimation. Regardless, the proposed model was more accurate, less prone to false positives, and computationally less expensive than the existing detection approaches proposed in [117]. Finally, it was also noted that the BUCB algorithm in the proposed CC model is likely to face issues when scaling up to more extensive networks in terms of response time in figuring out optimal configurations in the face of meter malfunctions [115]. In such a case, with more careful tuning and by tweaking the algorithm's sensitivity higher, it may be possible to decrease its response time.

4) Other Works: Several studies have applied the CC framework to other fascinating areas, fields, and applications in recent years. One such example of an interesting study has been proposed by Mazzù et al. [118], in which the authors implement a cognitive controller for far-distance object detection and tracking based on IR images or videos. Following the CDS framework, the CC-based approach uses multiple independent KFs and exploits their cooperation to understand object movement by taking advantage of the different dimensions that objects present themselves in at different distances [118]. The architecture of the proposed technique is described as a DBN to represent the perceptor and controller in a probabilistic way and provide the tools for signal processing [118]. The Q-learning algorithm is adopted in the cognitive controller for ensuring that the optimal policy is adhered to by representing the action-reward space as an HMM, and for further details on the implementation of the proposed approach, we refer the reader to the studies [118]. The results of the proposed method were compared against sever other state-of-the-art trackers, including the mean-shift algorithm [119], the fusion filter [120], which uses a covariance matrix trace-based fusion scheme, a modified particle tracker [121], and the least soft-threshold squares tracker [122]. With a dataset consisting of public real image sequences, the proposed technique was demonstrated to achieve tracking results with mses comparable to the other mentioned techniques, despite being a suboptimal implementation [118]. From our investigation of the literature, it is also evident that the proposed technique tends to struggle to perform in the presence of significant clutter. As such, this challenge may be addressed by using more state-of-the-art and robust filters, such as the CKF.

Fatemi et al. [123] propose another compelling application of CC, where the proposed approach is used to address the problem of observability in complex stochastic networks. The authors propose a goal-seeking supervisory system based on the CDS framework that regards the network as the environment. The responsibility of this supervisory system is to reconfigure and optimize sensory parts of a network to optimize and improve observability dynamically [123]. The CDS achieves this by reconstructing hidden states of the network based on information gathered from monitor nodes (a subset of nodes whose outputs are accessible to the CDS). Bayesian filtering is employed in the perceptual part of the system to reconstruct the physical state of the network. At the same time, CC is responsible for improving the accuracy of the reconstructed states in each PAC by controlling the information flow through the reconfiguration of sensors [123]. The CDS may need to increase the number of monitor nodes or remove redundant nodes to maximize the information available to the perceptor in the subsequent cycles. For more details on the implementation, which relies on advanced knowledge of graph theory techniques and the results of experimental simulations, we refer the ready directly to the literature [123]. However, the study results provide a good theoretical foundation for future studies regarding the efficient management of nodes or sensors in a network, especially in applications where physical sensing systems may be networked together like cognitive radar and cognitive radio technologies.

VI. COGNITIVE RISK CONTROL

In this section, CRC is introduced as the second overarching function and architecture, which fully adheres to the CDS framework. CRC extends upon CC by introducing another subsystem to the CDS, which is responsible for detecting and accounting for risky or uncertain events [5]. As with CC, any system augmented with the elements of CRC can be classified as a CDS.

Within Section VI, an exposition on the CRC architecture and a survey of recent works in the field will be presented to the reader. As proposed by Haykin [7] and Haykin et al. [8], CRC has yet to receive as much attention in the literature as its CC counterpart, and the first two precursor systems cognitive radio and cognitive radar. However, as will be demonstrated, CRC presents the potential to completely revolutionize a wide range of existing system types by providing them with the ability to identify, adapt to, and mitigate the effects of risky or uncertain events, and can even result in significant performance improvements. A detailed summary of all the surveyed works on CRC along with their key findings is presented at the end of the Section in Table 4.

A. Background and Motivation

In the world we live in today, which is experiencing a proliferation in the adoption and integration of CPSs with the physical world, environments are unavoidably prone to the unexpected occurrent of unpredictable events. CPS is defined as a new generation of embedded systems that leverage the power of interconnectivity and integrate aspects of the cyberworld with physical systems. These systems are transforming the way modern society lives, moves, and interacts in the physical world and are evident worldwide in infrastructure, air or ground transportation, electricity grids, and much more. Consequently, physical systems now more than ever are confronted with cybersecurity issues that can result in unexpected occurrences or uncertainties that may bring forth threats to safety or security breaches [124].

When a situation arises with a physical system, whereby the information is unknown and, therefore, difficult to deal with, the system is, thus, said to be dealing with uncertainty. When physical systems experience uncertainty, it is imperative to deal with and handle such unexpected or adverse events, collectively defined as risks. An illustrative example of such a scenario involving risk, as described in [7], considers an autonomous vehicle moving within a lane in a crowded street. Supposing a cyclist suddenly rushed out of their designated lane and across to the other side of the street in front of the autonomous vehicle. This situation has resulted in a sudden and dramatic risk to both parties. Consequently, there has been a growing focus in the literature concerned with providing physical systems with the means to function under the presence of uncertainties and bring risk-sensitive actions under control. In response, CRC is proposed as an architectural and functional model for risk control mechanisms, which is classified under the CDS framework.

B. Overview of Cognitive Risk Control

Inspired by the principles of neurophysiology, specifically predictive adaptation, the CRC model was first theorized in 2017 by Haykin [7] and then fully formulated shortly after by Haykin et al. [8]. CRC is essentially an extension of the CC framework discussed in Section V. There are two modes of operation in CRC: version I and version II. In version I, which deals with the system operating free of uncertainty, the CRC model reduces to the CC framework, as illustrated in Fig. 12. Otherwise, when operating in the presence of uncertainties, the CRC model switches to version II, which is much more complex in terms of structure and computation and will be the focus of discussion in this section.

The CRC model introduces a subsystem to the executive side of the CC model to allow for more elaborate thinking, which requires the introduction of a new component

Table 4 Summary of Published Works on CRC

Year	Authors	Reference	Research Application	P	M	A	I	Comments
2017	Haykin *et al.*	[8]	Original architecture	✓	✓	✓	✓	Proposal of original cognitive risk control architecture.
2018	Feng and Haykin	[128]	Connected and autonomous vehicles	✓	✓	✓	✓	CRC for transmit-waveform selection in CVR for robustness and effectiveness in the face of disturbances or adverse events.
2019	Feng and Haykin	[129]	Connected and autonomous vehicles	✓	✓	✓	✓	Anti-jamming in V2V communications is proposed using CRC in hybrid UAV-CAV networks through power control and channel selection in the presence of malicious actors.
2019	Feng and Haykin	[131]	Connected and autonomous vehicles	✓	✓	✓	✓	Extension of previous studies to 5G V2V communication-assisted transmit-waveform selection in CVR.
2020	Feng and Haykin	[132]	Connected and autonomous vehicles	✓	✓	✓	✓	C-CRC proposed to extend on previous studies which adopts a nonlinear model and a CKF for increased practicality. CVR and V2V communications treated as individual CDS, relying on information from one another to conduct both transmit-waveform selection, as well as power and channel selection for communications.
2019	Oozeer and Haykin	[116]	Smart grid control	✓	✓	✓	✓	Extension of previous where CC was implemented for smart grid control. CRC successfully applied to the previous CC work to also detect FDI attacks and mitigate their effects.

* P represents the PAC, M represents memory, A represents attention, I represents intelligence, ✓ represents the presence of cognitive process, and × represents the absence of cognitive process.

termed the classifier, as seen in Fig. 13. It can also be seen in Fig. 13 that there are two pairs of switches: switches 1 and 2, and switches 3 and 4. When operating under version II, switches 1 and 2 are open, which prevents the controller from directly acting on the physical system and providing feedback to the executive memory. Instead, a perturbed cognitive action is sent to the classifier along with a set of past actions from the executive memory. The classifier is then responsible for decision-making and subsequently updating the executive memory [8]. In contrast, when the physical system is operating free from uncertainty, or under version I, switches 1 and 2 are closed, while switches 3 and 4 are opened. In this situation, the controller can act on the physical system and update the executive memory directly.

The perturbed cognitive action of the classifier is of probabilistic origin, and the prospective past experiences from the executive memory are also probabilistic since they are randomly chosen from their own action space. In recognizing these facts, the Bayesian paradigm is invoked as the means for decision-making, setting the stage for CRC [8]. Using Bayes' rule, the probability of the perturbed action's

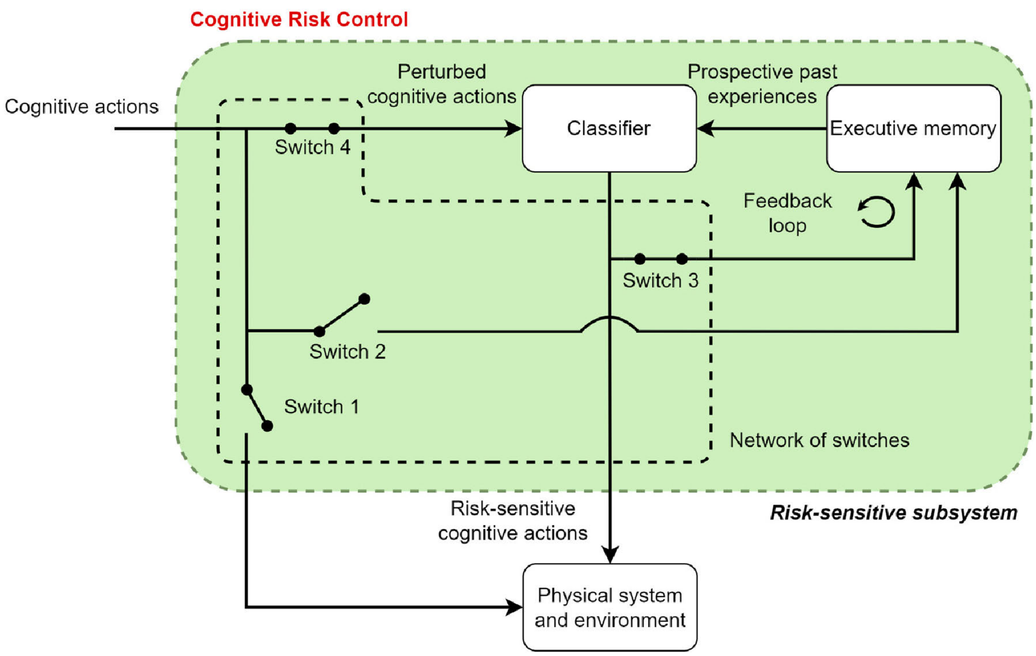

Fig. 13. *Architecture of the risk-sensitive subsystem responsible for dealing with risk in the CRC framework.*

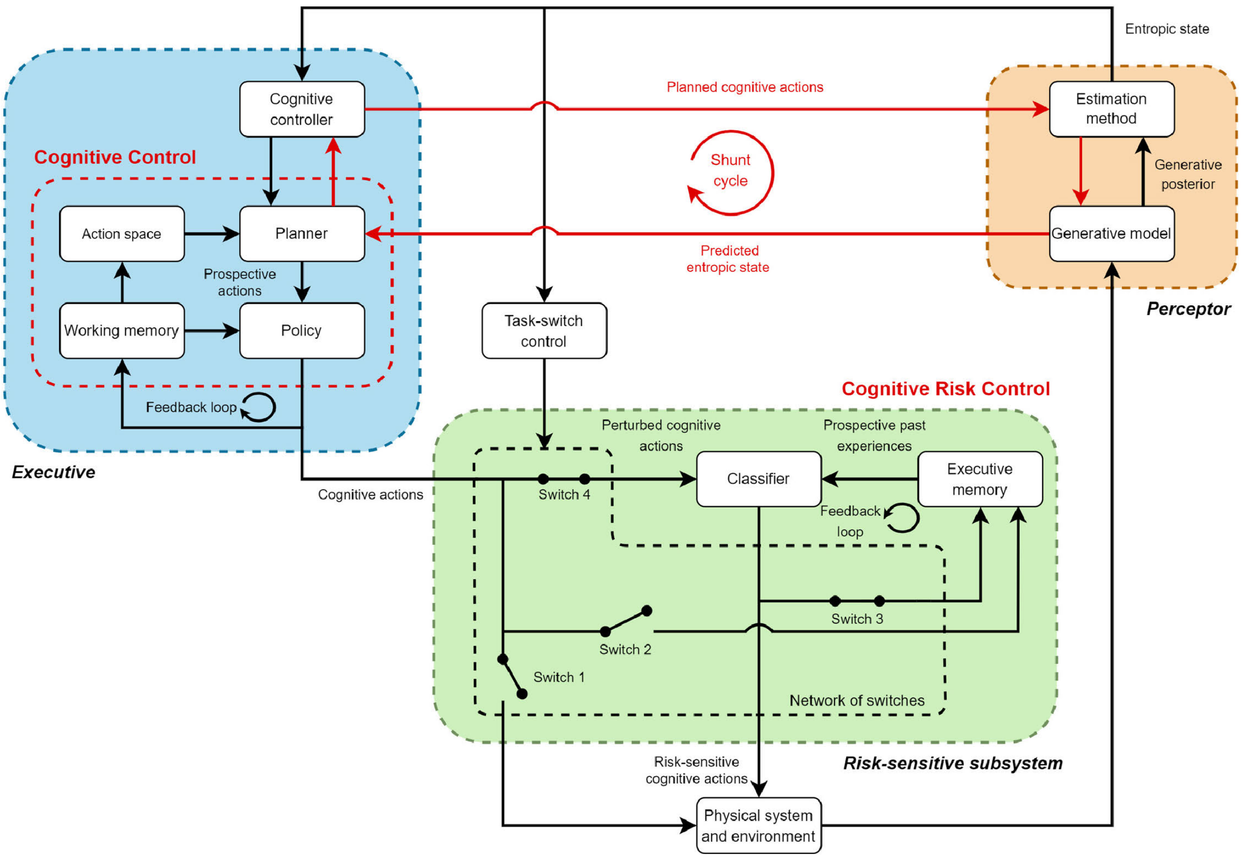

Fig. 14. ***Architecture of the CRC framework. The green elements represent the newly introduced risk-sensitive cognitive subsystem.***

posterior given a past experience is calculated for each of the past experiences in the selected set. The experience with the highest probability is subsequently defined as the risk-sensitive cognitive action directed to the physical system [8].

TSC is a function required in a CRC framework capable of exploiting the presence of the pairs of switches and controlling their configuration depending on the presence or absence of uncertainties. The basis for defining the procedures of TSC is the entropic rewards from the feedback channel. In CRC, the entropic reward can only assume positive or negative values and can never be zero. The key to defining TSC is in these two properties: positive rewards indicate the absence of uncertainty, and negative rewards indicate uncertainties [8]. With this approach, the choice of function to compute the rewards and the tuning of design parameters in the chosen function are critical considerations for implementing CRC in physical systems. Therefore, in summary, when uncertainties are absent, the entropic reward must be positive, and thus, switches 1 and 2 are closed, while switches 3 and 4 are open. Conversely, when uncertainties are present, the entropic reward must be negative, and therefore, switches 1 and 2 must be opened, while switches 3 and 4 are closed.

The resultant overall architecture of the CRC framework can be seen in Fig. 14, where the previously discussed risk-sensitive subsystem and its components, the classifier, and executive memory are colored in green. In the framework's literature, several sections are dedicated to discussing the PAC, its role within the framework, and the biological motivations behind its implementation in this architecture [8]. As for the cognitive process of memory, it manifests in the executive memory, which retains long-term knowledge of past experiences and actions, as well as in the working memory, which acts as a short-term memory interface between the perceptual and executive parts to help carry out learning and planning within each PAC [8]. There is no difference in the attention mechanism in CRC compared to CC and, as such, is identical to the methodology in CC, as discussed in Section V. Finally, the coordination of processes and mechanisms enabling algorithmic decision-making to pick a strategy for an optimal solution is explained as the facilitator of intelligence in this cognitive framework, along with the presence of local and global feedback loops.

C. Related Works in Cognitive Risk Control

1) Radar and Communications: Due to the fourth industrial revolution, an increasing number of breakthroughs have been witnessed in various fields, especially in areas of research involving UAVs [125] and CAVs [126]. In most current designs of these systems, multiple sensory systems, each with different merits and limitations, are required, such as LiDAR, radar, radio, and camera, to name just a few. These sensors provide multidomain information to a central computer, which is then responsible for making decisions to control various aspects of such systems, such as steering angles or acceleration and deceleration. The safety and security issues related to these fields, specifically with CAVs, have been extensively discussed by Feng and Haykin [127]. In this article, the authors also envision a new class of risk-sensitive, autonomous, connected, and electric vehicles, introduce the CDS, namely, its special function of CRC as the supervisor of these vehicles, and present a comprehensive overview of the theory involved [127].

The first experimental studies using the CRC framework were also performed by Feng and Haykin [128]. The authors study and apply the framework to a CVR system for self-driving cars. In their work, recognizing the threats posed to autonomous vehicles in the presence of uncertainties, the authors strive to improve the performance of vehicular radar systems in the face of such threatening circumstances. The literature describes a simple vehicle-following scenario and presents the architectural structure of the CRC tailored to the task of transmit-waveform selection in vehicular radar systems. In the described scenario, a host vehicle is moving forward, and ahead of it is a target vehicle moving in the same direction, both described by their own velocities and accelerations. Details on state-space dynamics and modeling of the scenario are provided, and we refer the reader directly to the literature in [128] for these specifics. The purpose of the proposed model is to deal with risky events caused by other physical entities robustly when applied as the supervisor for transmit-waveform selection in the radar system.

In their work, the authors modify the perceptual part of the CDS by removing the Bayesian generative model since, in the case of vehicular radars, observables are usually taken in a way that can be directly processed by the Bayesian filter [128]. Therefore, the Bayesian filter is now at the bottom of the perceptor, and the entropic-information processor is brought in to take its original place and maintain the feedforward link. Otherwise, the proposed work follows the same structure, as depicted in Fig. 14. The KF is chosen to model the vehicle-following scenario as the Bayesian filter and is formulated according to the choice of transmit waveform, which combines the LFM waveform with Gaussian amplitude modulation. The entropic state is computed using the filtered posterior from the KF as input by invoking Shannon's information theory. The entropic state calculates the entropic or internal rewards using a defined function and then passes them on to the executive. The TSC mechanism of the CRC framework is controlled by passing the internal rewards through a defined function, which is then subject to certain conditions and thresholds formulated within the literature to determine the presence or the absence of uncertainty [128]. A nearest-neighbor classifier is adopted in this work to select the particular memorized experience most similar to the perturbed cognitive action when CRC is triggered. The rest of the methodology follows the typical CC framework discussed in Section V and is also illustrated within the red dashed border in Fig. 14.

Through experimental simulations, the proposed CRC model using Q-learning for RL was compared against other approaches, such as a radar with fixed transmit waveform, the CC framework, and just Q-learning on its own for waveform design [128]. The performance of each model was compared using the RMSE computed against each model's five states: velocity and acceleration of the host vehicle, the longitudinal distance between the host and target vehicle, and finally, the velocity and acceleration of the target vehicle. Simulation results showed that the proposed model demonstrated the lowest RMSE for each state from presented qualitative graphs, with CC and Q-learning having very comparable performance [128]. These results demonstrate that the executive's learning algorithms will result in better decision-making and choices of action regardless of the choice of algorithm. The authors introduce a structural uncertainty term to the system model during the trial to induce a risky scenario in the experimentation, which lasts for less than a second. This scenario demonstrated that the Q-learning and CC algorithm could not adapt to this uncertainty and instead showed significant spikes and erratic behavior in the RMSE and required upward of eight seconds to recover. However, the proposed CRC model relative to the other approaches was only slightly affected in terms of RMSE and recovered within a matter of 2 or 3 s at most. Overall, the model achieved impressive results and was also deemed a promising alternative to traditional approaches in handling uncertainties and risky events in vehicular radar [128].

Further studies by Feng and Haykin were conducted in [129], where the authors seek to address the V2V communication problem in CAVs and UAvs. Specifically, the literature proposes and implements CRC in a CAV integrated within a UAV-CAV network to fend against malicious entities that may be equipped with the means for intelligent jamming. A system model is described in the literature, along with the proposed methodology for antijamming V2V communications, which includes formulating the environment in a manner that characterizes wireless channels between vehicles. The overall approach can be summarized as follows: first, power control for transmission is carried out with RL based on what is perceived by the system. Based on the selected power, TSC is used to determine whether the threshold for activation is reached, triggering CRC or not. If TSC is not triggered, then the power selected is executed as the cognitive action on the system. Otherwise, if TSC is triggered and CRC is active, channel and power reselection is carried out by the classifier and executive memory to escape the presence of possible jamming attacks, which are carried out as

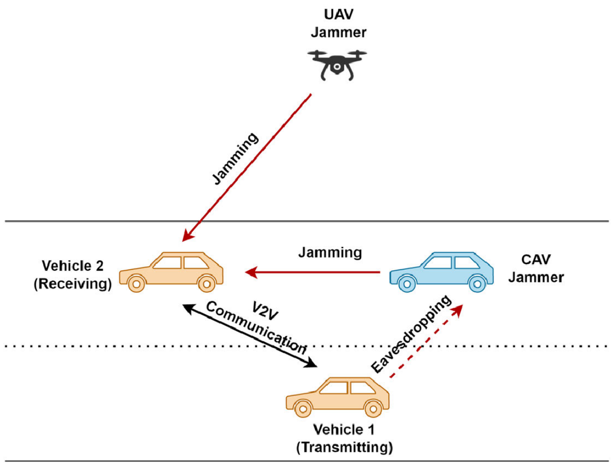

Fig. 15. ***Configuration of experimental simulations for CRC in a UAV-CAV network for antijamming in the presence of hybrid attackers (adapted from [129]).***

cognitive actions [129]. Novel power utility metrics are defined to evaluate the performance of both the transmitting (host) vehicle and the malicious entity with intelligent jamming in adjusting their transmission powers to achieve their respective goals.

The experimental configuration of the author's proposed studies can be seen in Fig. 15, which involves an intelligent CAV jammer, a static UAV jammer flying at a height above the transmitting (host) and receiving (target) vehicle. From the literature's results, the proposed CRC antijamming model was able to achieve the greatest power utility among other strategies. This includes the fixed strategy where the host vehicle stays in a fixed channel and transmits a constant power and a random strategy where the host vehicle keeps changing both channel and power randomly as an intuitive countermeasure to attacks [129]. At the same time, the proposed approach was most effective at reducing the power utility of the intelligent-jamming CAV. Furthermore, four channels were defined that could be selected by the host vehicle, whereby the UAV is occupying a fixed number of channels and transmitting at various powers. As the power transmitted by the UAV jammer in each channel was increased, the probability of the host vehicle selecting those channels to switch subsequently decreased. Also, as the height of the UAV increases over five hundred meters, its jamming effects were negligible since, at that point, the probability of a channel being selected was equal for all four channels [129]. Finally, the throughput of each approach was compared, from which the authors infer a maximum achievable throughput improvement in their proposed model of approximately 45% and 210% compared to the random and fixed strategies, respectively. It is postulated that such success may also be possible with this model in more complex networks facing even more sophisticated types of attacks [129]. The authors further verified these findings in a similar continuing study, in [130], which is focused on the analysis of the framework applied to CAVs that are subject to factors causing performance degradation issues encountered in more complicated scenarios.

Inspired by their previous success in applying the CRC model to transmit-waveform selection in CVR and for antijamming in V2V networks, the same authors proposed several further studies. For example, Feng and Haykin [131] use the insight gained from the two previously discussed works in this section to improve the performance of transmit-waveform selection in CVR with the assistance of 5G V2V communications. In this new study in [131], the methodology of incorporating the CRC into the design is almost identical as previously discussed in [128], differing mainly in the fact that the system model equations are now expanded to leverage information exchanged from V2V communications, such as location, velocity, and acceleration in the transmit-waveform selection process. The V2V-based approach for CVR realized even more improved performance in terms of robustness than in the previous study without V2V communications. For instance, the RMSE of each state with the V2V-assisted CRC approach and regular CRC is comparable most of the time. However, when the uncertainty is introduced, the newly proposed approach's peak RMSE is nearly half that of what is achieved without V2V assistance and is much smoother as it recovers back to optimal performance, instead of erratic and jerky behavior [131].

All of the studies just introduced and discussed have culminated in the most recent work of Feng and Haykin [132], whereby the authors now propose integrating CVR and V2V communications with a C-CRC model to bridge both systems with each other. The advantages of mutual assistance are studied with C-CRC by exploiting information originating from one of those systems, which may be insightful for the other system. Furthermore, unlike previous studies, a nonlinear target-tracking model is adopted, and a CKF is employed for the analysis [132]. In this approach, the formulation for the interference measure in V2V communications includes results from tracking and other practical factors inferred from those results, such as vehicle mobility and channel availability. The CVR is also reliant on information from the communication system to switch its operation based on a one- or two-vehicle model, where the latter indicates the presence of a second vehicle participating in target-tracking [132]. Both the CVR and the V2V communication systems are considered separate CRC models with their own risk-sensitive subsystem and associated TSC mechanism. Furthermore, the TSC in each system plays a role in their dual system in determining what information should be passed from one to another. C-CRC is responsible for the coordination between the two CDSs, and the overall process of the proposed architecture is shown in Fig. 16.

Going even further, the authors formulate the channel selection problem as an MAB problem, which is solved using the UCB algorithm [133]. With the approach, in each

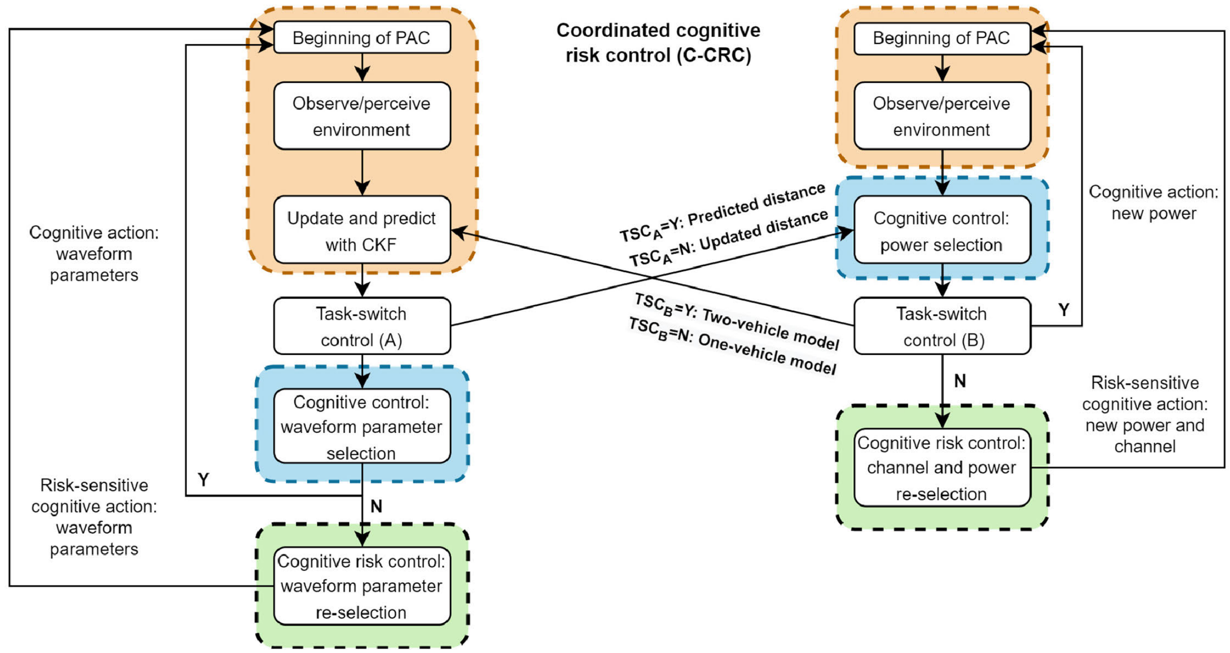

Fig. 16. ***Process flow diagram of the proposed C-CRC model (adapted from [132]) for bridging CVR and V2V communication systems in CAV.***

PAC involving a channel selection, the channel choice to switch to is the corresponding channel with the highest index defined by the UCB algorithm. A regret measure is introduced as a common performance metric in MAB problems and is used to evaluate the degree of how unnecessary or redundant a channel switch is [134]. The experimental simulations involved are identical to that illustrated in Fig. 15 from [129], except for the UAV jammer's presence. Otherwise, the authors show that the proposed C-CRC model outperformed other radar approaches, such as fixed transmit waveform and Q-learning by up to 70% and 67%, respectively, in reducing the peak RMSE reached in tracking the longitudinal distance of the car and jammer when faced with uncertainty. The traditional CRC design in [130] had comparable performance but was still inferior to the C-CRC in RMSE peak reduction by a margin of 41%. The trend of C-CRC achieving improved scores is apparent across all measures, such as tracking performance in terms of the utility of power selection in the vehicle and jammer communications, the total regret from channel selection, and, finally, user utility.

A limitation, however, is observed in the literature regarding the ability of V2V communications to keep up with crowded networks in certain environments or conditions. From further analysis of results relating to the effects of channel availability on power and channel selection, it is evident that the user utility will decrease, while jammer utility increases with less spectrum opportunity [132]. This scenario also results in a higher regret measure for the host vehicle, a lower MAB-related reward, and increased switching costs relating to channel selection. As such, vehicular networks with many entities sharing the available wireless resources in a local environment pose interesting and practical problems concerning V2V performance that require further attention from the research community. The authors also conclude by mentioning the investigation of security issues in large-scale adversarial CAV networks to be within the purview of their future research efforts.

2) Cybersecurity in Smart Grids: The deployment of smart grids in critical infrastructures requires thoughtful consideration of safeguarding against vulnerabilities and malicious attacks [135]. Despite its advantages, the intimate interconnectivity of cyber and physical systems in smart grids also introduces important issues relating to cybersecurity [136], [137]. A family of new attacks known as FDI or BDI attacks has been recently considered to be some of the biggest threats to smart grid networks [138], [139]. These attacks involve the introduction of maliciously crafted data packages to circumvent conventional statistical detection and removal approaches. The result of these attacks, when successfully injected into a system, is a negative influence on the estimation of states, which can lead to a cascade of incorrect control decisions with disastrous consequences. The current literature on FDI attacks in smart grids focuses mainly on the detection aspect of this problem [140]; however, there is a dearth of literature examining the issue of bringing these malicious attacks under control once detected. Furthermore, due to the reliance of most detection techniques on predefined thresholds, these techniques are useless when attackers know the detection method and the related threshold.

In response to these issues, Oozeer and Haykin [115] expanded upon their CC approach for smart grid attack detection, as discussed in Section V-C, to propose an improved CRC-enabled model capable of also defending against such attacks in [116]. In the original studies, the entropic state was used as a metric to detect the occurrence of FDI attacks indicated by the entropic state dropping below a defined threshold, thus setting the stage for TSC in the extended CRC version of the model. With the expanded framework, when an FDI attack is detected, and TSC is triggered, the cognitive controller is rendered inactive, while CRC is activated to defend against these attacks [116].

In this scenario involving CRC, realizing that FDI attacks aim to cause deviation in specific states to trigger a cascade of bad control decisions, the authors mention that the action space involved differs from CC. Rather than having an action space consisting of possible measurement weights as in the cognitive controller, CRC involves selecting tuning parameters to be applied to the dc system's configuration matrix [116]. First, however, the predictor or classifier must recognize the states at risk after an attack is detected. The affected states are identified by whether they exceed the maximum deviation allowed by a formulation dependent on each estimate's mean stored in the perceptual memory, as described in the literature [116]. Subsequently, upon identification of the states under attack, the planner is responsible for carefully selecting tuning parameters in the columns of the dc system's configuration matrix corresponding to the affected states without disrupting the estimation of other states [116]. During this planning phase of operation, each shunt cycle is dedicated to addressing the risks associated with one of the states at a time, and a new reward associated with a particular action in the cycle is determined. The BUCB algorithm, as proposed in [115], is then responsible for optimizing the policy in a manner prioritizing actions that will bring current states under attack back to a state closest to past perceptual memories. The actions achieving the highest quantile from the BUCB algorithm, similar to CC, are stored in the working memory and applied when the shunt cycles have elapsed. Once the affected states are brought back within the acceptable ranges, the risk is then considered under control, and no more actions will be applied to those columns of the system configuration matrix. Finally, when the attacks are identified to have ended, a mechanism is introduced by equipping the TSC with memory and a watchdog timer responsible for restoring the system configuration to its unaltered form and marking the end of the current PAC [116].

The experimental simulations conducted within the author's studies are similar in configuration to those conducted in their previous studies from [115], which involve the IEEE four-bus and 14-bus networks. In the four-bus network, the literature demonstrates how the cognitive controller and CRC can work in conjecture to bring FDI attacks under control once they have been introduced to the system. The network configuration matrix of the system is detailed in the study along with other pertinent parameters, and it is mentioned that the simulations run for a total of 2000 s while allowing for 15 shunt cycles in each PAC for learning and planning. The action space for CRC consists of 63 possible tuning values, whereby relevant columns of the network configuration matrix can be tuned with a specified range of values. Three states are measured in the four-bus network, and an attack is introduced to the first two states 1000 s into the simulation lasting for 300 s. FDI attacks are simulated by shifting the phase angles of the desired states by specified values [116]. From the graphs of the results provided in the study, the proposed CRC model was shown to effectively detect the injected attacks through the sharp drops in the entropic state and subsequently identify which states are affected. Otherwise, the unaffected state is dealt with as normal using the CC part of the model. The CRC only takes 20 cycles until the estimates or measurements for the affected states are brought under control and restored to a tolerable threshold before the attacks occur [116]. When the attacks end, the proposed model still operates under CRC for 39 additional cycles, the reason cited by the authors being that the model is ensuring that conditions regarding the matching of current and past experiences are met. Subsequently, the adjusted network configuration matrix is restored to its normal state before triggering TSC and invoking CRC. When experimenting with the model on the larger 14-bus network to demonstrate scalability as more states are under attack, which also involved raising the number of shunt cycles conducted to 20, the performance is deemed consistent with the previous trial. The CRC model is able to detect the attacks on the six affected states out of 13 states instantaneously. The attacks are brought under control, and the states are restored to appropriate levels within seconds, while the CDS requires around 61 cycles until it switches back to the CC mode. Overall, the experimental results demonstrate the effectiveness of the CRC approach for FDI attacks [116].

However, the limitations of the proposed studies are that the detection time can be affected and increased when other types of FDI attacks, such as the slowly evolving ramp attack, are applied [116]. Furthermore, scaling up the architecture to bigger and more realistic networks will require more shunt cycles to be conducted in each PAC, thus posing significant challenges in terms of computing power and efficiency. This issue is further exacerbated by the fact that, in the presence of other types of FDI attacks, such as evolving ramp attacks, an increased sampling time of the dc estimator is required to overcome them. Another potential use of this CDS in this application that the author's studies have not explored is to not only identify attacked states but also to identify which sensors or meters have been attacked. A final remark is made in the literature, whereby it is postulated that enacting a defined threshold on the absolute estimated error of the estimated measurements could be used as an approach to identify the attacked meters in a network [116].

VII. COGNITIVE INTERNET OF THINGS: RISE OF A NEW CDS

This section covers the topic of CIoT, which is a field that has been given less attention than the previously discussed fields of cognitive radio, cognitive radar, CC, or CRC. In the aforementioned fields, it can be said that practical architecture and methodology were presented upon the initial proposal of each application in the literature. However, this is not the case for CIoT, which instead has only been theoretically discussed in the literature. Several theoretical frameworks have been proposed and, however, offer no practical value or direction toward the actual implementation of a CIoT architecture.

As will be shown Sections VII-B and VII-C, despite the proposal of theoretical frameworks for CIoT, there is still a lack of sufficient effort toward the implementation and description of a methodology, which would facilitate an effective and practical application of the CDS principles in the field of IoT. The authors hope that the following survey on the motivations, outstanding issues in IoT, and the subsequent theoretical CIoT framework proposed will facilitate and accelerate further research in the field and ultimately result in the same successes witnessed in the previous applications augmented with CDS capabilities. Finally, a summary of the surveyed works along with any key findings is detailed in Table 5.

A. Background and Motivation

In the wake of the fourth industrial revolution, the augmentation of electronic devices with the power of the Internet has become prevalent. Many aspects of life, spanning areas such as wearable technology, healthcare, home appliances, and transportation, are becoming increasingly interconnected. The IoT is envisioned as a full-scale integration of all physical objects with the cyberworld and the evolution from simple control systems based on sensors and actuators to more expansive systems able to exchange data between devices over the Internet for more efficient and accurate decision-making.

Embedded systems are one of the main components of IoT devices, designed to conduct certain functions within larger systems, and are responsible for controlling many devices in common everyday use. CPSs have seen tremendous benefits from the proliferation of IoT. Research toward the applications and advancements of IoT technology has gained significant attention from industrial and academic communities in the past years, further accelerating progress in the field. Furthermore, many enabling technologies continue to be developed as time continues, fuelling innovations that have led to new low-cost, low-power hardware, and the creation of new communication protocols and novel technologies, such as RFID and NFC [141].

IoT continues to revolutionize many industries as its applications and benefits grow, spanning domains such as transportation, healthcare, agriculture, communications, smart grids, commerce, infrastructure management, mining, manufacturing, and many more [142]. In this new age, the cyber–physical world demands new autonomous data-driven self-decision-making capabilities in a resource-constrained environment. The power of IoT to decentralize computing power and increase the availability of data has helped to overcome local computing power issues in embedded systems [143]. This power is especially true for training a new generation of control algorithms that use ML and artificial intelligence models. In recent years, especially in the manufacturing industry, IoT has allowed companies to collect vast amounts of data through newly developed MESs. These datasets are valuable for companies as they could be thoroughly and rigorously analyzed for insights to improve operations, utilize resources more efficiently, and reduce costs [143]. The heterogeneity of the various sensors deployed in IoT systems also presents unique challenges in managing different types of data and the complexity of integration. Furthermore, parallel and distributed processing and the processing of nonlinear, high-dimensional data are also limiting factors in the analysis of datasets as they grow to larger sizes [6]. Therefore, the exploitation of such data in the most effective manner presents challenges that have sparked the need for a new framework of analysis and action implementation.

Big data-driven applications demand more intelligent decision-making to allow for more flexible and efficient operations through cooperative self-organized and self-optimized behaviors [144], [145]. As such, many frameworks have been proposed to improve IoT systems' decision-making capabilities to manage the flow of information and responsive action more effectively [142]. More specifically, a field of research that has recently been proposed and gaining traction in the research community is CIoT [6]. The CIoT approach strives to incorporate cognitive capabilities into IoT systems in a framework inspired by human cognition [146].

B. Overview of Cognitive Internet of Things

In the studies relating to CDS, all the previously discussed areas of study, such as cognitive radio, cognitive radar, CC, and CRC, were initially studied and pioneered by Dr. Haykin. The proposed cognitive frameworks in the mentioned areas have enabled and fuelled the research community to further drive advancements in their fields. Furthermore, a significant factor contributing to the exponential growth in almost all of the mentioned research fields has been the presence of such frameworks to provide a foundation providing structure to the academic community. The IoT, however, is a relatively newer application of CDS, which has not yet received considerable attention among scholars. In recent years, however, there has been a noticeable ramping up in effort in the literature to establish a CIoT framework inspired by the trailblazing work of Dr. Haykin with CDS.

The first and most influential general framework presented in the literature for CIoT was proposed by

Table 5 Summary of Published Works on CIoT

Year	Authors	Reference	Research Application	P	M	A	I	Comments
2014	Wu *et al.*	[6]	CIoT framework	✓	✓	✓	✓	First theoretical CIoT framework proposed. Inspired by but diverges slightly in structure and ontology from CDS.
2017	Feng *et al.*	[149]	CIoT framework	✓	✓	✓	✓	Theoretical framework for CIoT in smart homes strictly following CDS principles.
2018	Pérez-Torres *et al.*	[150]	CIoT framework	✓	✓	✓	✓	Experimental simulations applying CIoT to on-device sensing in smartphones to extract and learn from information about human mobility. Resulted in increased energy improvements with proposed CDS.
2016	Rawat *et al.*	[141]	Cognitive radio-enabled IoT	✓	✓	×	✓	Survey on the need for and use of cognitive radio for M2M and IoT.
2017	Khan *et al.*	[21]	Cognitive radio-enabled IoT	✓	✓	×	✓	Survey on most prominent existing cognitive radio-based IoT architectures and future research direction.

* P represents the PAC, M represents memory, A represents attention, I represents intelligence, ✓ represents the presence of cognitive process, and × represents the absence of cognitive process.

Wu et al. [6] to enhance the intelligent allocation of resources, automatic network operation, and intelligent service provisioning. An illustration of the proposed, generalized CIoT framework is depicted in Fig. 17, which is described as a bridge between the physical world (with general physical or virtual objects or resources) and the social world (with human demand, social behavior, and others) [6]. There are four significant layers in the CIoT framework, as can be seen in Fig. 17. The first layer is the sensing control layer and is comprised of a perceptor to sense the physical environment through incoming stimuli and actuators to control the perceptor via the environment. Next, the data-semantic-knowledge layer is responsible for effectively analyzing data from the perceptor to form useful knowledge. The useful knowledge abstracted from the previous layers is then used in the decision-making layer to facilitate reasoning and planning among interactive agents. The dual function of this useful knowledge is to support human and social services, and stimulate action and adaptation to the physical environment [6]. Finally, the service evaluation layer interfaces with social networks and manages on-demand provisioning. Novel metrics are proposed to evaluate the quality of the services provided, which are passed as feedback to the decision-making layer to present an overall structure governed by cost and profit dimensions while considering computational, storage, energy, and device utilization efficiencies [6].

The PAC is the first cognitive process of the proposed CIoT framework, just as in a CDS. However, the remaining four cognitive processes in the author's CIoT framework are massive data analytics, semantic derivation and knowledge discovery, intelligent decision-making, and on-demand service provisioning [6]. Massive data analytics in this framework is concerned with developing algorithms for effective analytics of massive amounts of data and overcoming current issues with heterogeneous data. These algorithms can be classified into one of four groups: heterogeneous, nonlinear, high-dimensional, or parallel and distributed data processing algorithms. Skar's theorem to address heterogeneous data and the use of kernel-based learning for nonlinear data [6] are some examples of techniques presented to deal with some of the encountered data issues. With semantic derivation and knowledge discovery, the former deals with extrapolating context, ontology, and semantic standardizations, and the latter utilizes techniques that fall under the association, outlier, or cluster analysis approaches to achieve intelligence by realizing underlying correlations from the data [6]. Intelligent decision-making concerns itself with reasoning, planning, and selecting the most optimal course of action for an agent to deliver an optimal solution for the problem at hand. The authors suggest multiagent learning and game theoretic approaches as suitable candidates for intelligent decision-making [6]. Finally, on-demand service provisioning entails the support of various services to human or social networks, such as infrastructure-as-a-service, platform-as-a-service, sensing-as-a-service, and everything-as-a-service, which are topics already extensively investigated (see [147] and [148]) and, therefore, not a significant focus of the proposed framework [6].

Rather than following the exact structure of a CDS, this framework diverges slightly in structure and ontology. For example, the sensing control layer is directly related to the PAC in terms of perceiving and interacting with the environment in the presence of local and global feedback loops. Although the description of the proposed CIoT framework accounts explicitly for the PAC and intelligence, memory and attention are not explicitly mentioned as cognitive processes, contrary to the guidelines of the CDS framework. However, despite this, we note that both memory and attention can be identified to exist but under different ontologies. Specifically, memory is addressed as a need to be able to store whatever is learned about the physical environment or social networks [6]. As for attention, it is described in the framework as the mechanism behind the ability to adapt via resource-efficient mechanisms that allow for effective and robust decision-making [6].

C. Related Works in Cognitive IoT

1) Cognitive IoT Frameworks: The possibilities of broad adaptability of CIoT to different scenarios have motivated the academic community to continue expanding the literature on CIoT research and applying the framework to various applications and contexts. As such, since the work of Wu et al. [6] in proposing the CIoT framework was

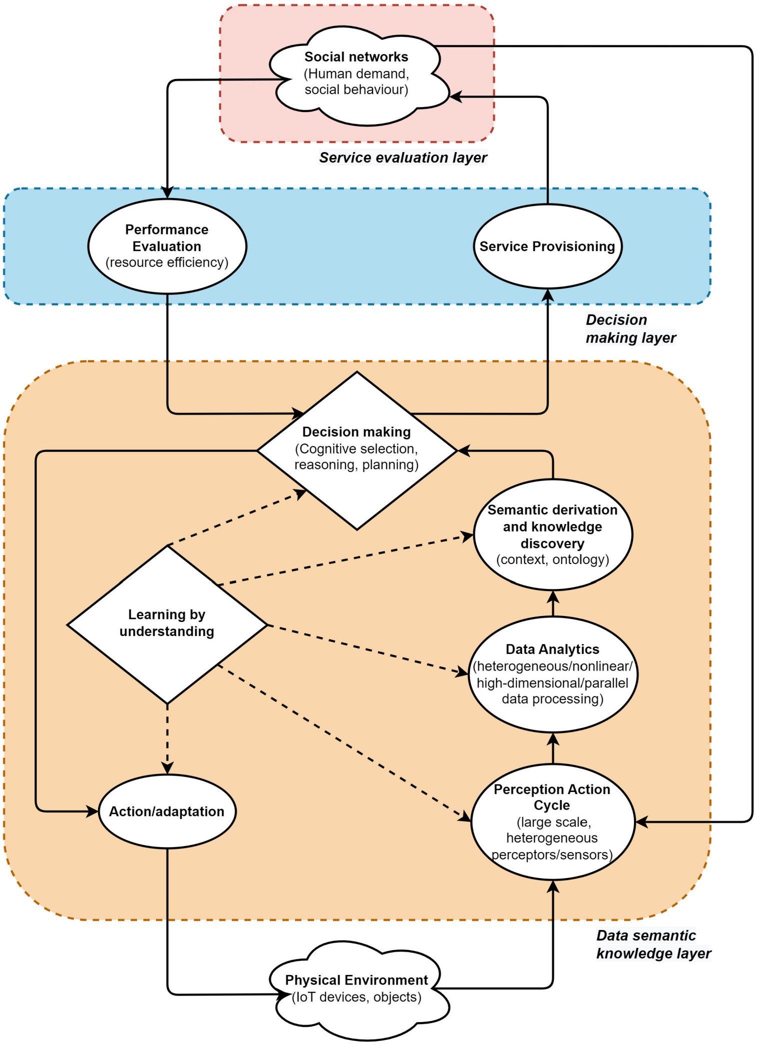

Fig. 17. ***Schematic of the theoretical CIoT framework adapted from [6] with the breakdown of the layers and processes.***

previously discussed, there have been more recent studies proposing more refined frameworks that adhere to the CDS structures.

Acknowledging the efforts made in [6], Feng et al. [149] proposed a CIoT framework that is designed in exact accordance with the CDS structure and specifically tailored the discussion to the application of smart homes. According to the authors, a smart home is viewed as an environment where the control of different home appliances is managed remotely and automatically, with the overall goal of improving the resident's quality of life. This application of CIoT is fascinating due to its parallels with many fiction and science-fiction fantasies in the way the authors envision it. For instance, a scenario is discussed in the literature, which describes a person gradually falling asleep on a sofa during the weekend. A smart home comes into play by slowly decreasing the light intensity, adjusting the air conditioner settings, enabling the home alarm system, and adjusting other settings or appliances to provide an optimal sleeping environment. Although the literature's scope does not extend beyond a theoretical discussion, the studies form a solid foundation for further research and advances in the field.

For a CIoT implementation in the smart home, an appropriate set of sensors to perceive the environment must be equipped in the household. Such sensors are dependent on the application of interest and, in this particular scenario, may include light sensors on blinds and curtains to control light shed through windows, acoustic sensors on doors and TVs for voice control, and temperature sensors to control the heating and air conditioning, and can even go as far as pressure sensors in couches, which would try to detect the state of the resident and adjust to become a bed [149]. With these signals rallied to a real-time control system built over a network, control signals are sent to corresponding actuators in that network. The sensing and actuating mechanisms described and, more importantly, the feedback links from the perceptors that carry information to the executive serve to satisfy the PAC in the author's framework [149]. The cognitive process of memory is implemented through perceptual memory and executive memory. The perceptual memory recognizes distinctive features using a Bayesian model and subsequently categorizes them statistically using a Bayesian filter [149]. In the executive memory, which keeps track of past chosen actions and their corresponding effectiveness, RL is adopted as the learning mechanism responsible for choosing the best action based on environmental rewards, maximizing the accumulated rewards over time as a consequence of the selected actions [149]. Attention is present in both the executive and perceptual, and is responsible for the efficient use of resources, such as directing information gathering and allocating processing power based on strategic importance. Essentially, attention is described by the authors to be facilitated by a hierarchical, multilayered structure of Bayesian modeling and RL in the perceptual and executive parts, respectively [149]. Finally, as familiar with the CDS framework, intelligence builds upon the previous three cognitive processes to facilitate optimal decision-making.

Another CDS-inspired framework, specifically for on-device sensing, was proposed by Pérez-Torres et al. [150]. The motives and purpose of this framework differ slightly compared to the ones just previously discussed in which this framework serves to specifically address issues associated with the energy and computational power limitations on mobile devices. Generally, mobile sensing systems are designed to assume limited energy and computing power for processing the vast amounts of real-world data necessary for current IoT applications and standards [150]. Therefore, ML and other data preprocessing needs are often offloaded to cloud-based solutions, often associated with their own challenges [151]. Furthermore, with the advancements in research areas, such as smart cities and transportation, specific sensors in IoT devices, especially location sensors, can play a critical role in tackling scalability issues but often consume significant amounts of power from smart devices [152]. The proposed on-device CIoT framework aims to amortize the energy requirements of mobile systems, such as smartphones, by learning an expanded spatiotemporal model of user mobility from detected stay points and frequently visited areas. Through event-driven processing, the system will orchestrate the asynchronous operation of the PAC within the CDS, according to and only when mobility events are detected, providing the system with an opportunity to reach idle states and save power [150].

Within the author's framework, time and memory hold relevant roles for the continuous operation of the PAC, where the former allows the incremental learning of information about the surroundings to produce a VRE. The VRE is an internal memory structure for elaborating inferences and predictions about future states and is in the perception block of the proposed framework depicted in Fig. 18 [150]. As the CDS adapts with time, the authors discuss memory blocks as a way of focusing system attention to time windows that may have significant amounts of information, just as the perceptual attention in a CDS focuses on extracting relevant context information. In the perception, the authors propose using pattern recognition or ML techniques, such as SVMs or ANNs, to identify relevant events [150]. Upon detecting an event, the VRE is updated through the information learned from the higher level analysis of perceptual memory. The PRM, as seen in Fig. 18, is responsible for producing meaningful interpretations of observed events and provides the cognitive controller with estimates of future states to account for future system reactions. The working memory, which is in the PRM, thus, has the primary goal of mapping the system's interpretations with possible responses and associating the perceptual and executive memories [150]. Finally, the executive is explained as the mechanism responsible for dynamically adapting the system's behavior toward the defined goal by selecting the most appropriate policy for the cognitive actions to actuate in the environment. Further details and specifics about the practical implementation of the framework, specifically the cognitive controller, can be found in another study published by Pérez-Torres et al. [152].

Acknowledging the infancy of the research in the field and the proposed on-device CDS framework, the authors provide a case study of an implementation of their proposed approach. Datasets from real-world trials conducted with smartphones were used to demonstrate through experimental simulations that it was possible to achieve energy savings ranging from 25% to 66% with the proposed framework [150]. Furthermore, the computational and energy overhead of the CDS framework were not substantial enough and managed to outperform in terms of energy savings compared to the case of just periodically disabling modules, such as the GPS. Several challenges are highlighted, including the privacy and security of mobile information, and vulnerability to data manipulations due to the system's reliance on perception, bringing up further security challenges. However, with further research effort and attention to this young field, the authors postulate that devices enhanced with this CDS framework will prove to be invaluable in applications such as mobile health, travel assistants, and mobility mining for logistics, and further accelerate the arrival of a fully connected world [150].

2) Cognitive Radio for IoT: In the last decade, many advancements have been made in microelectronics, specifically in the development of new, cheaper, and more power-efficient embedded systems and communication protocols and technologies, such as RFID, NFC, and WSNs. Furthermore, the widespread adoption of M2M technologies, which connect machines, devices, and objects to the Internet, plays a significant role in facilitating interconnectivity among large-scale heterogeneous systems. All the mentioned factors play a direct role in accelerating the growth and proliferation of IoT and bring forth new issues and challenges that stand in the way of future growth.

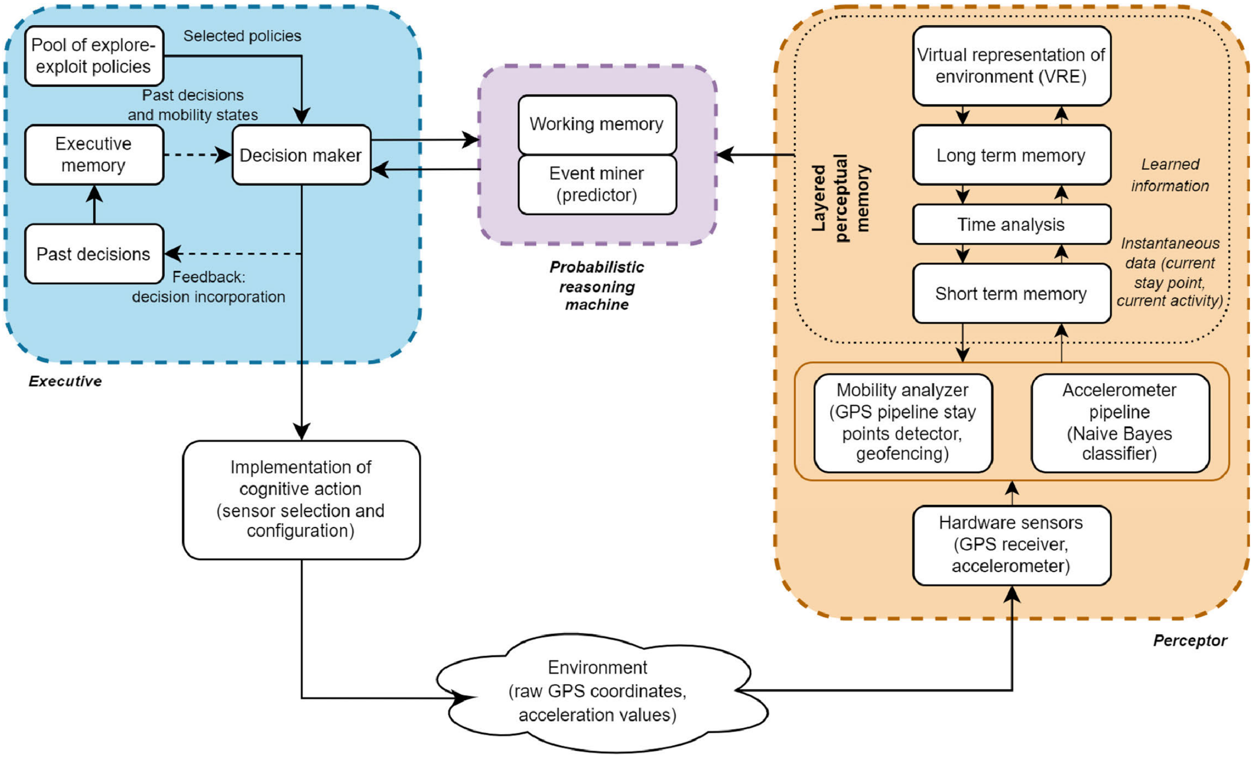

Fig. 18. ***Schematic of the components and processes of an on-device CDS sensing framework for the IoT system (adapted from [150]).***

The need for cognitive radio in IoT as promising enabling communication technology is presented by Rawat et al. [141]. The authors highlight the new technologies enabled by IoT and the major problems posed, most critically the spectrum and bandwidth allocation for the quickly increasing number of IoT devices deployed. An inefficient radio band allocation and routing management would effectively create a bottleneck in IoT development, as, when systems grow larger, they also become less feasible due to the reduced spectrum availability. Making the point that the growth of IoT has already displayed adverse effects from spectrum congestion, the authors survey the literature on applying cognitive radio to IoT to address those issues [141]. The survey covers and discusses topics including, but not limited to, the emerging challenges of autonomy, scalability, energy efficiency, and heterogeneity in terms of user equipment capabilities, complexity, and environments [141]. Furthermore, a taxonomy is provided of the literature that classifies the approaches of each study into two classifications: those that address flexible and efficient networking and those tackling the issues of heterogeneity. Finally, future challenges are presented to steer future research directions and further expand progress in this area.

Khan et al. [21] further the discussion and emphasize the need for cognitive radio-enabled IoT with a more recent review. In their work, the authors thoroughly cover and survey topics that address topics such as the standardization efforts with IoT and cognitive radio, potential applications, spectrum-related work, and highlighting issues and challenges. Furthermore, the authors extend and go beyond previous literature by summarizing architectures and frameworks with prototypes and real-world scenarios. For more details and a discussion on research challenges and issues on this specific topic of cognitive radio for IoT, we refer the readers to [21] and [141] for recent surveys on the field.

VIII. DISCUSSION AND OPEN ISSUES

The CDS framework's potential to revolutionize the design of physical systems has been made evident throughout this survey. Specifically, the need for and capability of CDS as a solution to reduce or eliminate human intervention in the operation of real-world systems in various applications has been highlighted by the increasing research interest in the field. These points hold especially true when considering the applications of cognitive radio and cognitive radar, which have both received considerable attention from the research community, as can be deduced from the significant advances made in each of the respective fields and the fact that they have diverged into their own respective fields of study. In comparison, the other surveyed areas of the CDS framework, such as CIoT, CC, and CRC, are still relatively young and, therefore, present more interesting challenges and opportunities yet to be addressed. However, it is in the authors' beliefs that further research into the area of CC and CRC, specifically toward implementing those architectures into new applications, is one of the most significant potential avenues for future researchers to make an impact.

This section will summarize the key findings and trends observed in the surveyed literature, offering insight into their challenges and limitations while suggesting worthwhile avenues for future research efforts. A timeline summarizing the key milestones and advancements of CDS discussed in this section is graphically illustrated in Fig. 1.

A. Cognitive Radio

Cognitive radio has been demonstrated to be an effective approach for solving the issues relating to the scarcity of the electromagnetic spectrum, allowing users not otherwise licensed to use a range of frequencies to do so in a manner without any degradation of availability or performance for the licensed entity. Spectrum sensing is considered one of the most important tasks in cognitive radio and has also seen most of the published studies in this field. Traditionally, this task relied on a priori knowledge of primary user signals; however, the state-of-the-art techniques surveyed in this article use nonparametric approaches, which eliminate the need for such knowledge while demonstrating robustness to disturbances and low SNR conditions. Some of these techniques involve the use of ML algorithms, such as CNNs. On the other hand, channel-state estimation and spectrum access techniques have not received the same amount of attention. Regardless, heightened interest has been demonstrated toward the use of ML and ML in cognitive radio, as surveyed in [153], a trend that we also note to be prevalent in other aspects of CDS research, as we will demonstrate further in this section.

Open challenges in cognitive radio that has been brought to this survey's attention include the need for further research in cooperative sensing techniques, especially in terms of security in the cooperation amongst cognitive users as networks scale in size and the possibilities of being targeted by malicious attacks. The major open challenge in cognitive radio could be argued to be that this application has yet to be revisited since the proposal of the CDS framework. It was demonstrated in this survey that cognitive radio, while motivated by human cognition, does not adhere to Fuster's principles of cognition and the CDS framework. Instead, cognitive radio is considered a precursor to the CDS framework's development. Thus, it can be hypothesized that, with efforts directed toward adapting cognitive radio to adhere to the CDS principles, additional functionalities or improvements in utility and performance may be realized. For instance, by implementing cognitive radio with CC, it can be hypothesized that more effective policies for accessing and distributing the available spectrum can be realized with RL and its learning and planning mechanisms. Similarly, this theory can be extended to consider the application of CRC in cognitive radio by accounting for and mitigating uncertainties associated with detecting and accessing unstable spectrum holes. Both mentioned approaches may result in improved performance and reliability of cognitive radio and even address the spectrum issue by increasing the utilization of the RF spectrum.

The proliferation of 5G communication standards, which consume more power than traditional standards in current electronic devices, poses a rewarding challenge for future researchers. This is an identified area, whereby significant contributions can yet be made by the CDS framework for cognitive radio, which is closely related to the field of CIoT. Auspiciously, by augmenting such devices with cognitive radio capabilities and further investigating how the CDS framework can learn user behavior and preferences, improved power consumption rates and quality of service can be realized.

Finally, as will also be noted in Section VIII-B with cognitive radar, there is a dearth of literature studying the practical validity of cognitive radio in physical environments. A cognitive radio testbed would provide researchers with an effective means to accurately evaluate experimental results in real scenarios and potentially reduce costs substantially.

B. Cognitive Radar

Inspired by the echolocation abilities of bats, cognitive radar is a notable example of biomimicry in engineering design—whereby the cognitive radar adapts its transmitted waveform depending on the task at hand and based on its perception of the environment. Like cognitive radio, cognitive radar has received significant amounts of attention and effort from the research community. As covered in this survey, significant advancements have been made in performance in various applications with cognitive radar compared to traditional fixed transmit-waveform radar systems. The literature on waveform design for cognitive radar has improved accuracy in single-target and multitarget tracking scenarios and targets in dense, urban, multipath environments. Furthermore, waveform design techniques have been proposed to integrate radio communications with cognitive radar to use information from multiple radars in tandem, offering significant opportunities for intelligent surveillance and monitoring applications. It has also been demonstrated that cognitive radar relies heavily on estimation techniques for perception, such as the KF and CKF. We postulate that investigation into more advanced or recent techniques may prove to be a fruitful avenue for future researchers. An example of such is the novel SIF proposed in [154], which is a suboptimal filter that demonstrates an inherent amount of robustness to uncertainties due to a switching gain.

The issues related to the lack of adherence of cognitive radio to CDS principles are also present with cognitive radar. Mainly, it has been observed that most of the literature on cognitive radar does not refer to or adhere to the cognitive processes of the CDS framework. However, the difference is that cognitive radar was eventually revisited by the researchers behind the framework, whereby it was shown that cognitive radar with CC can demonstrate significant improvements in tracking accuracy. As such, most of the issues associated with cognitive radar's implementation as an adherent CDS can be attributed to those limitations inherent with CC. This is especially apparent when considering that most of the surveyed literature inferred that the main limiting factor for further improvements with cognitive radar is its computational processing overhead. This is an issue that arises in cognitive radar during the transmit-waveform selection process by the cognitive controller, as well as in the learning and planning process involved. The cause of this issue has been attributed to the complex nature of the transmit-waveform's action space in such applications. As such, research toward addressing the computational efficiency of CC for cognitive radar systems would enable and facilitate conducting practical experimentations to confirm the superiority of such systems in real-world scenarios and not just in simulated settings.

C. Cognitive Control

CC has been introduced as a general architecture of CDS that is additive to current system designs, including adaptive controllers and neurocontrollers, allowing them to learn from interactions and experience and perform more robustly in realistic environments. The information gap or entropic state was introduced and described as the measure that the cognitive controller aims to minimize. In doing so, the entropic state also controls the state of the perceptor. The CC framework, as demonstrated in this survey, has been successfully implemented in various fields and applications, and resulted in significant benefits and improvements in various aspects.

The benefits hypothesized to be brought by the CDS framework were verified for the first time with CC involved in the waveform design of cognitive radar systems. Specifically, it was shown that the new and fully cognitive CC-enabled cognitive radar was able to achieve further improvements in terms of tracking and state estimation accuracy, as also discussed earlier in this section. Other innovative applications involve CBTC systems, where CC was responsible for ensuring reliable communications between the trains and control centers to improve the control performance, efficiency, and costs associated with these systems. CC in CBTC was shown to improve the smoothness of train acceleration and braking profiles while reducing energy expenditures, all while lacking proper implementations of attention and memory. As such, it can be postulated that investigation and research into the implementation of these two mechanisms to fully complete the adherence of CBTC systems to the CC architecture will yield further improvements. When tasked with the supervision of a smart grid, CC can detect bad measurements through the entropic state and account for them by configuring the importance of affected meters in the network to maintain the smooth and reliable performance of the grid and power distribution. In such applications, it has been demonstrated that CC can effectively reconfigure the weights of measurements from sensors when they may be malfunctioning to maintain accurate estimation of the system states regardless of the presence of faulty meters and bad measurements. Another interesting example involved implementing CC as a supervisor of complex stochastic networks to study the problem of observability, where the model is responsible for selecting the optimal subset of monitor nodes to observe from an entire set. This application may be useful in situations where costly sensors must be placed on an experimental setup, and as such, CC may be used to determine the optimal number and configuration of sensors to observe the system.

In all the mentioned applications, the KF and RL play critical roles in the operation of CC, and as previously mentioned, it may be promising to explore the use of robust estimation techniques, such as the SIF. Also, it has been demonstrated that the computational overhead associated with the Q-learning algorithm for RL, as commonly used in the literature, is considered a limiting factor. These issues require further investigation to ensure the applications' scalability to real-world scenarios, as repeatedly noted in the surveyed literature to be a significant open issue.

We bring to the reader's attention several observations made from our review of the surveyed studies on the CC literature. First, the CC architecture has not yet received the same level of attention in the research literature as precursor applications such as cognitive radio and cognitive radar. We attribute this to several reasons, with one being the relative novelty of the CDS field. Despite being proposed a decade prior to the writing of this survey, the CDS framework and its first application of CC were the subjects of many noninsignificant refinements in terms of theory and implementation throughout the subsequent years. Over those years, the authors have only applied their framework to cognitive radar applications. This brings us to the second limiting factor contributing to the lack of a plethora of literature applying CDS and CC, which is the fact that the agnostic nature of the framework and its potential use in other applications has not been adequately showcased. As such, we believe with this survey, and further research efforts applying these concepts to other new applications will fuel accelerating growth in the field. Finally, we acknowledge that, while, in theory, the concepts of CC and the cognitive processes entailing may be rather straightforward, the task of practically implementing them may be much more difficult. A cognitive process in one application and the methodology behind its implementation may not necessarily be as intuitively applied and transferred to other applications. Thus, these extra considerations compound the difficulty and increase the barrier to entry to CDS research.

Otherwise, the CC framework demonstrates significant potential in improving the performance of traditional systems by equipping them with a sense of cognition and intelligence. With the combined findings in this field, many applications can benefit by being augmented with CC through future research. Such examples include the controls of industrial plants and their physical processes, patient monitoring and diagnostic testing in smart e-Health systems, and countless other possibilities. This is all in virtue of the agnostic nature of CDS and CC, specifically in their additive design nature, allowing their implementation alongside existing systems without the need for significant or intrusive modifications to existing infrastructure.

D. Cognitive Risk Control

The CRC extends the CC framework to account for and manage the risks or uncertainties that a system may face by introducing a risk-sensitive subsystem to the CC model. When such a situation is detected in this architecture, the entropic state is formulated so that its sign becomes negative. The reversal of this sign triggers the activation of the risk-sensitive subsystem to bring the risk under control and adapt accordingly. This subsystem introduces a classifier to decide upon the best course of action in risky scenarios based on a set of planned prospective actions according to past learned experiences. When the risk vacates, the subsystem is deactivated and circumvented, and the control of the system is back solely in the hands of CC. The CRC framework has been implemented and found useful in securing the wireless communications between autonomous vehicles from malicious attacks, offering even better performance than CC in the same task.

Similarly, CRC has been extensively researched in the context of autonomous vehicles as a means of controlling the communication between other vehicles, target tracking, and fending against malicious entities, which may be jamming communications. In such cases, CRC has been demonstrated to be effective in transmit-waveform selection of the CVR systems under the presence of structural or external uncertainties. As well, when responsible for V2V communications of a network of CAV, CRC enables the detection of jamming attacks and the switching of channels to overcome them. In addition, a C-CRC model has been proposed, which coordinates between two separate CRC models, each of which is responsible for the CVR or vehicular communications of CAvs. With C-CRC, each model is formulated to depend on information from its complement model to improve the tracking performance and maintain constant and effective communication by guarding against jamming attacks. Overall, CRC has been demonstrated to improve tracking accuracy, communications, and safety in autonomous vehicle systems.

Furthermore, in smart grid networks, instead of just configuring the meters or measurements in a network like CC, CRC can adapt the entire system to manage and eliminate the effects of FDI attacks on the system's states in seconds. Specifically, CRC was implemented to reconfigure the system matrix in the presence of FDI attacks to overcome and mitigate their effects while maintaining accurate estimates of the smart grid's states. With a suggested formulation provided in [115], it is postulated that the model may be expanded upon to identify exactly which sensors in the grid network are subject to the attack.

Among the biggest concerns with CRC, as in CC, is the computational complexity of the model and the processing power required for its operation. There is a consensus in the surveyed literature that the number of shunt cycles for learning and planning in most studies did not prove to be sufficient and must be significantly increased, further supporting the need for efforts to improve the computational efficiency of such models. These issues are a significant obstacle to realizing such technology in real-world, practical settings, which we stress as critical considerations that require further effort and attention. Otherwise, we believe that the greatest potential for future research lies in the investigation of implementing the CRC architecture to novel applications and systems to spark the rise of a new class of intelligent cognitive systems with capabilities exceeding that of their predecessors.

E. Cognitive Internet of Things

The last application of the CDS framework surveyed in this article is CIoT, which aims to tackle the issues associated with the various problems faced by IoT devices. These problems include limitations in energy and compute power, connectivity issues due to the mass growth of devices, heterogeneity of data from different sensors, and standardization and scalability. CIoT has also been envisioned as a means to control all aspects of sensors and actuators in connected environments, such as smart homes. In a scenario such as the smart home, CIoT would be equipped to determine the house occupants' state and adjust their environment accordingly, such as by dimming the lights, lowering the volumes of electronics, and arming the home security system when they are falling asleep. Another use of CIoT has been studied, which involves using an on-device CDS to learn the mobility of users through their mobile devices and improve the computational and power efficiency of the device by enabling it to adapt accordingly to their habits.

However, the field of CIoT is still in its very early stages. Although there has recently been interest in researching an appropriate framework or structure, the availability of substantial efforts to experimentally validate them is extremely limited and mostly not attempted yet. Instead, the field's surveyed literature presents theoretical perspectives that bring to light the opportunities for future research to investigate and experimentally validate the viability of the proposed frameworks. Finally, the need for cognitive radio technology in CIoT has been repeatedly expressed in the surveyed studies to combat the increasing scarcity of the electromagnetic spectrum due to the mass number of electronic devices continuously being deployed.

F. Emerging Trends and Future Works

In summary, there are several trends and challenges apparent from the studied works and recent advances in the field of CDS, which have been discussed. Most importantly, however, there is a consensus among researchers that the potential for ML techniques to revolutionize research in this domain further presents much promise and cannot be ignored. The cognitive processes of memory and attention in CDS may benefit the most from such models, and one example of how this can be implemented is through an anomaly detection model in the perceptor, the executive, or both. An autoencoder is a type of neural network, which can be used, for instance, to assist in the detection of risk in CRC and TSC. They may be helpful as autoencoders learn to replicate the most salient features from data, and risky scenarios can be defined as anomalies with characteristics assumed to differ from normal scenarios noticeably, which will be replicated poorly by autoencoders. The use of ML models in the CDS framework is associated with its own set of issues and challenges. Due to the sequential nature of data and its availability in a CDS, online learning methods are critical to update the best predictor for future data at each step and dynamically adapt to new patterns. However, online learning methods are prone to catastrophic interference, where previously learned information is abruptly forgotten upon newly learned information. It is also imperative to consider both an online and an incremental learning approach, where input data are continuously used to extend the model's existing knowledge. Accordingly, the classifier in CRC may also benefit from using more state-of-the-art ML models, bearing in mind the factors mentioned above.

It is worth noting that there has been a relatively slower uptake and advancement in some regards of the field of CDS. Some elements of the framework, such as the cognitive processes, for example, are often easier to capture than others. In some applications, this difficulty may be more significant for one or more of the cognitive processes. Furthermore, when it may be simple to capture these elements, the matter may be further complicated again by the fact that it is also often difficult to package and coordinate the utility of these processes in one coherent system. We mention these facts as we believe that they are relevant and even the main answer when asking the question as to why there is a lack of practical, physical adoption, or implementation in the literature and, instead, an abundance of experimental simulations in place to verify the proposed research. There is no question that many advantages can be brought to existing systems with the adoption of CDS principles, and it is recognized that this may be a simpler task in theory than it is in practice. However, with this survey, we hope to bridge these gaps and narrow the barrier of entry, which exists between theory and practice. Furthermore, regardless of whether or not future research efforts include all elements of CDS in their work, incremental improvements, nonetheless, contribute significantly to helping advance the field and attracting further research.

Other noteworthy and emerging ML-based techniques that will likely support the advancement of CDS in the next years include adaptive ML, xAI, NLP, and physics-based ML. These areas will likely improve the intelligence and language capabilities of CDS, which will ultimately improve system efficiency and uptake. Users will become more comfortable with these systems as they become more embedded within our society.

We leave the reader with final comments and insight into the fields of CC and CRC, both of which we regard to be in their infancy. Although the potential impact of these CDS frameworks on the literature can be considered rather significant, the applications in which they have been implemented are still rather limited. However, a wide range of unexplored applications may benefit from being equipped with CDS functionality, which presents low-hanging fruit for future researchers. In particular, we envision the emergence of a new class of CDS in various fields, one such example being cognitive robotics and mechatronic systems to advance further the capabilities of autonomous systems, such as self-driving vehicles, humanoid robots, and possibly even terrestrial and extra-terrestrial crafts and drones. Furthermore, a cognitive supply chain management framework to improve logistical aspects, such as inventory management, route and path planning, and navigation in many industries may yield considerable time and cost reductions. A cognitive healthcare approach in decision-making and coordination of resources in healthcare settings is also envisioned as an area that can witness rapid advancement in the coming years. Similarly, a cognitive industrial process control in various production or manufacturing settings involving chemical or mechanical processes may facilitate a more effective and robust integrated approach. Such an approach to process controls could enable the design of larger, more complex processes and result in overall increased benefits in terms of reliability, safety, and, most importantly, economics. Furthermore, the ability to predict if a product will fail before it is fully manufactured or assembled will improve product reliability and reduce manufacturing costs (e.g., battery cells in electric vehicles) [155]. The list of applications mentioned is not exhaustive whatsoever, but rather the contrary, as we believe that the possibilities with the CDS framework are limited only by human imagination.

IX. CONCLUSION

In this survey, CDSs and their various applications have been thoroughly surveyed to present the first effort to consolidate the information from the plethora of literature published in this young and developing field. Cognitive radio and cognitive radar, which are the earliest and most significantly researched applications motivated by human cognition, are introduced and discussed along with the most recent works and advances in each of the respective fields. It was also shown and discussed that these two fields were considered to be precursors to the CDS framework in which they were proposed prior to its introduction in the literature. Similarly, other more recently proposed applications of the framework that has yet to receive critical attention from the literature, such as CC, CRC, and CIoT, are also introduced and extensively surveyed for the first time in this work. The methodology behind this study was driven by the mission to motivate and facilitate further research into CDSs. We achieved this by informing the reader of the advances in each specific area, detailing the surveyed literature's advantages and limitations, and offering suggestions and directions for future efforts. In conclusion, the contents and findings of this survey will serve as the foundation for future research and prove valuable to the efforts of other researchers in this exciting new field.

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REFERENCES

[1] S. Haykin, *Cognitive Dynamic Systems: Perception-Action Cycle, Radar and Radio*. Cambridge, U.K.: Cambridge Univ. Press, 2012.
[2] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Sep. 2005.
[3] S. Haykin, "Cognitive radar: A way of the future," *IEEE Signal Process. Mag.*, vol. 23, no. 1, pp. 30–40, Jan. 2006.
[4] S. Haykin, "Cognitive dynamic systems," *Int. J. Cogn. Inform. Neural Intell.*, vol. 5, no. 4, pp. 33–43, 2011.
[5] S. Haykin, M. Fatemi, P. Setoodeh, and Y. Xue, "Cognitive control," *Proc. IEEE*, vol. 100, no. 12, pp. 3156–3169, Dec. 2012.
[6] Q. Wu et al., "Cognitive Internet of Things: A new paradigm beyond connection," *IEEE Internet Things J.*, vol. 1, no. 2, pp. 129–143, Apr. 2014.
[7] S. Haykin, "The cognitive dynamic system for risk control [point of view]," *Proc. IEEE*, vol. 105, no. 8, pp. 1470–1473, Aug. 2017.
[8] S. Haykin, J. M. Fuster, D. Findlay, and S. Feng, "Cognitive risk control for physical systems," *IEEE Access*, vol. 5, pp. 14664–14679, 2017.
[9] P. R. Rao, "Biomimetics," *Sadhana*, vol. 28, pp. 657–676, Jun. 2003.
[10] A. Hamon and Y. Aoustin, "Cross four-bar linkage for the knees of a planar bipedal robot," in *Proc. 10th IEEE-RAS Int. Conf. Humanoid Robots*, Nashville, TN, USA, Dec. 2010, pp. 379–384.
[11] Z. Xu and E. Todorov, "Design of a highly biomimetic anthropomorphic robotic hand towards artificial limb regeneration," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2016, pp. 3485–3492.
[12] I. Kotseruba and J. K. Tsotsos, "40 years of cognitive architectures: Core cognitive abilities and practical applications," *Artif. Intell. Rev.*, vol. 53, no. 1, pp. 17–94, Jan. 2020.
[13] P. Langley, J. E. Laird, and S. Rogers, "Cognitive architectures: Research issues and challenges," *Cogn. Syst. Res.*, vol. 10, no. 2, pp. 141–160, 2009.
[14] W. Duch, R. J. Oentaryo, and M. Pasquier, "Cognitive architectures: Where do we go from here?" in *Proc. 1st Artif. Gen. Intell. Conf.*, 2008, pp. 122–136.
[15] A. Cangelosi and M. Asada, *Cognitive Robotics*. Cambridge, MA, USA: MIT Press, 2022.
[16] J. M. Fuster, *Cortex and Mind: Unifying Cognition*. Oxford, U.K.: Oxford Univ. Press, 2003.
[17] S. Haykin and J. M. Fuster, "On cognitive dynamic systems: Cognitive neuroscience and engineering learning from each other," *Proc. IEEE*, vol. 102, no. 4, pp. 608–628, Mar. 2014.
[18] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: Recent advances, new challenges, and future research directions," *Sensors*, vol. 19, no. 1, p. 126, Jan. 2019.
[19] Y. Wang, Z. Ye, P. Wan, and J. Zhao, "A survey of dynamic spectrum allocation based on reinforcement learning algorithms in cognitive radio networks," *Artif. Intell. Rev.*, vol. 51, no. 3, pp. 493–506, Mar. 2019.
[20] S. Z. Gurbuz, H. D. Griffiths, A. Charlish, M. Rangaswamy, M. S. Greco, and K. Bell, "An overview of cognitive radar: Past, present and future," *IEEE Aerosp. Electron. Syst. Mag.*, vol. 34, no. 12, pp. 6–18, Jun. 2019.
[21] A. A. Khan, M. H. Rehmani, and A. Rachedi, "Cognitive-radio-based Internet of Things: Applications, architectures, spectrum related functionalities, and future research directions," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 17–25, Jun. 2017.
[22] S. Haykin, "Cognitive dynamic systems," *Proc. IEEE*, vol. 94, no. 11, pp. 1910–1911, Oct. 2006.
[23] S. Haykin, "Cognitive dynamic systems: Radar, control, and radio [point of view]," *Proc. IEEE*, vol. 100, no. 7, pp. 2095–2103, Jul. 2012.
[24] S. Haykin, A. Amiri, and M. Fatemi, "Cognitive control in cognitive dynamic systems: A new way of thinking inspired by the brain," in *Proc. IEEE Symp. Adapt. Dyn. Program. Reinforcement Learn. (ADPRL)*, Orlando, FL, USA, Dec. 2014, pp. 1–7.
[25] M. Fatemi and S. Haykin, "Cognitive control: Theory and application," *IEEE Access*, vol. 2, pp. 698–710, 2014.
[26] J. Marinho and E. Monteiro, "Cognitive radio: Survey on communication protocols, spectrum decision issues, and future research directions," *Wireless Netw.*, vol. 18, no. 2, pp. 147–164, Feb. 2012.
[27] S. Grafling, P. Mahonen, and J. Riihijarvi, "Performance evaluation of IEEE 1609 WAVE and IEEE 802.11p for vehicular communications," in *Proc. 2nd Int. Conf. Ubiquitous Future Netw. (ICUFN)*, Jeju, South Korea, Jun. 2010, pp. 344–348.
[28] S. Mazahir, S. Ahmed, and M.-S. Alouini, "A survey on joint communication-radar systems," *Frontiers Commun. Netw.*, vol. 1, Feb. 2021, Art. no. 619483.
[29] J. Mitola and G. Q. Maguire, "Cognitive radio: Making software radios more personal," *IEEE Pers. Commun.*, vol. 6, no. 4, pp. 13–18, Apr. 1999.
[30] J. I. Mitola, "Cognitive radio: An integrated agent architecture for software defined radio," Ph.D. dissertation, Roy. Inst. Technol., Stockholm, Sweden, May 2000, Accessed: Jun. 13, 2020. [Online]. Available: https://elibrary.ru/item.asp?id=5242514
[31] B. Benmammar and A. Amraoui, "Cognitive radio," in *Radio Resource Allocation and Dynamic Spectrum Access*. Hoboken, NJ, USA: Wiley, 2013, pp. 23–38.
[32] *Spectrum Policy Task Force*, document 02-135, Federal Communications Commission, Washington, DC, USA, Nov. 2002.
[33] S. Haykin, "Fundamental issues in cognitive radio," in *Cognitive Wireless Communication Networks*. Boston, MA, USA: Springer, 2007.
[34] J. M. Peha and S. Panichpapiboon, "Real-time secondary markets for spectrum," *Telecommun. Policy*, vol. 28, nos. 7–8, pp. 603–618, Aug. 2004.
[35] S. Atapattu, C. Tellambura, and H. Jiang, "Energy detection based cooperative spectrum sensing in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 4, pp. 1232–1241, Apr. 2011.
[36] S. Kim, J. Lee, H. Wang, and D. Hong, "Sensing performance of energy detector with correlated multiple antennas," *IEEE Signal Process. Lett.*, vol. 16, no. 8, pp. 671–674, Aug. 2009.
[37] J. Ma, G. Y. Li, and B. H. Juang, "Signal processing in cognitive radio," *Proc. IEEE*, vol. 97, no. 5, pp. 805–823, May 2009.
[38] K. B. Letaief and W. Zhang, "Cooperative communications for cognitive radio networks," *Proc. IEEE*, vol. 97, no. 5, pp. 878–893, May 2009.
[39] A. Sahai, N. Hoven, and R. Tandra, "Some fundamental limits on cognitive radio," in *Proc. 42nd Allerton Conf. Commun., Control Comput.*, Monticello, IL, USA, Oct. 2004, pp. 1–11.
[40] S. Shankar N., C. Cordeiro, and K. Challapali, "Spectrum agile radios: Utilization and sensing architectures," in *Proc. 1st IEEE Int. Symp. New Frontiers Dyn. Spectr. Access Netw.,. DySPAN.*, Baltimore, MD, USA, Nov. 2005, pp. 160–169.
[41] W. A. Gardner, "Exploitation of spectral redundancy in cyclostationary signals," *IEEE Signal Process. Mag.*, vol. 8, no. 2, pp. 14–36, Apr. 1991.
[42] W. A. Gardner and C. M. Spooner, "Signal interception: Performance advantages of cyclic-feature detectors," *IEEE Trans. Commun.*, vol. 40, no. 1, pp. 149–159, Jan. 1992.
[43] H. Reyes, S. Subramaniam, N. Kaabouch, and W. C. Hu, "A spectrum sensing technique based on autocorrelation and Euclidean distance and its comparison with energy detection for cognitive radio networks," *Comput. Electr. Eng.*, vol. 52, pp. 319–327, May 2016.
[44] S. Haykin, D. J. Thomson, and J. H. Reed, "Spectrum sensing for cognitive radio," *Proc. IEEE*, vol. 97, no. 5, pp. 849–877, May 2009.
[45] K. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine learning techniques for cooperative spectrum sensing in cognitive radio networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 11, pp. 2209–2221, Nov. 2013.
[46] W. Lee, M. Kim, and D. Cho, "Deep cooperative sensing: Cooperative spectrum sensing based on convolutional neural networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 3, pp. 3005–3009, Mar. 2019.
[47] C. Liu, J. Wang, X. Liu, and Y.-C. Liang, "Deep CM-CNN for spectrum sensing in cognitive radio," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 10, pp. 2306–2321, Oct. 2019.
[48] M. Morelli and U. Mengali, "A comparison of pilot-aided channel estimation methods for OFDM systems," *IEEE Trans. Signal Process.*, vol. 49, no. 12, pp. 3065–3073, Dec. 2001.
[49] A. Petropulu, R. Zhang, and R. Lin, "Blind OFDM channel estimation through simple linear precoding," *IEEE Trans. Wireless Commun.*, vol. 3, no. 2, pp. 647–655, Mar. 2004.
[50] T. Peken, G. Vanhoy, and T. Bose, "Blind channel estimation for massive MIMO," *Analog Integr. Circuits Signal Process.*, vol. 91, no. 2, pp. 257–266, 2017.

[51] I. Rashad, I. Budiarjo, and H. Nikookar, “Efficient pilot pattern for OFDM-based cognitive radio channel estimation—Part 1,” in *Proc. 14th IEEE Symp. Commun. Veh. Technol. Benelux*, Delft, The Netherlands, Nov. 2007, pp. 1–5.
[52] R. Datta, N. Michailow, S. Krone, M. Lentmaier, and G. Fettweis, “Generalized frequency division multiplexing in cognitive radio,” in *Proc. 20th Eur. Signal Process. Conf.*, Bucharest, Romania, Aug. 2012, pp. 2679–2683.
[53] R. Datta, N. Michailow, M. Lentmaier, and G. Fettweis, “GFDM interference cancellation for flexible cognitive radio PHY design,” in *Proc. IEEE Veh. Technol. Conf. (VTC Fall)*, Quebec City, QC, Canada, Sep. 2012, pp. 1–5.
[54] H. Ye, G. Y. Li, and B.-H. Juang, “Power of deep learning for channel estimation and signal detection in OFDM systems,” *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.
[55] M. Soltani, V. Pourahmadi, A. Mirzaei, and H. Sheikhzadeh, “Deep learning-based channel estimation,” *IEEE Commun. Lett.*, vol. 23, no. 4, pp. 652–655, Apr. 2019.
[56] C. Luo, J. Ji, Q. Wang, X. Chen, and P. Li, “Channel state information prediction for 5G wireless communications: A deep learning approach,” *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 227–236, Jan. 2020.
[57] I. F. Akyildiz, W. Y. Lee, and K. R. Chowdhury, “CRAHNs: Cognitive radio ad hoc networks,” *Ad Hoc Netw.*, vol. 7, pp. 810–836, Jul. 2009.
[58] P. Setoodeh and S. Haykin, “Robust transmit power control for cognitive radio,” *Proc. IEEE*, vol. 97, no. 5, pp. 915–939, May 2009.
[59] A. Ahmad, S. Ahmad, M. H. Rehmani, and N. Ul Hassan, “A survey on radio resource allocation in cognitive radio sensor networks,” *IEEE Commun. Surveys Tuts.*, vol. 17, no. 2, pp. 888–917, 2nd Quart., 2015.
[60] E. Ahmed, A. Gani, S. Abolfazli, L. J. Yao, and S. U. Khan, “Channel assignment algorithms in cognitive radio networks: Taxonomy, open issues, and challenges,” *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 795–823, 1st Quart., 2016.
[61] Y. Xu, X. Zhao, and Y.-C. Liang, “Robust power control and beamforming in cognitive radio networks: A survey,” *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 1834–1857, 4th Quart., 2015.
[62] X. Li, J. Fang, W. Cheng, H. Duan, Z. Chen, and H. Li, “Intelligent power control for spectrum sharing in cognitive radios: A deep reinforcement learning approach,” *IEEE Access*, vol. 6, pp. 25463–25473, 2018.
[63] S. Haykin, “Cognition is the key to the next generation of radar systems,” in *Proc. IEEE 13th Digit. Signal Process. Workshop 5th IEEE Signal Process. Educ. Workshop*, Marco Island, FL, USA, Jan. 2009, pp. 463–467.
[64] G. Schuller and C. F. Moss, “Vocal control and acoustically guided behavior in bats,” in *Echolocation Bats Dolphins*. Chicago, IL, USA: Univ. Chicago Press, 2004, pp. 3–16.
[65] C. Chiu, W. Xian, and C. F. Moss, “Adaptive echolocation behavior in bats for the analysis of auditory scenes,” *J. Exp. Biol.*, vol. 212, no. 9, pp. 1392–1404, May 2009.
[66] M. R. Bell, “Information theory and radar waveform design,” *IEEE Trans. Inf. Theory*, vol. 39, no. 5, pp. 1578–1597, Sep. 1993.
[67] Y. Yang and R. S. Blum, “MIMO radar waveform design based on mutual information and minimum mean-square error estimation,” *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 1, pp. 330–343, Jan. 2007.
[68] S. Haykin, Y. Xue, and T. N. Davidson, “Optimal waveform design for cognitive radar,” in *Proc. 42nd Asilomar Conf. Signals, Syst. Comput.*, Pacific Grove, CA, USA, Oct. 2008, pp. 3–7.
[69] T. N. Davidson, “Efficient design of waveforms for robust pulse amplitude modulation,” *IEEE Trans. Signal Process.*, vol. 49, no. 12, pp. 3098–3111, Dec. 2001.
[70] H. He, P. Stoica, and J. Li, “Waveform design with stopband and correlation constraints for cognitive radar,” in *Proc. 2nd Int. Workshop Cognit. Inf. Process.*, Elba, Italy, Jun. 2010, pp. 344–349.
[71] J. Song, P. Babu, and D. P. Palomar, “Optimization methods for designing sequences with low autocorrelation sidelobes,” *IEEE Trans. Signal Process.*, vol. 63, no. 15, pp. 3998–4009, Aug. 2015.
[72] Y. Nijsure, Y. Chen, S. Boussakta, C. Yuen, Y. H. Chew, and Z. Ding, “Novel system architecture and waveform design for cognitive radar radio networks,” *IEEE Trans. Veh. Technol.*, vol. 61, no. 8, pp. 3630–3642, Oct. 2012.
[73] D. Garmatyuk, J. Schuerger, Y. T. Morton, K. Binns, M. Durbin, and J. Kimani, “Feasibility study of a multi-carrier dual-use imaging radar and communication system,” in *Proc. Eur. Radar Conf.*, Munich, Germany, Oct. 2007, pp. 1473–1476.
[74] S. Haykin, A. Zia, I. Arasaratnam, and Y. Xue, “Cognitive tracking radar,” in *Proc. IEEE Radar Conf.*, Arlington, VA, USA, 2010, pp. 1467–1470.
[75] S. Haykin, A. Zia, Y. Xue, and I. Arasaratnam, “Control theoretic approach to tracking radar: First step towards cognition,” *Digit. Signal Process.*, vol. 21, no. 5, pp. 576–585, Sep. 2011.
[76] I. Arasaratnam and S. Haykin, “Cubature Kalman filters,” *IEEE Trans. Autom. Control*, vol. 54, no. 6, pp. 1254–1269, May 2009.
[77] S. Haykin, Y. Xue, and P. Setoodeh, “Cognitive radar: Step toward bridging the gap between neuroscience and engineering,” *Proc. IEEE*, vol. 100, no. 11, pp. 3102–3130, Nov. 2012.
[78] K. L. Bell, C. J. Baker, G. E. Smith, J. T. Johnson, and M. Rangaswamy, “Cognitive radar framework for target detection and tracking,” *IEEE J. Sel. Top. Signal Process.*, vol. 9, no. 8, pp. 1427–1439, Dec. 2015.
[79] R. Gui, W.-Q. Wang, Y. Pan, and J. Xu, “Cognitive target tracking via angle-range-Doppler estimation with transmit subaperturing FDA radar,” *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 76–89, Feb. 2018.
[80] G. E. Smith et al., “Experiments with cognitive radar,” *IEEE Aerosp. Electron. Syst. Mag.*, vol. 31, no. 12, pp. 34–46, Dec. 2016.
[81] P. Chavali and A. Nehorai, “Scheduling and power allocation in a cognitive radar network for multiple-Target tracking,” *IEEE Trans. Signal Process.*, vol. 60, no. 2, pp. 715–729, Dec. 2011.
[82] P. Chen and L. Wu, “Waveform design for multiple extended targets in temporally correlated cognitive radar system,” *IET Radar, Sonar Navigat.*, vol. 10, no. 2, pp. 398–410, 2016.
[83] P. Chen, C. Qi, L. Wu, and X. Wang, “Estimation of extended targets based on compressed sensing in cognitive radar system,” *IEEE Trans. Veh. Technol*, vol. 66, no. 2, pp. 941–951, Feb. 2017.
[84] M. Elad, “Optimized projections for compressed sensing,” *IEEE Trans. Signal Process.*, vol. 55, no. 12, pp. 5695–5702, Dec. 2007.
[85] J. A. Tropp, “Greed is good: Algorithmic results for sparse approximation,” *IEEE Trans. Inf. Theory*, vol. 50, no. 10, pp. 2231–2242, Oct. 2004.
[86] L. Wang, W. Zhu, Y. Zhang, Q. Liao, and J. Tang, “Multi-target detection and adaptive waveform design for cognitive MIMO radar,” *IEEE Sensors J.*, vol. 18, no. 24, pp. 9962–9970, Dec. 2018.
[87] J. Li and P. Stoica, “MIMO radar with colocated antennas,” *IEEE Signal Process. Mag.*, vol. 24, no. 5, pp. 106–114, Sep. 2007.
[88] A. M. Haimovich, R. S. Blum, and L. J. Cimini, “MIMO radar with widely separated antennas,” *IEEE Signal Process. Mag.*, vol. 25, no. 1, pp. 116–129, Jan. 2008.
[89] N. A. Goodman, P. R. Venkata, and M. A. Neifeld, “Adaptive waveform design and sequential hypothesis testing for target recognition with active sensors,” *IEEE J. Sel. Topics Signal Process.*, vol. 1, no. 1, pp. 105–113, Jun. 2007.
[90] Z.-Q. Luo, W.-K. Ma, A. M.-C. So, Y. Ye, and S. Zhang, “Semidefinite relaxation of quadratic optimization problems,” *IEEE Signal Process. Mag.*, vol. 27, no. 3, pp. 20–34, May 2010.
[91] P. Chavali and A. Nehorai, “Cognitive radar for target tracking in multipath scenarios,” in *Proc. Int. Waveform Diversity Design Conf.*, Niagara Falls, ON, USA, Aug. 2010, pp. 000110–000114.
[92] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,” *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Mar. 2002.
[93] K. Witrisal, E. Leitinger, P. Meissner, and D. Arnitz, “Cognitive radar for the localization of RFID transponders in dense multipath environments,” in *Proc. IEEE Radar Conf. (RadarCon13)*, Ottawa, ON, Canada, Apr. 2013, pp. 1–6.
[94] T. Strohmer, M. Emami, J. Hansen, G. Papanicolaou, and A. J. Paulraj, “Application of time-reversal with MMSE equalizer to UWB communications,” in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dallas, TX, USA, Dec. 2004, pp. 3123–3127.
[95] I. D. Landau, R. Lozano, M. M’Saad, and A. Karimi, *Adaptive Control: Algorithms, Analysis and Applications*, 2nd ed. New York, NY, USA: Springer-Verlag, 2011.
[96] K. J. Åström and B. Wittenmark, *Adaptive Control*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1995.
[97] P. M. Nørgård, O. Ravn, N. K. Poulsen, and L. K. Hansen, *Neural Networks for Modelling and Control of Dynamic Systems: A Practitioner’s Handbook*. New York, NY, USA: Springer-Verlag, 2000.
[98] G. V. Puskorius and L. A. Feldkamp, “Parameter-based Kalman filter training: Theory and implementation,” in *Kalman Filtering and Neural Networks*, S. Haykin, Ed. New York, NY, USA: Wiley, 2001, pp. 23–67.
[99] M. Buss, S. Hirche, and T. Samad, “Cognitive Control,” in *The Impact of Control Technology*. Piscataway, NJ, USA: IEEE Control Systems Society, 2011, pp. 167–173.
[100] W. Hilal, A. Giuliano, S. A. Gadsden, and J. Yawney, “A review of cognitive dynamic systems and its overarching functions,” in *Proc. IEEE Int. IoT, Electron. Mechatronics Conf. (IEMTRONICS)*, Toronto, ON, Canada, Jun. 2022, pp. 1–10.
[101] C. E. Shannon, “A mathematical theory of communication,” *Bell Syst. Tech. J.*, vol. 27, no. 3, pp. 379–423, Jun. 1948.
[102] Y. Niv, “Reinforcement learning in the brain,” *J. Math. Psychol.*, vol. 53, no. 3, pp. 139–154, 2009.
[103] P. Dayan and Y. Niv, “Reinforcement learning: The good, the bad and the ugly,” *Current Opinion Neurobiol.*, vol. 18, no. 2, pp. 185–196, 2008.
[104] D. J. Surmeier, J. Plotkin, and W. Shen, “Dopamine and synaptic plasticity in dorsal striatal circuits controlling action selection,” *Current Opinion Neurobiol.*, vol. 19, no. 6, pp. 621–628, Dec. 2009.
[105] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. Cambridge, MA, USA: MIT Press, 2018.
[106] R. M. Murray, K. J. Astrom, S. P. Boyd, R. W. Brockett, and G. Stein, “Future directions in control in an information-rich world,” *IEEE Control Syst.*, vol. 23, no. 2, pp. 20–33, Apr. 2003.
[107] H. Wang, F. R. Yu, L. Zhu, T. Tang, and B. Ning, “A cognitive control approach to communication-based train control systems,” *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1676–1689, Aug. 2015.
[108] L. Zhu, F. R. Yu, B. Ning, and T. Tang, “Cross-layer handoff design in MIMO-enabled WLANs for communication-based train control (CBTC) systems,” *IEEE J. Sel. Areas Commun.*, vol. 30, no. 4, pp. 719–728, May 2012.
[109] W. Sun, F. R. Yu, T. Tang, and S. You, “A cognitive control method for cost-efficient CBTC systems with smart grids,” *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 3, pp. 568–582, Mar. 2017.
[110] X. Wang, L. Liu, T. Tang, and W. Sun, “Enhancing communication-based train control systems through train-to-train communications,” *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1544–1561, Apr. 2019.
[111] L. Lei et al., “Stochastic delay analysis for train control services in next-generation high-speed railway communications system,” *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 48–64, Jan. 2016.

[112] M. L. Tuballa and M. L. Abundo, "A review of the development of smart grid technologies," *Renew. Sustain. Energy Rev.*, vol. 59, pp. 710–725, Jun. 2016.

[113] R. Deng, J. Chen, X. Cao, Y. Zhang, S. Maharjan, and S. Gjessing, "Sensing-performance tradeoff in cognitive radio enabled smart grid," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 302–310, Mar. 2013.

[114] X. Fang, Y. Han, J. Wang, and Q. Zhao, "A cognitive control approach for microgrid performance optimization in unstable wireless communication," *Neurocomputing*, vol. 355, pp. 168–182, Aug. 2019.

[115] M. I. Oozeer and S. Haykin, "Cognitive dynamic system for control and cyber-attack detection in smart grid," *IEEE Access*, vol. 7, pp. 78320–78335, 2019.

[116] M. I. Oozeer and S. Haykin, "Cognitive risk control for mitigating cyber-attack in smart grid," *IEEE Access*, vol. 7, pp. 125806–125826, 2019.

[117] R. Xu, R. Wang, Z. Guan, L. Wu, J. Wu, and X. Du, "Achieving efficient detection against false data injection attacks in smart grid," *IEEE Access*, vol. 5, pp. 13787–13798, 2017.

[118] A. Mazzù, P. Morerio, L. Marcenaro, and C. Regazzoni, "A cognitive control-inspired approach to object tracking," *IEEE Trans. Image Process.*, vol. 25, no. 6, pp. 2697–2711, Jun. 2016.

[119] Y. Li, S. Liang, B. Bai, and D. Feng, "Detecting and tracking dim small targets in infrared image sequences under complex backgrounds," *Multimedia Tools Appl.*, vol. 71, no. 3, pp. 1179–1199, 2014.

[120] A. Mazzù, S. Chiappino, L. Marcenaro, and C. S. Regazzoni, "A switching fusion filter for dim point target tracking in infra-red video sequences," in *Proc. 17th Int. Conf. Inf. Fusion*, Salamanca, Spain, 2014, pp. 1–6.

[121] Y. Boers and J. N. Driessen, "A track before detect approach for extended objects," in *Proc. 9th Int. Conf. Inf. Fusion*, Florence, Italy, Jul. 2006, pp. 1–7.

[122] D. Wang, H. Lu, and M.-H. Yang, "Robust visual tracking via least soft-threshold squares," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 26, no. 9, pp. 1709–1721, Sep. 2016.

[123] M. Fatemi, P. Setoodeh, and S. Haykin, "Observability of stochastic complex networks under the supervision of cognitive dynamic systems," *J. Complex Netw.*, vol. 5, no. 3, pp. 433–460, 2017.

[124] R. Poovendran et al., "Special issue on cyber-physical systems," *Proc. IEEE*, vol. 100, no. 1, pp. 6–12, Jan. 2012.

[125] M. Chen, M. Mozaffari, W. Saad, C. Yin, M. Debbah, and C. S. Hong, "Caching in the sky: Proactive deployment of cache-enabled unmanned aerial vehicles for optimized quality-of-experience," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 5, pp. 1046–1061, May 2017.

[126] B. Paden, M. Čáp, S. Z. Yong, D. Yershov, and E. Frazzoli, "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Trans. Intell. Veh.*, vol. 1, no. 1, pp. 33–55, Mar. 2016.

[127] S. Feng and S. Haykin, "Cognitive dynamic system for future RACE vehicles in smart cities: A risk control perspective," *IEEE Internet Things Mag.*, vol. 2, no. 1, pp. 14–20, Mar. 2019.

[128] S. Feng and S. Haykin, "Cognitive risk control for transmit-waveform selection in vehicular radar systems," *IEEE Trans. Veh. Technol.*, vol. 67, no. 10, pp. 9542–9556, Oct. 2018.

[129] S. Feng and S. Haykin, "Anti-jamming V2V communication in an integrated UAV-CAV network with hybrid attackers," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Shanghai, China, May 2019, pp. 1–6.

[130] S. Feng and S. Haykin, "Cognitive risk control for anti-jamming V2V communications in autonomous vehicle networks," *IEEE Trans. Veh. Technol.*, vol. 68, no. 10, pp. 9920–9934, Oct. 2019.

[131] S. Feng and S. Haykin, "V2V communication-assisted transmit-waveform selection for cognitive vehicular radars," in *Proc. IEEE Can. Conf. Electr. Comput. Eng. (CCECE)*, Edmonton, AB, Canada, May 2019, pp. 1–6.

[132] S. Feng and S. Haykin, "Coordinated cognitive risk control for bridging vehicular radar and communication systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 5, pp. 1–16, Dec. 2020.

[133] P. Auer, N. Cesa-Bianchi, and P. Fischer, "Finite-time analysis of the multiarmed bandit problem," *Mach. Learn.*, vol. 47, no. 2, pp. 235–256, 2002.

[134] J.-Y. Audibert, R. Munos, and C. Szepesvári, "Exploration–exploitation tradeoff using variance estimates in multi-armed bandits," *Theor. Comput. Sci.*, vol. 410, no. 19, pp. 1876–1902, Apr. 2009.

[135] A. Humayed, J. Lin, F. Li, and B. Luo, "Cyber-physical systems security—A survey," *IEEE Internet Things J.*, vol. 4, no. 6, pp. 1802–1831, May 2017.

[136] X. H. Yu and Y. S. Xue, "Smart grids: A cyber-physical systems perspective," *Proc. IEEE*, vol. 104, no. 5, pp. 1058–1070, May 2016.

[137] G. Liang, S. R. Weller, J. Zhao, F. Luo, and Z. Y. Dong, "The 2015 Ukraine blackout: Implications for false data injection attacks," *IEEE Trans. Power Syst.*, vol. 32, no. 4, pp. 3317–3318, Jul. 2017.

[138] Y. Liu, P. Ning, and M. K. Reiter, "False data injection attacks against state estimation in electric power grids," *ACM Trans. Inf. Syst. Secur.*, vol. 14, no. 13, pp. 1–33, May 2011.

[139] J. Hao, R. J. Piechocki, D. Kaleshi, W. H. Chin, and Z. Fan, "Sparse malicious false data injection attacks and defense mechanisms in smart grids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 5, pp. 1–12, Oct. 2015.

[140] S. Cui, Z. Han, S. Kar, T. T. Kim, H. Poor, and A. Tajer, "Coordinated data-injection attack and detection in the smart grid: A detailed look at enriching detection solutions," *IEEE Signal Process. Mag.*, vol. 29, no. 5, pp. 106–115, Sep. 2012.

[141] P. Rawat, K. D. Singh, and J. M. Bonnin, "Cognitive radio for M2M and Internet of Things: A survey," *Comput. Commun.*, vol. 94, pp. 1–29, Nov. 2016.

[142] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347–2376, 4th Quart., 2015.

[143] C. Perera, C. H. Liu, S. Jayawardena, and M. Chen, "A survey on Internet of Things from industrial market perspective," *IEEE Access*, vol. 2, pp. 1660–1679, 2014.

[144] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of Things for smart cities," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 22–32, Feb. 2014.

[145] A. Giuliano et al., "Efficient utilization of big data using distributed storage, parallel processing, and blockchain technology," in *Proc. SPIE*, 2022, pp. 22–33.

[146] A. Giuliano, W. Hilal, N. Alsadi, S. A. Gadsden, and J. Yawney, "A review of cognitive dynamic systems and cognitive IoT," in *Proc. IEEE Int. IoT, Electron. Mechatronics Conf. (IEMTRONICS)*, Toronto, ON, Jun. 2022.

[147] D. Guinard, V. Trifa, S. Karnouskos, P. Spiess, and D. Savio, "Interacting with the SOA-based Internet of Things: Discovery, query, selection, and on-demand provisioning of web services," *IEEE Trans. Services Comput.*, vol. 3, no. 3, pp. 223–235, Jul./Sep. 2010.

[148] A. Zaslavsky, C. Perera, and D. Georgakopoulos, "Sensing as a service and big data," in *Proc. Int. Conf. Adv. Cloud Comput.*, Bangalore, India, 2013, pp. 1–8.

[149] S. Feng, P. Setoodeh, and S. Haykin, "Smart home: Cognitive interactive people-centric Internet of Things," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 34–39, Feb. 2017.

[150] R. Perez-Torres, C. Torres-Huitzil, and H. Galeana-Zapien, "An on-device cognitive dynamic systems inspired sensing framework for the IoT," *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 154–161, Sep. 2018.

[151] X. Sun and N. Ansari, "EdgeIoT: Mobile edge computing for the Internet of Things," *IEEE Commun. Mag.*, vol. 54, no. 12, pp. 22–29, Dec. 2016.

[152] R. Pérez-Torres, C. Torres-Huitzil, and H. Galeana-Zapién, "A cognitive-inspired event-based control for power-aware human mobility analysis in IoT devices," *Sensors*, vol. 19, no. 4, p. 832, Feb. 2019.

[153] M. Bkassiny, Y. Li, and S. K. Jayaweera, "A survey on machine-learning techniques in cognitive radios," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1136–1159, 3rd Quart., 2012.

[154] S. A. Gadsden and M. Al-Shabi, "The sliding innovation filter," *IEEE Access*, vol. 8, pp. 96129–96138, 2020.

[155] O. Surucu et al., "PROGNOS: An automatic remaining useful life (RUL) prediction model for military systems using machine learning," in *Proc. SPIE*, Jun. 2022, pp. 233–245.

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