A Review of Reinforcement Learning Approach for cognition on pooled-spectrum used by re-configurable systems

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ABSTRACT

Leveraging high-quality demands of cognitive communication on auto-negotiation places much demand on efficient machine learning technique. Cognitive agents change transmission/reception parameters to communicate efficiently during cognition. Reconfigurable Communication system (RCS) are capable of implementing experience replays to achieve high-quality network demand whenever agents perceive network conditions. Engaging peering technique to offer dynamism in frequency selection, spectrum negotiation, adaptations for engaging planning, decision and actions, reconfiguration is achieved via cognition. co-operative communication in RCS places much demand on accurate spectrum-sensing. With single agent, passive algorithms are implemented sharing sensed-information, but learning becomes pivotal process while achieving end-to-end goal over shared-spectrum. For this reason, reinforced learning is demanded in cognitive systems for learning environmental parameters to objectively meet application requirements of dynamic spectrum access (DSA). To this purpose, Markov model is presented using investigative analysis of sequential processes to demonstrate reinforced decisions required during cognition. For optimal performance and desired returns over pooled spectrum, Markov processes enable multiple agents participation to offer cumulative rewards of faster/active decisions rather than passively implemented decision with single agent. Reinforced learning (RL) over shared-spectrum facilitates continuous learning via experience replays. Better reward, achievable with multiple agents also guarantee profitable information-sharing in pooled-spectrum. Also, co-operatively communicating hosts enable active decisions to enhance network-wide performance. Therefore, RL offer continuous learning beneficial to reconfigured systems. In addition, facilitated thorough experience replays, evidently implemented for active learning and suitable decisions, RL is preferred deep learning technique guaranteed with machine learning efficiency needed for cognition performances in RCS.

CCS Concepts

Artificial Intelligence---Data management procedures;300, machine learning---reinforcement techniques;500, graph-based methodology---markov process;500, cognitive computing modeling; 300, radio spectrum resources;100 and **shared-spectrum techniques;100.**

Keywords

Cognition, markov process; machine learning; reinforcement learning; reward.

1. INTRODUCTION

Re-configurable Communication System (RCS) is an intelligent model characterized with cognition and reconfiguration computational processes. Cognition techniques and DSA computations embeds observation, orientation and machine learning (ML). In cognitive radio networks, cognitive process is importantly applied to enable reconfiguration and DSA implementations. Cognitive cycle implements spectrum sensing, spectrum sharing, spectrum mobility and spectrum handover described in [1] and reviewed in [2]. Cognitive Radio Technology (CRT) is guided by Wireless Regional Area Network (WRAN) IEEE 802.22 standard, described as emerging technology in [3] and based on Software Defined Radio (SDR) technology. Also specified by Institute of Electrical Electronics Engineers, CRT enabled interoperability with lower standards and CR feature DSA to increase spectrum-resource utilization by wireless systems [4].

Cognitive networking (CN) wireless communication paradigm enable spectrum-sharing, whereby cognitive agents change transmission/reception parameters to efficiently communicate while avoiding interference with licensed users [5]. CR architecture, intelligently co-ordinates radio resources on one hand while implementing ML techniques on the other hand to deliver services as described in [6]. Shared-spectrum and associated DSA techniques enable co-existence of both licensed and unlicensed hosts in CRT. Through learning and reasoning techniques of machine learning, unlicensed hosts strategize and temporarily occupy unused licensed-spectrum majorly, to alleviate spectrum scarcity illusion highlighted in [7].

Infrastructural wireless model provided environments for several ML techniques to be applied on CR spectrum for addressing network management issues, including spectrum sensing, spectrum selection, adaptive routing and spectrum-mobility [8]. RCS model generally provides dynamic network shaping using core idea of SDR's remotely controlled hardware described in [9] to offer opportunistic communication over white spaces.

Discussed in [10], design specifications for RCS model provides ubiquitous, interactive and collaborative sensing, which enabled CR hosts engage *peering* technique to potentially commission each host agent to scale over sub-carriers, which are activated for opportunistic and multiple access and communication efficiency in mobility.

Typically, spectrum optimization in CRN is evaluated using cross-layer (CL) techniques and implementation of cognitive medium access control (cogMAC) functions described in [11] to enable collaborating *peers* enhance spectrum resource utilization. Also, CRT and associated DSA continuously deliver reliable and qualitative service through envisioned ML techniques, symbolically offer higher data rates in RCS framework [12]. Therefore, RCS model is basically Cognitive Radio System (CRS), equipped with ML computations and standardized by IEEE802.22WG [3]. For guaranteed and best-effort Quality of Service (QoS) requirements, CR-CL design specifications reported in [11] provided ubiquitous access, scaling and improved performances in wireless communication.

Reinforcement Learning (RL), an online machine learning paradigm is considered the most suitable for agents to discover optimal sequence of actions required for performing required tasks while agents interact with its environment [13]. An exhaustive review on RL application in CR literature was surveyed and presented in [14] as application-driven and learning methodology-driven taxonomies to analyze impact of RL techniques in CR networking. Leveraging the high-quality demands of wireless communication on auto-negotiation places much demand on efficient learning techniques. This is characterized in experience-based RL techniques, which is implemented to scale network performance.

2. RE-CONFIGURABLE SYSTEM FRAMEWORK

Reconfigurable communication system as intelligent framework, consists of cognitive hosts agents, defined for discrete-time stochastic process modeled-mobility over a random waypoint $P_i(x)$selection where $x = 1, \dots, t$, is characterized with CRT technology and DSA techniques. The framework provision for reliable, qualitative and continuous service whereby dynamic model is created by movements to initiate self-organization through observation/orientation while learning is facilitated for activation and decision for reconfiguration [15].

RCS framework model of cognitive agents (CA), is equipped for reconfiguration based on facilitated cognition as shown in Figure 2. Host agents, distinguished as licensed or unlicensed in [15], is enabled to transmit or receive in wide area simulation (1cm approximated as 100kilometres on plane surface). Characteristic performance of the model was discussed in [16] while proposed protocol for implementing spectrum-handover was evaluated in [17]. RCS agents are cognitively-equipped hosts, modelled with mobility in [15] and enabled to periodically scan allocated channels of frequency-spectrum to communicate while licensed hosts (LH) is idle. Unlicensed Host (UH) finds another white-space to operate upon request of spectrum by LH.

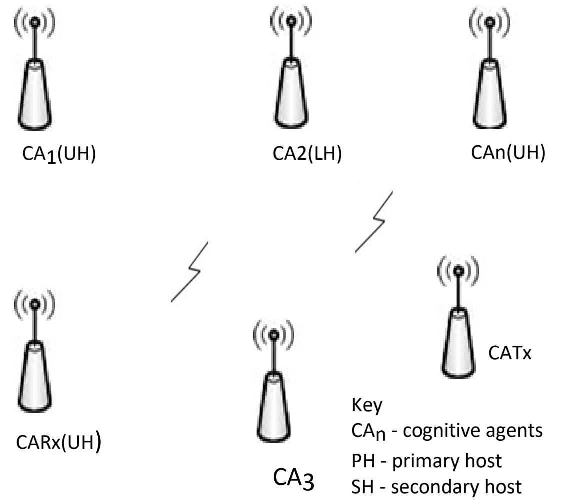

Figure 1. Conceptual RCS

Through cognition process, UH are made to transmit or receive over licensed channel for reasonable amount of time without interference with LU, but implements spectrum-mobility to transfer communication to a white space, and in agreement with given specifications in [11] requires host agents first resolving layer-2 (cogMAC) configuration problem before establishing network-wide communication.

2.1 Cognition Processes and Actions

Cognition is initiated via spectrum sensing and observation processes. Cognitive cycle enable hosts step through various stages to observe, orient, plan, learn and decide for actions. Orientation with the environment initiates spectrum-sensing and observations shown in Figure 2. RCS model architecture for continuous activities within cognition cycle before reconfiguration is initiated as illustratively discussed in [15]. Action distribution over each defined states of sensing, sharing, mobility and handover) was modelled by Distribution Coordination Function (DCF).

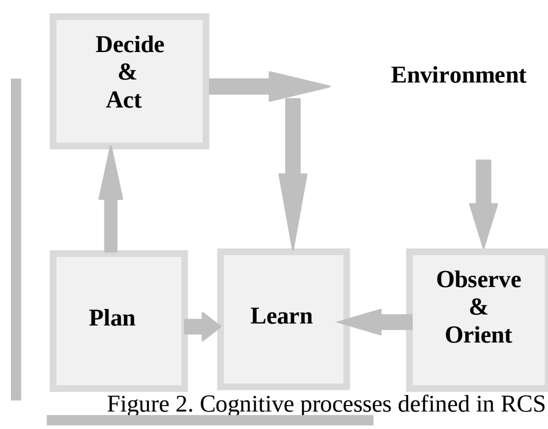

Figure 2. Cognitive processes defined in RCS

For effective CL functionality, reconfiguration is facilitated by adaptation of cognitive agents to parameters observed in the environment. Through deep learning methodology, RL is facilitated to enable host agents generate experiences, on stepping through the cognition stages illustrated in Figure 2.

2.2 **Shared-Spectrum by RCS agents in stochastic environment**

Stochastic process is defined for RCS as randomly controlled phenomenon by probability law, where unlicensed agents are enabled to utilize unused licensed channel to maximize communication throughput without causing perceptible drop in QoS to channel owners. Required agility for abstracting control from forwarding network data is associated with cognitive processes. Embedded cognitive processes cycles until agents decisively change states based on action outputs. To this end, Neighbour Discovery Algorithm was formulated for RCS in [18] and proofs to evaluate connected graph properties to abstract RCS capabilities was presented in [19].

Peering agents implement collaboration in spectrum-sensing based on Latin square to enable cognitive process associate spread-signal technique over large number of distributed subcarriers [15]. Centralized cognitive architecture presented in [15] established defined orthogonality principle evaluated in [16] for both licensed and unlicensed agents. Two signal functions x_q and x_k respectively defined for licensed and unlicensed hosts over interval $[a, b]$ is expressed in (1).

$$\langle x_q \cdot x_k \rangle = \int_a^{\mathrm{bU}} x_q(t) \cdot x_k(t) \mathrm{dt} = \{1, k = q| \quad (1)$$

Their combination is zero except for $x_q(t) = x_k(t)$. This property enable coexistence of LH and UH transmitting on same spectrum band with the following proofs:

2.2.1 *Proof: Universality of channel availability*

Let each host be assigned a unique identifier $[1 \ldots N]$, where *N* is the upper bound of hosts in the RCS, and $A_U = \{c_1, c_2, \ldots, c_M\}$represents the universal set of available channels, potentially accessible by all hosts.

All hosts are aware of N, M andA_U and each host i if equipped with *r* multiple-input-multiple-output (MIMO) transceivers, where $1 \leq r \leq min(M, N)$, is aware of channel availability setA_i, which is same for every node.

2.2.2 *Proof: Neighbour characteristics of host agents*

Hosts i and j are *neighbours* represented by undirected edge or pair of directed edges in graph. Transmission between hosts is achieved by single hops and $A_i \cap A_j \neq 0$ whenever i and j are within each other's radio access range but communication between non-neighbour hosts is achieved by *multi-hop* transmission.

2.3 Markov Chain Process and Properties

Markov chain as fundamental stochastic processes, satisfies the Markov property of predicting the past and future states independently of known present state. With known current state, additional information of past state(s) are not required to make predictions of future. Simplicity of Markov as *memoryless* process allows great reduction of parameters for cognition processes and also suggests its suitability in real-world processes. Since the chain symbolize sequence of random variables X_{n+1} enabled to be conditionally independent of $X_{0,,\ldots,}X_{n-1}$ given X_n, process output $Y_n$is independent of past states $X_{0,,\ldots,}X_{n-1}$provided state X_n is known. Also, a transition matrix $(T)$of transition probabilities, enables RCS dynamics with host state S_t to capture all relevant information concerning agents' behaviour from history.

Therefore, Markov Process for RCS model presented in Figure 3 is a tuple (S, P) where *S* is set of states (s) and *P* is property defining each state of sensing, sharing, mobility or handover.

S_t is Markov. To make (2) valid whenever S_t is current state and S_{t+1} the next state. S is finite set of **states** (*sensing, sharing, mobility, handover*) observed in RCS cognition processes.

$$P(S_{t+1} \vee S_t) = P(S_{t+1} \vee S_0) \quad (2)$$

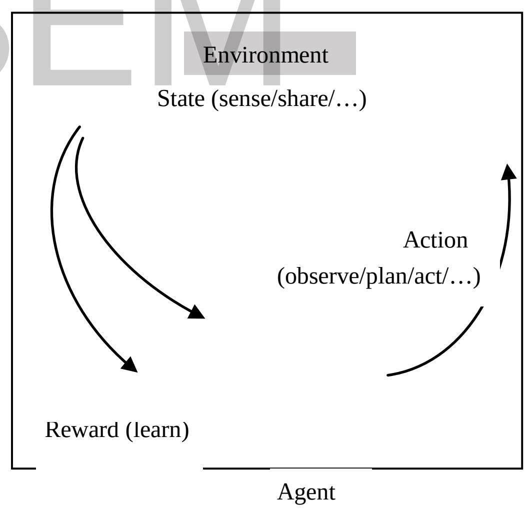

Figure 3. Markov Process States

Reward property of Markov process indicates continuous learning as host agents actively switch between states to take decisions appropriately among actions including observe, plan, act, orient or learn. *Return* is measurable on target network as cumulative reward and Markov Reward culminates to Markov Decision Process (MDP) whenever rewards are attached to transitions probabilities [20].

2.3.1 *Markov Reward Process (MRP)*

Markov Reward Process (MRP) is expressed in (3) as a tuple $(S, P, R, \curlyvee)$; where S is the finite set of **states** (*sensing, sharing, mobility, handover*); P is state transition probability matrix, $P_{sse'} = P[S_{t+1} = s' \vee S_t = s]$ for spectrum sensing;

R is the reward function, $R_s = E[R_{t+1} \vee S_t = s]$ and $\curlyvee$is a discount factor on reward, $\curlyvee \in [0,1]$
(3)

Extra quantity-reward, attached to every observation made on the environment during transition from states within cognitive process is MRP and a Markov chain with transition- valued actions. MRP is therefore, a Markov chain with decision, with values assigned to the transitions towards decisions - sense, orient, observe etc during cognitive processes. Observations are better estimates of transition probabilities in practice and stationarity property is implied in Markov chain where transition probability may not change over times [21].

2.3.2 *Markov Decision Process (MDP)*

Markov Decision Process is MRP with decision and *return*. To arrive at decisions, the transition matrix is conditioned with value function to obtain Reward **R** for taking decision Actions **A** and subsequent **return G_t**. G_t is the total discounted reward **R** from time-step **t** on state **s**. G_t is a long-term reward of host at state ***s*** when host agent no longer (passively) observe state transition but actively choose an action from set of actions **A**.

Therefore, MDP, expressed in (4) is a tuple $(S, A, P, R, \curlyvee)$;

where S is finite set of cognition states (sensing, sharing, mobility, handover); A finite set of cognitive **actions** (observe, orient, plan, decide, learn,…,act); and P the state transition probability matrix, given as $P^a{}_{sse'}$ $=$P$[S_{t+1} = s' \vee S_t = s, A = a]$ for cognitive spectrum-sensing state; R is the reward function, R_s^a $=$E$[R_{t+1} \vee S_t = s, A = a]$ and $\curlyvee$is a discount factor on reward, $\curlyvee \in [0,1]$ (4)

2.4 Optimized CogMAC for Perceptual Computing

In the decision problem of each communicating host agent, cognitive process is patterned by Markov chain to ensure each agent decides best action to actively participate and/or select based on current state and not on previous state(s). This is the basis for hosts interacting with the environment during spectrum-scanning and spectrum-sensing. These conditions are utilized in the exploration of experience replays until the experiences are exploited in goal-oriented reinforcement learning (RL). Each host agent is subjected to available operating parameters in the operating environment.

Operating parameters required and defined for cognition includes bandwidth (*B*), error-rate €, transmission power (ρ), centre frequency (*w*) and modulation index (*b*). Throughput (*Th*) evaluation by divide-and-conquer approach in multi-carrier transmission over *M* channels enable cognitive hosts engage in non-continuous orthogonal frequency division multiplexing, where each sub-carrier frequency has its own set of *x* and *y* variables as illustrated in (5) and (6).

Symbolically,

$$x = \{b, e, \rho, Th, B, l\} \tag{5}$$

and

$$x = \sum_{i=1}^{n} w_i \cdot f_{i(\acute{x})} \tag{6}$$

where the weights *w* and biases *f* are fine-tuned via backpropagation and training to give correct predictions as resultant outputs. In the event of wrong predictions, the system propagates to retrain and update weights and biases to reduce errors as discussed in [22] and [23].

With *N* cognitive host agents, each *n* has complete control over the external parameters *x* that are jointly sensed and pooled for sharing as discussed in [24]. Containing both license and unlicensed hosts, the pooled spectrum universally provide opportunistic access for all cognitive host agents to recognize what is going on within the environment. This forms the basis for perceptual computation model expressed in (7), assuming a constant value of specific centre frequency $(\omega$.

$$\acute{x}{=}j = 1, \ldots M\Big(n = 1, \ldots, N\big(\{b_{i,n}, e_{i,n}, p_{i,n}, Th_{i,n,} B_{i,n}, l_{i,n}, \omega_{i,n}\}\big)\Big) \tag{7}$$

3. MODELING MARKOV PROCESS FOR COGNITIVE STATES

Cognitive process events includes *spectrum sensing (sse)* and *spectrum sharing (ssh)* as distinct states, actively implemented by host agents in RCS. Markov process enable cycles switching between these states, according to some laws of dynamics to establish the Markov decision process. With repeated switching, system changes are observed as replays and experiences are generated from replays.

With the Markov property, generated experience enable future to be independent of past but only the present. A transition matrix (T)containing transition probabilities is defined for system dynamics with state S_t capturing all relevant information for target from history.

Therefore, Markov Process algorithm specified for RCS is given in (8) as a tuple (S, P) where *S = {sensing, sharing, mobility, handover}* states and *P* the transition probability for S_t provided

$$P(S_{t+1} \vee S_t) = P(S_{t+1} \vee S_0) \tag{8}$$

3.1 **State-space created with experience replay**

RCS agents interacts with each other to activate reconfiguration. Agents generate experience via these interactions and experiences grow in replays, managed as buffer. State-space property created the model expressed in (8) as a tuple (s, a, r, s') where *s* is the state for any action *a*, where *r* is the reward for next state *s'*.

The target network is, therefore, obtained from expected return of reinforced learning model in (9).

$$Q(s,a) = r + \curlyvee\, max_{a'}\, Q(s', a') \qquad (9)$$

3.2 **Quantitative analysis of MDP**

Based on the cognitive processes defined for RCS as presented in Figure 2, switching between states such as spectrum-sensing (*sse*) and spectrum-sharing (*ssh*) is modeled as transition probabilities, observed as episodes in practice. These transitions are quantitatively assumed to determine MRP using specified model presented in Figure 4. With transition probabilities as better estimates in quantitative analysis than observations, rewards applicable to each action within sensing state is quantified assuming the implied stationarity property of no change of decision in states over transition period.

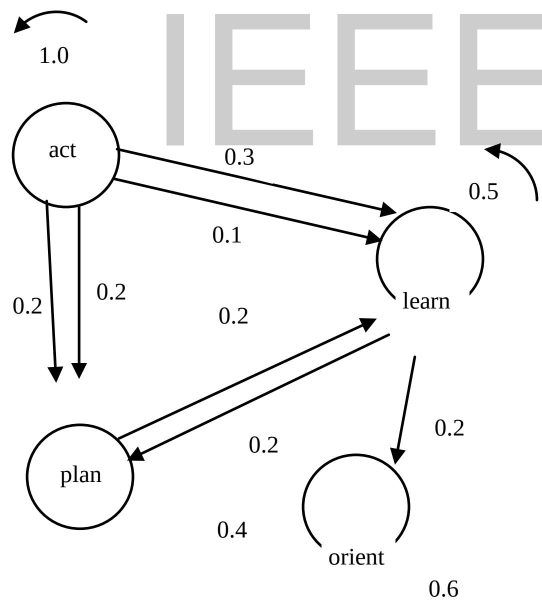

Figure 4. Sample episode of transitions

Attaching reward values to transition episodes illustrated in Figure 4, matrix *T* is obtained as shown in Table 1.

Table 1. Observed episodes of decisions in sensing state

	Orient	Plan	Learn	Act
Orient	0.6	0.4	0.0	0.0
Plan	0.0	0.1	0.7	0.2
Learn	0.0	0.2	0.5	0.3
Act	0.2	0.2	0.1	0.5

3.21 *Value function of sensing state*

Value function *V(s)* of MRP is expressed in (10) to capture expected return over the states where G_t is made to represent cumulative reward of collaboratively taken actions.

$$V(s) = \sum [G_t \vee S_{t=s}] \qquad (10)$$

Observed reward values given in Table 2 showed stationarity property of MRP, which also implied no reward since state transition reward are either positive or negative based on decisive actions taken in cycles.

Table 2. Transitions with reward

State transition	**reward**
orient => orient	1
orient => plan	1
plan => act	3
plan => learn	1
act => act	-1
act => learn	-3
act => plan	1
learn => learn	5
learn => act	2
learn => plan	1

Using expression (10), decision rewards based on all actions are quantified as follows:

$$V(act) = -3 * 0.5 + 2 * 0.3 + 1 * 0.2 = 0.7$$
$$V(orient) = 1 * 0.6 + 1 * 0.4 = 1.0$$

$$V(learn) = 5 * 0.5 + 2 * 0.1 + 1 * 0.2 = 2.9$$
$$V(plan) = 3 * 0.7 + 1 * 0.2 = 2.3$$

Value function of the state learn indicated highest reward of 2.9, which is an indication of reinforcement. Minimal reward of 0.7 is obtained in actions while 1.0 is expended on orientation.

Cumulative reward G_t,which is the **Return** on experience replays and actions is expressed as extra-quantity-reward given in (11):

$$G_t = 0.7 + 1.0 + 2.9 + 2.3 = 6.9 \qquad (11)$$

Total discount of sensing state is 6.9 where discount $\curlyvee = 0$, $\curlyvee \in [0,1]$ and V = 0 is the present value of future rewards.

4. RESULT AND DISCUSSIONS

MDP is quantitatively analyzed to illustrate universality of host agents over shared-spectrum. Replay is enhanced by collaboration and peering between host agents in RCS model. Interoperation within participating hosts defined by expression (1) included both licensed and unlicensed occupants benefiting from shared-spectrum.

The extra-quantity reward obtainable via RL is beneficial to RCS models as proved in (8) because cumulative reward will enable host agents observe state transitions passively but actively choose actions more profitably each time it senses the environment. Under this arrangement, greater return is achieved with collaborations and greater probability for target states is attributed to efficient **learning.**

Through RL, replay experiences generated offer better estimation of fine-tuned operating parameters required for backpropagation techniques of neural network model expressed in (5). Peering and collaboration of host agents make RCS jolt into actions over pooled and shared-spectrum to achieve greater rewards than single agent where spectrum parameters are inefficiently utilized when accessed by licensee owners as evaluated in (6).

5. CONCLUSION

Cognition is essential process while dynamic spectrum technology remains the underlying implementation in RCS. Potency of reinforcement learning (RL) as preferred deep learning method signifies greater learning reward as target networks attract more profits. Cognition is targeted for reconfiguration where active sequential decision is based on current state.

RL approach offer continuous learning beneficial to reconfigured systems. RL approach equip host agents to discover optimal sequence required to achieve greater performances while interacting continuously (repeatedly) using Markov Decision Process (MDP) principle. In addition, the experience replays, which is facilitated thorough RL approach evidently implement active learning and desirable decisions. RL is therefore preferred as deep learning technique to achieve guaranteed machine learning efficiency, which are for better performances for cognition in RCS.

cumulative reward of $G_t = 6.9$ Better utilization of resources are return**s** due to learning efficiency, with all actions of act + orient + plan + learn profitably implemented.

and for reconfiguration using CR-CL computational techniques specified in [26], all operating parameters evaluated in [25] remain valid

Guaranteed continuous learning and greater reward is beneficial to resource-sharing and increased system profitability, these findings therefore suggests RL as deep learning technique suitable for future generation RCS.

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