Reinforcement Learning in Fog-based Internet-of-Things: Applications and Research Issues

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Abstract—**Reinforcement learning (RL) is an unsupervised learning technique in which an agent learns optimal behaviour through interaction with the environment. Reinforcement learning algorithm has been widely used to significantly improve system performance within the IoT domain. In this paper, we present a comprehensive survey of trending issues within the IoT ecosystem that can be tackled using state-of-the-art RL techniques. Furthermore, we give an in-depth analysis into the application of these RL-based algorithms in the emerging fog-based IoT networks. Finally, we propose alternative research directions that may yield better outcomes.**

Index Terms—**Reinforcement learning (RL), Internet-of-Things (IoT), Fog-based IoT, Q-learning.**

I. Introduction

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OVER the years, there has been several applications of machine learning (ML) in IoTs and Cyber-physical systems (CPS). From nest learning thermostats that predicts the temperature in a room during a particular time of day to industrial robots that facilitate the automation process, machine learning algorithms and their applications are becoming more popular. Another interesting application is the Amazon personal assistant that has the capability of learning voice patterns, the Jaguar's Land Monitoring system, which depends on a complex software that allows the automobile to observe, predict, monitor and notify the car's passengers to assist the driver automatically delegate his tasks and minimize the burden of driving.

Optimization is a very old field with interesting algorithms that has been used to solve simple to complex problems in various areas. Many optimization algorithms use reinforcement learning (RL) techniques to optimize the behaviour of devices in the IoT ecosystem. For instance, in Intelligent Transport Systems (ITS), where cars act smartly, optimality in the interaction between cars and the environment is highly required. Several CPS applications like the Industrial Internet of Things (IIoT), smart grid, and ultimately smart cities, will allow intelligent machine-type interactions. These interactions may often will require robust algorithms that evolve and are adaptable, in order for the IoT devices to be able to achieve desired objectives given some set of operational parameters.

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With the inherent heterogeneity in the IoT ecosystem and devices operating in a highly dynamic environment, it becomes necessary to leverage robust and resource-fitting machine learning techniques that will match the resource-constrained nature and stochastic behaviour of the IoT network. Moreover, the magnanimity of the IoT has led to the emergence of the fog-based IoT architecture [1], which promises to run IoT-enabled applications for real-time control and analytics, with millisecond response time. The realization of an optimal real-time control and data analytics is subject to the ability for agents to make optimal decisions that will improve the overall performance in the network. As such, we aim to examine RL techniques as used in previous research to help us understand the intrinsic benefits to the future IoT networks.

The contribution of our work is three-fold, which are listed as follows.

1) We review of some RL algorithms, and highlight key aspects that will drive future fog-based IoT networks.
2) We also perform simulations on some techniques considering some IoT scenarios. We also present detailed RL applications and use cases within the CPS (Intelligent transportation systems, smart grid, smart homes, smart health-care, and smart environment) to demonstrate how different techniques presented in the paper fuse to provide desirable objectives.
3) We also present a variety of open research challenges and suggest possible future trends for building intelligence in IoT, with regard to the latest development in the field.

The remainder of this work is organized as follows. In Section

II. Reinforcement Learning in IoT

Reinforcement Learning (RL) is learning that involves mapping situations to actions with an objective of maximizing a numerical reward. Actions are made by an agent, which have the ability to sense the state of the dynamic environment and consequently take actions that influence its environment. RL facilitates sequential decision making under uncertainty, thereby making it a useful tool in prediction of non-linear phenomenon [7]. Several work have been published in the area of RL in IoT and CPS, however, there has not been any detailed review that covers their applicability in IoT and the underlying research issues in this field.

A. Basic Overview

1) Q-Learning: Q-learning is also known as an off-policy temporal difference (TD) learning algorithm, which allows the agent to learn about an optimal policy using an exploratory policy [8], [9], [10]. The Q-learning algorithm can be simply defined by

$$\begin{aligned} Q_{t+1}(s_t, a_t) &:= Q_t(s_t, a_t) \\ &+ \alpha\Big[r_{t+1} + \gamma \max_a Q_t(s_{t+1}, a) - Q_t(s_t, a_t)\Big]. \end{aligned} \tag{1}$$

2) W-Learning: Unlike Q-learning which is a single-agent, single-policy learning technique, W-learning is a multi-agent, multi-policy learning technique that has been used on non-cooperating agents [14]. The W-learning algorithm is given by

$$\begin{aligned} W_i(s) &:= (1-\alpha)W_i(s) \\ &+ \alpha\Big[Q_i(s, a_i) - (r_i + \gamma \max_a Q(s', a_i'))\Big]. \end{aligned} \tag{2}$$

3) SARSA: State-action-reward-state-action (SARSA) is an On-policy TD learning algorithm, which the agent learns an action-value function instead of a state-value function. SARSA always converges to an optimal policy so long as all state-action pairs are visited an infinite number of times.

$$\begin{aligned} Q_{t+1}(s_t, a_t) &:= Q_t(s_t, a_t) \\ &+ \alpha\Big[r_{t+1} + \gamma Q_t(s_{t+1}, a_{t+1}) - Q_t(s_t, a_t)\Big]. \end{aligned} \tag{3}$$

B. Related Research in IoT

Over the years, many perceived problems within the IoT domain have began to receive research attention, some of which are categorized as follows.

1) *Energy allocation and utilization within the network*: IoT devices deplete energy in several ways, such as when transmitting and receiving data, listening to the medium, performing computation or even changing position. There exist several research that have used RL and its variants to optimize energy usage in different domains, some of which could be modified to suit the resource-limitation in the typical IoT domain. Zhong *et al.* in [2] designed sensor energy utilization and power allocation in IoT sensors to maximize the total data throughput of the system. They proposed a low-complexity algorithm to optimally solve the two formulated sub-problems. The energy utilization sub-problem was formulated as a MDP, while the power allocation sub-problem was approached using discrete optimization. The proposed algorithm performed better than some simple heuristics when simulated. However, the work considered a scenario where the channel state is perfectly known.

   A Markov-based analytical model was integrated with a RL process in Conti *et al.* [22] to optimize the server activation policy, where optimal control of an energy storage system in a green fog-computing node is needed to improve the system performance, hereby allowing the system to bear high job arrivals even at low-power generation periods. The fog-computing nodes used in this work are not typical of those used in a typical fog-based IoT environment. A Q-learning-based adaptive power management was proposed by Debizet *et al.* in [28] to optimize the power consumed during the suspend state of an Internet-of-Things (loT) System-on-Chip (SoC) with eight embedded power states. The algorithm out-performed some expert-based solution for most suspend sequences under 12000 cycles, however, with an additional power cost. Just like the traditional IoT architecture, the fog-based IoT networks are often power-constrained and as such, require low complexity learning algorithms to optimize the energy utilization.
2) *Latency Minimization*: Mission-critical and delay-sensitive IoT application can effectively leverage the intelligence of some RL techniques. An RL approach that made use of evolution strategies for real-time task assignment among fog servers was introduced by Mai *et al.* in [23] to minimize the total computation latency during a long-term period. The paper claimed that the proposed model is scalable when the number of IoT devices increases, however, no experimentations were carried out on a real-world IoT scenario. A dynamic programming based duty cycle control technique was employed by Li *et al.* in [26] to provide an optimal solution to an inventory control problem. The focus was on optimizing the duty cycle by jointly considering energy efficiency, end-to-end delay and reliability of the network. A two-hop cluster tree network model was used in the work. A distributed multi-agent Q-learning algorithm was proposed by Liu *et al.* in [31] to optimize both the motorized and non-motorized traffic. The work considered several constraints to help depict real operational scenarios. The paper applied AI powered Internet-of-Things (AIoT) technologies for traffic light control, which is a key to the success of ITS. However, the approach was limited to stationary agents. A dynamic programming approach was deployed by Routray *et al.* in [30] to provide near optimal results under high traffic conditions in an IoT network scenario with consideration for node mobility. A DP approach was used in routing in a dynamically changing network. However, all the nodes in the network were assumed to be routers, which is often not the case in a typical IoT environment.

   Despite the interesting proximity feature of IoT end-devices to the network edge in the fog-based IoT network, delay is prevalent due to several bottlenecks, which may lead system failure or operational hazard for critical applications. These techniques may be used to minimize the delay especially for high priority communications.
3) *Channel assessment and intelligent routing*: Prior to communicating via a link, it is very useful for nodes within the network to assess the communication medium. Learning by experience using some RL techniques will go a long way in minimizing number of loss packets in highly stochastic IoT environment. A Q-learning relay selection algorithm was introduced by Jadoon *et al.* in [3] to maximize the through-

put in a typical cooperative network with relays supporting communication between source and destination. The relays were assumed to be the states, with three possible actions of remaining in the present state with relay r or choosing $r+1$ or $r-1$. However, the outage analysis was carried out without a closed-form expression for the outage probability within the network. Furthermore, in an attempt to reduce the complexity of the formulated problem, the problem algorithm did not consider the relays (states) which do not satisfy the minimum mutual information constraint. A scalable parallel Q-learning algorithm was introduced by Camelo *et al.* in [33] to minimize communication cost. The work considered distributed and resource-constrained environment. A Q-learning-based duty cycle control technique was introduced by Li *et al.* in [25] to provide improved performance and reliable M2M communication for IoT applications. However, the proposed Q-learning based duty cycle control only considered a two-hop cluster tree network in evaluating the performance of the system. Despite system dynamics and heterogeneity within the ultra-distributed IoT environment, it is important for devices which are mobile to move seamlessly without degradation of the quality of service (QoS) when communicating. Moreover, the communication should be ubiquitous irrespective of technology or domain within the system. As such, the RL techniques will play a very important role in areas of IoT device/service discovery, which will support adaptability and interfacing between devices and sub-networks within the IoT domain.

4) *Scheduling*: Wen *et al.* in [9] formulated an automated energy management system (EMS) rescheduling problem as a reinforcement learning (RL) problem. Simulations were carried out using Q-learning technique on a specific scenario with good results. The paper considers the EMS to act as an agent for energy users. A variant of Q-learning, Deep Q-learning, was introduced by Zhu *et al.* in [11] to maximize system throughput by applying appropriate scheduling strategy for cognitive radio-based IoT networks. This work performed poorly when compared with the strategy iteration algorithm, though with a reduced computational complexity.
5) *Resource Allocation and Services*: An RL-based resource allocation in fog radio access networks was presented by Nassar *et al.* in [34] for various IoT environments. A cooperative reinforcement learning algorithm was introduced by Khan *et al.* in [29] for adaptive power allocation in D2D communication. When compared with the Distributed RL algorithm, the proposed approach provides better system throughput as well as D2D throughput with less interference to pave way for the massive MTC in IoT. However, the experiments were conducted in a single cell. The RL-based mapping table (RLMT) and RL-based resource allocation algorithms were introduced by Gai *et al.* in [13] to handle cost mapping tables creation and for optimal resource allocation in IoT content-centric services. The work was limited to the use QoE in examining service level, which allowed a dynamic resource allocation and avoided a fixed task table. A semi-supervised DRL model that suits IoT and smart city services was introduced in Mohammadi *et al.* in [19], using both labeled and unlabeled data for performance improvement and accuracy in the learning agent. The work employed an indoor localization based on the Bluetooth low energy signal strength, and limited its findings to a single floor of a building.

TABLE I
SOME RELATED WORK ADDRESSING KEY ISSUES

Issues	*IoT*	*WSN*
Energy allocation and utilization	[2], [22], [28]	[35], [36]
Latency Minimization	[23], [26], [31], [30]	[37], [38]
Channel assessment and intelligent routing	[3], [33], [25]	[44]-[47]
Scheduling	[9], [11]	[39]
Resource Allocation and Services	[34], [29], [13], [19]	[40], [41]

C. Research in WSN

In [35], a reliable and energy-efficient routing (REER) protocol was proposed using a geographic routing approach. The work considered the idea of a central entity, called a reference node (RN), which is assumed to be situated at an ideal location between source and destination. Several other cooperative nodes, which contend to relay data, are assumed to be situated around the RN. The work was able to examine the trade-off between reliability and energy-efficiency when the distances between RNs was adjusted. The work in [36] proposed an improvement to [35], addressing the issue of scalability in a dynamic network. As such, a novel distributed multi-hop cooperative communication scheme (DMC) was proposed to improve certain QoS metrics such as the communication energy, hop count, and end-to-end delay. However, both approaches assumed complete prior knowledge of the network environment. In [37], a multi-agent reinforcement learning-based multi-hop mesh cooperative (MRL-CC) mechanism for the improvement of some QoS metrics such as the end-to-end delay, packet delivery ratio in the WSNs. The work out-performed the work in [38], which incurred higher delay, and was distance-based, which is not suitable for a dynamic network environment. Though the mobility of the cooperative nodes were taken into account when learning the optimal policy, the MRL-CC failed to consider the power dissipated by the power-constrained devices.

A self-organizing RL technique for scheduling the wake-up cycles of nodes was proposed in [39] to effectively ensure the successful delivery of messages along a routing tree while minimizing interference. A node synchronization /desynchronization strategy was used to minimize interferences, as well as decrease the data retrieval and energy consumption. Experimentation was carried using three static topologies (line, mesh and grid) with results averaged over 50 runs, however, this does not depict a typical dynamic IoT environment. In [40], a distributed independent reinforcement learning (DIRL) techniques, which is based on Q-learning, was introduced to allow autonomous self-learning applications with inherent support for efficient task management. The DIRL approach showed significant performance improvement when compared to traditional static scheduling schemes. A resource management framework based on a two-tier RL scheme was proposed in [41] to enable autonomous self-learning and adaptive applications with inherent support for efficient resource management. However, the approach in [40], [41] only considered task scheduling.

A RL-based Q-routing technique, the Feedback Routing for Optimizing Multiple Sinks (FROMS), was proposed in [44], [45] to enable efficient routing to multiple sinks without overhead. Simulations were done under scenarios where the sink nodes are mobile and with consideration for node failure. However, the mobility pattern and speed was bounded. Moreover, an important cost metric such as the energy consumed by the mobile nodes was not considered. In [46], an evaluation was carried out on the previously proposed FROMS framework using real WSN hardware. The objective was to show that machine learning algorithms could be efficiently deployed on resource-constrained devices. However, during the implementation phase, certain bottlenecks were encountered such as dynamic memory allocation, interference in the wireless channel, poor data gathering, and difficulty in handling lost or corrupted packets. As such, a data clustering and aggregation approach, CLIQUE, was proposed in [47] to minimize the energy expended by the selecting a cluster head using Q-learning. The approach was able to save significant amount of energy when compared to the traditional and random cluster head selection approach.

III. Reinforcement Learning within the IoT Domain

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TABLE II
CLASSIFICATIONS OF SOME RELATED RESEARCH

Objective	*Work*	*Agent (number)*	*Policy*	*Collaborative*	*Algorithm*
Maximize data throughput	[3]	MA (20)	SP	Yes	Q-learning
	[5]	MA (4)	SP	No	Decentralised Q-learning
Optimize traffic	[31]	MA (-)	SP	Yes	Q-learning
Minimize communication cost	[25]	SA	MP	No	Q-learning
	[33]	MA (16)	SP	No	Q-learning
Optimize scheduling strategy	[9]	SA	SP	No	Q-learning
	[12]	SA	SP	No	W-learning
Optimize power allocation	[29]	MA (100)	SP	Yes	SARSA(λ)
Optimize resource allocation	[13]	SA	SP	No	Q-learning

TABLE III
RESEARCH IN IOT USING REINFORCEMENT LEARNING

Paper	*Algorithm*	*Agents resides*	*Multi-agent*	*Problem addressed*
[51]	Q-learning	UAV	Yes	Trajectory design where UAVs sense and send data to base stations (BS) from IoT things
[19]	Deep RL	Fixed access point	No	Indoor localization based on BLE signal strength
[52]	Deep RL	IoT device	No	Energy consumption, computation latency, and task drop rate from IoT devices

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