Decentralised Reinforcement Learning in Fog-based Internet-of-Things

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***Abstract*—Reinforcement learning (RL) algorithms offers more insights about the overall futuristic functionalities for intelligent Internet-of-Things (IoT) devices. With the explosive growth in the number of IoT devices, as well as the highly-distributed deployments of these devices today, managing the IoT devices centrally becomes infeasible. As such, several disruptive paradigms have emerged, one of which is the fog computing-based IoT, which aim towards shifting computation, control, and decision-making closer to the network edge. However, mobility and power-constrain of these fog devices remains an issue of concern. In this paper, we apply a q-learning algorithm to minimize the outage in communication within a fog-based IoT network, by optimizing the power-control parameter of the agent, as well as optimizing the physical position. Furthermore, the agent was able to efficiently minimize the energy consumed by the fog relay and the IoT sensor, while guaranteeing efficient transmission.**

***Index Terms*—Reinforcement learning (RL), Fog-based Internet-of-Things (IoT), q-learning, communication outage, energy management.**

I. Background

THE fog computing-based IoT paradigm aims at moving computation, control, and decision-making within the IoT ecosystem closer to the network edge [1]. The key driver of this paradigm are fog devices, which may be energy-constrained or not, and can either be mobile or static. The deployment and efficient utilization of these fog devices will contribute to the success of future IoT systems [2], one of which is serving as relays to overcome communication outages due to obstacles or long distances between a source node and a remote destination node where IoT services may be rendered.

However, in order for devices to communicate efficiently with minimal outage (loss of transmitted packets), several bottlenecks may arise, one of which is the efficient utilization of energy by power-constrained IoT devices. Energy can be used up when these devices unnecessarily increase their power-level in order to communicate with neighbouring devices within the network, conversely, energy can be saved when the devices regulate their transmission power, especially in situations when they are relatively close to the communicating parties. For example, an IoT end-device that transmits at high power irrespective of the channel conditions or proximity of its neighbours may drastically deplete its energy and die-out, hence, resulting in communication breakdown due to a point-of-failure within the network. Another challenge to be addressed is the energy consumed due to mobility. In order to deliver on some acceptable quality-of-service (QoS) within the IoT ecosystem, it is imperative for devices to be mobile, however, these devices are at risk of draining most of their energy on movement. For instance, energy will be inefficiently used if a power-constrained fog device decides to move closer to the communicating party only to relay very few numbers of packets, though having a guarantee that all the packets are delivered to the destination. However, if the size of the number of packets to be relayed is large, it may be optimal for the fog device to move closer, hence, conserving the energy of the IoT end-device, who can now transmit at a lower power level.

Moreover, since power-control mechanisms and smart mobility are critical in minimizing outages in communication, these devices should be able to learn when to increase, decrease, or maintain their power-levels or to move efficiently in order to increase the long-term performance of the network. More so, near-optimal actions from these devices are required to drive several smart cities applications, most importantly the Industrial IoT (IIoT), where industrial robots are deployed to act intelligibly in a dynamic industrial setting, and intelligent monitoring applications, where surveillance drones are deployed in militarised zones to meet stringent quality-of-service (QoS) requirements [3].

An iterative algorithm based on the steepest descent method was proposed in [3] to optimize communication performance a multi-tier fog-based IoT architecture, where a fog device acts as an amplify and forward relay that transmits received information from a sensor node to a higher hierarchically-placed destination fog device, which offers some localized services. However, the centralized solution is not scalable with increasing number of devices. In [8], a relay and mobility scheme for IoT (REMOS-IoT) was proposed to improve the network QoS by effective resource management and decision-making. The centralized REMOS-IoT algorithm introduced also considered the mobility of fog gateways/relays in improving the network throughput, however, energy management of these power-constrained IoT devices was not considered. Considering the highly-distributed nature of deployed IoT devices, it becomes infeasible to manage devices centrally [4]. As such, reinforcement learning can be effectively deployed on fog devices to allow them to act independently based on their local experiences in the environment, i.e. each fog device should be able to learn independently without a central entity.

A decentralised stateless Q-learning approach was proposed in [4] to improve aggregate throughput in four coexistent wireless networks (WN). Each WN was considered to be an agent running the stateless Q-learning algorithm with agents having action space as channel number, and transmit power (dBm). A lightweight distributed learning approach was proposed in [7] to increase energy efficiency and reliability

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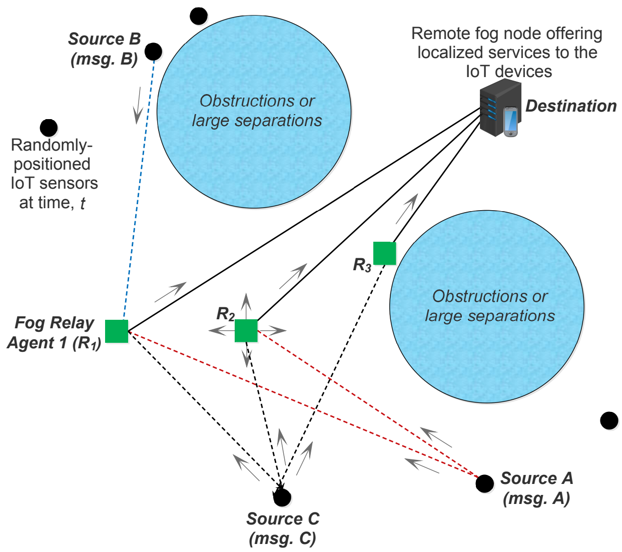

captionSystem model.

of IoT communications. There was significant performance improvement when the proposed algorithm was compared to a centralized optimized strategy. Transmit power, sub-channel, and spreading factor made up the action space. However, the system model in both works was rather hierarchical than distributed, ie. each WN was assumed to be an independent central entity with no specifications to what is learnt within each sub-network. Though IoT is defined as a large-scale network where various sub-networks coexist [1], applying RL to end-devices within sub-network may bring about meaningful performance improvement in the overall IoT network.

The main contribution of this paper is to propose a decentralised reinforcement learning approach as in [6] that addresses communication performance within a fog-based IoT architecture. First, we assumed a single-agent scenario of possible state-action pair for each communication scenario as seen in Fig. I, where an agent may be faced with a unique topology and environment. Next, in order to guarantee energy-efficient communications for the fog devices in the dynamic environment, we apply a decentralised q-learning algorithm, where each agent observes its position with respect to the communicating party, as well as its present transmit power level and learns to take actions that minimize loss of packets, as well as efficient energy utilization.

The remainder of this work is organized as follows. In Section II, we reviewed related works, and present our proposed approach in Section III. In Section IV, we evaluate the proposed fog-based IoT system, and present the results in Section V. Section V concludes the paper and outlines future directions.

II. Problem Definition

In this section, we provide full description of the system model, as well the RL approach used to address the problem. The Mobile Fog Relay Agent (MFRA) and its environment are discussed below.

A. MFRA environment

States: The states are defined as a tuple, $\langle$Outage communication cost ($\mathcal{P}_{out}$) /Energy status of the fog relay (J) /Neighbour potential to relay message (Availability of redundant nodes)$\rangle$.

- Outage communication cost: Outage observations from the environment is estimated using (1) from [3], which gives an estimate of the communication outage when the agent takes an action, such as changing power levels or location, or both.
- Energy expended by fog relay: This observation gives the agent insight on how much energy by the fog agent when following policy $\omega_i \in \omega_{fog}$. If the fog agent continues to take sub-optimal actions, it depletes its energy and dies out.
- Neighbour potential to relay message (Availability of redundant nodes): This observation gives the agent insight on the availability of redundant nodes that can help in relaying same type of message emanating from a particular IoT sensor. If there exist no potential relay agent to convey message from an IoT sensor to a remote destination, then the agent should learn to remain active for that transmission phase. However, if there exist one or more potential relays agents, the agent should learn to take no action to help conserve energy and improve the longevity of the network.

$$\mathcal{P}_{out} = 1 - (1 + 2\Psi^2 \ln \Psi) \exp\Big(- \frac{N_0 \tilde{\kappa}}{P_I (D_I + \delta)^{-\sigma}} \Big), \quad (1)$$

where $\Psi = \sqrt{(N_0 \tilde{\kappa})/(P_R(D_S + \delta)^{-\sigma})}$, and $\mathcal{P}_{out}$ is an expression for the outage probability with values between 0 and 1. We assume a predefined threshold $\tilde{\kappa}$ which determines the outage in communication, P_I is transmit power of the IoT sensor, P_R is transmit power of the fog relay agent, D_I is the distance between IoT sensor and fog relay agent, and D_S is the distance between fog relay agent and destination node. We assume a small change in the position of the fog relay agent, $\delta = \pm 0.25m$, N_0 to be the channel noise, and σ to be the path-loss exponent.

B. MRFA agent

We apply a the Q-Learning algorithm, an RL approach which requires no prior knowledge of the environment by the agent. In Q-learning, the agent interacts with the environment over periods of time according to a policy ω. At every time-step $k \in N$, the environment produces an observation $s_k \in \mathbb{R}^{D_s}$. By sampling, the agent then picks an action a_k over $\omega(s_k)$, $a_k \in \mathbb{R}^{D_a}$, which is applied to the environment. The environment consequently produces a reward $r(s_k, a_k)$ and may end the episode at state s_N or transits to a new state s_{k+1}. The agent's goal is to minimize the expected cumulative cost, $\min_\omega \mathbb{E}_{s_0,a_0,s_1,a_1,\ldots,s_N} \Big[\sum_{i=0}^{N} \gamma^i \mathcal{C}(s_i) \Big]$, where $0 \leq \gamma \leq 1$ is the discount factor, and $\mathcal{C}$ is the overall cost function of our model.

First, the agent takes an initial random action a_k and gets observations from the environment which corresponds to that action, as well as a reward. It then discretizes the continuous observations emanating from the environment into a $3 \times 3 \times 3$ state space corresponding to the tuple, $\langle$Outage communication cost ($\mathcal{P}_{out}$) /Energy status of the fog relay (J) /Neighbour potential to relay message (Availability of redundant nodes)$\rangle$. The agent then updates it's Q-values at each time-step k following (2).

$$Q(s_k, a_k) := Q(s_k, a_k) + \alpha\Big[r_{k+1} + \gamma \max_{a} Q(s_{k+1}, a) - Q(s_k, a_k)\Big], \quad (2)$$

where α is the learning rate, which determines the impact of new experience on the Q-value, r_{k+1} is the reward the agent receives by being in s_{k+1} from s_k. Based on the policy followed by the agent, it gets observations and rewards from the environment.

Action space: The actions are move and transmit by fog relay, and select a power-level and transmit by IoT end-device, which make up eight possible actions.

- Mobility: Move by $\pm\delta$ and transmit, where $\delta = \pm 0.25m$ and mobility range (m) = [-30, 30]
- Power-level: Choose power-level and transmit, P, where transmit power ranges (W) = [0.001, 0.01, 0.15, 0.2, 0.25, 0.3]

Goal: The goal is for the agent to learn to minimize the outage communication cost ($\mathcal{P}_{out}$) and energy consumed by the fog relay agent (J), ie. keeping all nodes within the link alive while ensuring that the packets received in each transmission phase does not fall below the pre-defined threshold, which was set at 95%.

Rewards: The reward function used is given in (3) as

$$R = \begin{cases} 100, & \text{if } goal == Reached \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

Metrics: Outage probability, i.e. the ratio of the number of packet lost to those transmitted, which we measure in percentages, and energy status of the fog relay agent, i.e. the ratio of depleted energy to the initial capacity in Joules, which we measure as a percentage.

The MFRA's learning process is summarized in Algorithm 1. A new learning episode is terminated when the agent attains the pre-defined goal of minimizing the communication outage in the link, or when either the fog relay or the IoT sensor dies out due to taking sub-optimal actions without getting to the goal. When an fog relay moves closer to the communicating parties, the IoT sensor uses a lower power level as compared to when it is far away, hereby saving IoT sensor energy. However, mobility have some cost and if the fog relay continues to move in order to minimize the communication outage, it may die out soon, hereby causing a point-of-failure to the network. As each episode is completed, a reward of 100 points is given to the agent if it reaches its goal and a 0 points otherwise. The reward is updated in the Q-learning table, with environmental information updated as well.

Algorithm 1 MFRA Learning Process

```
Initialize: Power levels triggered from sensors (W) = [0.001, 0.01, 0.15, 0.2, 0.25, 0.3], δ = ±0.25m and mobility range (m) = [-30, 30]
top:
ResetEnvironment()
state ← MapLocalObservationToState(env)
action ← QLearning.SelectAction(state)
if action == "move close and Tx" then
    Env.EstimateOutage (1)
    Env.EstimateFogEnergyStatus
else if action == "move away and Tx" then
    Env.EstimateOutage (1)
    Env.EstimateSensorEnergyStatus
else if action == "choose power level and Tx" then
    Env.EstimateOutage (1)
    Env.EstimateSensorEnergyStatus
endif
InvokePolicy(ExponentialDecay)
UpdateQLearningProcedure() (2)
CurrentState ← NewState
if goal == "Reached" then return Reward = 100,
else if goal != "Reached" or Agent == Death then return Reward = 0
endif
EndEpisode goto top.
```

TABLE I
ACRONYMS

Acronym	*Definition*
RL	Reinforcement learning approach
RB_CS	Rule-based + centralised selection
RB_RR	Rule-based + round robin selection
RB_R	Rule-based + randomized selection

III. Experimental Setup

We carried out experimentation using the Python IDE 3.7.2, and considered a single agent to help us compare our proposed approach with the baseline.

A. Baselines

In this work, we consider three existing baselines, namely:

1) RB_CS:
2) RB_RR:
3) RB_RR:

B. Indicators

To evaluate our proposed approach, we examine the convergence of our approach in minimizing the steps it takes the agent to get to its goal, the energy utilization of the fog relay and IoT sensor.

TABLE II
SIMULATION PARAMETERS

Parameter	*Values*
D_I	35 metres
P_I	[0.001, 0.3] Watts
D_S	35 metres
P_R	0.3 Watts
δ	± 0.25 metres
Mobility bound	[-35, 35] metres
Noise power N_0	2×10^{-7} Watts
Path-loss exponent σ	3
Pre-defined threshold κ	1
Discount factor γ	0.9
Learning rate α	0.1
Precision ε_{GD}	0.00001
Episodes N	100
Iteration runs	100000
Policy ϵ	$e^{-0.0015N}$

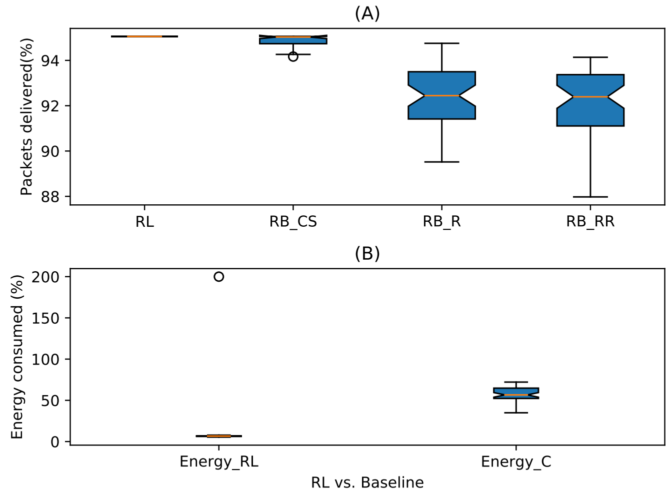

Fig. 1. Comparison of RL with baselines over 50 runs in a 2 agents environment.

IV. RESULTS AND DISCUSSIONS

In this section, we present the results of the fog-based IoT system. We compare the proposed approach with some baseline by evaluating the percentage of packets successfully transmitted via potential fog relay agents, then we examine energy utilization of our proposed approach with the baseline.

A. Proposed approach vs. baseline

We compared our proposed RL approach with existing baselines. Simulations were done using Python IDE 3.7.2, and Table II shows a summarises the parameters used in the experiments. For the sake of evaluation, we considered the last forty episodes to ensure convergence in the learning process. Fig. **??** (A) shows the percentage of packets successfully transmitted when two fog relay agents are deployed to convey message from an IoT sensor to a remote destination. We observe that about 95% packets in our proposed approach is successfully transmitted. The RB_CS strategy performed closely to the proposed approach with values ranging between 94% - 94.7% packets successfully transmitted. This performance is based on the assumption that a central controller selects the best performing agent in each transmission phase. We observe lesser variability in the RB_CS baseline as compared to RB_RR and RB_R strategies.

The RB_R strategy, which has normally distributed values of the packet received, with values ranging between 89.2% - 94.5% performed slightly better than the RB_RR strategy, which is left-skewed, with values ranging between 88% - 94%. In general, we observe variability mostly in the baselines as compared to our proposed approach.

B. Energy utilization

Fig. **??** (B) depicts the percentage of energy consumed by potential fog relay agents in the network. Our proposed RL approach out-performs the baseline by a wide margin. A higher variation is observed in the baseline as compared to the proposed approach. This shows that the decentralized learning by agents within the system significantly improves its energy utilization. The agents can learn when not to be active in order to minimize energy cost. Overall, the performance of the proposed approach yields better results than the baseline.

V. RELATED WORKS

Considering the dynamics and heterogeneity within the ultra-distributed IoT environment, it is important for communication devices which are mobile to move seamlessly without degrading quality of service (QoS). More so, the constrained devices should communicate efficiently without depleting all their energy by transmitting at high-power, which may have long-term consequences to the network. Several non-RL-based approaches have been proposed to optimize the communication performance in IoT based networks, however, when some parameters in the network are changed, these approaches may fail. The work in [3] considered a multi-tier fog-based IoT architecture where a mobile/static fog node acts as an amplify and forward relay that transmits received information from a IoT sensor node to a higher hierarchically-placed fog device, which offers some localized services. In order to minimize the outage in communication, an iterative algorithm based on the steepest descent method (SDM) was proposed to jointly optimize the mobility pattern and power-control parameters. However, the work did not take into consideration the performance of the approach in a decentralised IoT environment. Furthermore, each time the topology is changed, the agent will need to recompute the gradient in other to act optimally, which is infeasible to achieve.

RL can be applied to a new environment, since the it allows the agent to learn, by take actions that will improve its long-term return. Furthermore, RL can be applied to multiple agents. In [4], a decentralised, multi-agent-based stateless Q-learning approach was proposed, where no information about neighbouring nodes are available to agents. Though the paper was able to improve aggregate throughput in the network, by allowing the networks modify both the transmission power and the channel used, however, high variability was observed in the throughput of the individual networks. Only eight agents were observed using a stateless Q-learning approach. The work did not adequately depict the distributed nature of the IoT network. Moreover, topology dynamism was completely ignored.

Several works in WSN have applied the decentralised RL technique. In [11], a multi-agent reinforcement learning-based multi-hop mesh cooperative (MRL-CC) mechanism for the improvement of some QoS metrics in the WSNs. 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, as well as the overall outage in communication.

In [10], 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.

We present a decentralised reinforcement learning approach that adequately addresses some key performance issues within the IoT domain. The main task of our work is to minimize global outage in communication within a fog-based IoT network, by optimizing the power-control parameter of the potential mobile fog-relay agent (MFRA), as well as optimizing the position of each relaying agents in the network. As such, each MFRA is compelled to take certain actions that may influence its environment. However, the duration it takes the MFRA to learn is significantly influenced by the state space, as well as the possible set of actions [9]. The variables for the state, action and reward of an agent may be discrete or continuous, with the former represented as small interval of values which imply distinct levels [12], and can easily be represented in a tabular form. However, it is difficult to represent continuous space using q-learning tables. The work in [13] considered a RL agent that explores continuous state and action space using Gaussian unit search behaviour. Other works [9], [15] considered the reduction of states by eliminating states that are unlikely to occur. However, this may pose a big risk especially in a highly dynamic environment. RL can be effective for learning action policies in discrete stochastic environments, but its efficiency can decay exponentially with increasing state space [14]. Our proposed problem is approached by discretizing the continuous state space observed from the environment.

In this paper, we assume the following.

1) The MFRA is completely oblivious of its environment, and as such, has no prior knowledge of the overall cost function.
2) The MRFA may change its position in order to ensure better communication. Also, the MFRA may change its position (2D/3D) depending on the scenario considered.
3) The MFRA has an objective of learning to make actions that yield better outcomes within its local view of the environment.
4) The states are be divided into discrete levels to overcome the exponential decay in the efficiency of the proposed approach due infinite state space.
5) The MFRA independently tries to optimize power usage and moves in a direction that maximizes the communication outage.

VI. Conclusion and Future works

We aim to apply the q-learning algorithm on a multi-agent fog-based IoT system where multiple agents compete to transmit reliably in a highly dynamic environment, where interference contributes significantly to communication outages within the network. For instance, agents may take actions that can have direct consequences on neighbouring agents, which may have further impact on other agents within the network. For instance, if an agent decides to increase the transmit power beyond some threshold in order to boost its communication capabilities, its action may result in channel interference to its immediate neighbours, and worst, it may deplete its energy fast, and die-out, leading to link failure that can affect the performance of the entire network. This will be looked at in our future work.

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