DEEP LEARNING BASED INTERFERENCE MANAGEMENT IN A D2D COMMUNICATION NETWORK

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Abstract

As a device-centric communication system, fifth generation (5G) is associated with wider bandwidth, higher throughput, lower latency, and improved system capacity compared with previous generations. However, the attendant challenge of interference in the D2D communication network engenders degradation in the network's performance. Hence, a deep reinforcement learning (DRL) based technique to manage co-tier interference in a D2D network is proposed. A DRL algorithm with Multi-Headed Individual Actor Critic (MHAIC) based on power control and resource allocation was developed. The algorithm used online real-time information. Simulated results revealed that the throughput initially increased with increase in number of D2D pairs and peaked at 80 D2D pairs before decreasing. Furthermore, our model results were bench-marked with previous algorithms and the achieved throughput was superior by at least 40.74% higher than existing control DRL schemes, thus implying the efficiency of the current approach. The technique maximized the network throughput, ensured quality of service (QoS) requirements of both D2D users and Cellular Users (CUs) and thus provided a more reliable and efficient communication environment.

Keywords: *D2D communication, Interference Management, Deep Reinforcement Learning, Throughput.*

Introduction

The new decade promises a better communication system, which is the fifth generation (5G) communication system with higher data bandwidth, higher throughput, lower latency, and increased system capacity among others (Gandotra & Jha, 2016). Many technologies and schemes, such as modulation techniques, radio access techniques, or distributed computing, could be reused in 5G (Gandotra & Jha, 2016; Hassan et al., 2018). Device to device (D2D) communication is an application in 5G technology which enables user devices in proximity to communicate directly with each other without cellular infrastructure, that is, limiting the participation of the Base Station (BS) in their communication, thereby reducing the load on the BS and reducing latency and power efficient transmission (Jameel et al., 2018). In the traditional cellular network, data packets are uploaded to the BS via the uplink resources before they are routed to the intended destination via the downlink (Fodor et al., 2012). The benefits of D2D include higher data rate and spectrum efficiency, lesser transmission power, improved capacity and less congestion. These benefits are obtained at the cost of interference, which occurs as a result of spectrum sharing between cellular users (CUs) and D2D users as well as between D2D pairs re-using the time-frequency resources (Safdar et al., 2017).

Various deep Learning algorithms have been used to proffer interference management solutions in the D2D network and have proven to achieve better results in terms of throughput than traditional methods (Budhiraja et al., 2021; Shi et al., 2020; Tan et al., 2021; Wang et al., 2021). Kim et al. (2020), proposed an approach which attained a near optimal cell throughput while suppressing interference to BS as the IoT-D2D transmitter decides the transmit power independently from an BS and other IoT-D2D devices. The proposed approach achieved a significant reduction in the signalling overheads; however, it uses belated information and do not update real-time which was similar to the drawbacks in Zhou (2021). The approach used by Shi et al. (2020) provided more efficient strategies for power allocation and also performed better than conventional methods, however, it used overaged network information also, hence, optimum result was not attained.

Hence, the current study is aimed at modelling an interference management technique for co-tier interference in a D2D network using online information updated in real-time. Specifically, a Deep Reinforcement Learning (DRL) algorithm based on power control and resource allocation for managing co-tier interference was developed and simulated. Moreover, results from the developed approach were benchmarked with similar algorithms from previous works. The research outcome addressed some challenges associated with co-tier interference in a D2D Network, which in turn increased the quality of service (QoS) of the D2D devices.

System Model

This work concentrates on the inband underlay network architecture which allows D2D users (D2D users) and cellular users (CUs) to use the same licensed radio spectrum assigned to the cellular operators and the D2D users reuse the allocated resources, thereby, leading to efficient use of the spectrum. The use of the same resource blocks by multiple D2D causes interference on the cellular users (cross-tier) as well as the D2D users (co-tier) and this has an impact on the QoS on the network. The QoS also depends on appropriate power level control on both the cellular devices and the D2D. As the D2D pairs are increased, there is an increasing chance co-tier interference and hence, a need to manage the interference cause for better QOS.

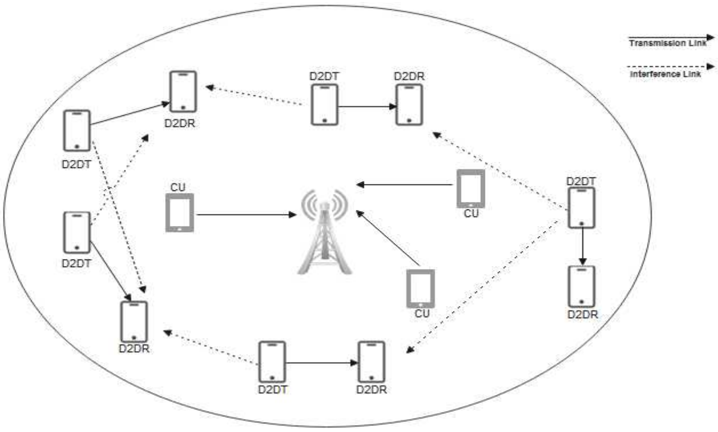

Figure 1: System Model

Theoretical formulation

The model is a cellular network uplink was considered with a base station (BS) at the network centre, *I* number of cellular users (CUs) and *J* number of D2D pairs, which were randomly distributed within the coverage area of the BS, as shown in Figure 1.

We denote CU(*i*) and D2D pair(*j*) as the *i*-th CU and *j*-th D2D pair, respectively, and $i \in I = \{1, 2, ..., I\}$ and $j \in J = \{1, 2, ..., J\}$ are the set of CUs and D2D pairs, respectively. The channel gains of the interference links from D2D T *j* to the BS and CU *i* to D2D-T *j* are similarly defined as g_t^{jB} and g_t^{ij} , respectively, along with the channel gain of D2D pair *j* as g_t^{j} . Since channel gains g_t^{iB} and g_t^{jB} are known at the BS, this information can easily be transmitted to all D2D users. It is hard however for D2D users to obtain the channel gain from the *j*th D2DT to the *i*th CU (g_t^{ij}).

The system is a fully decentralised setting, hence, D2D users must make decisions without knowledge of the decisions of other D2D users. As a result, there is a possibility that multiple D2D users will decide to access the same RB at the same t. This leads to 'collision', which is the main cause of interference in the network. For simplicity of the simulation, the assumption is that there is no co-tier interference and a perfect collision model such that no interfering users can carry out transmission. Accordingly, the signal to interference plus noise ratio (SINR) of the ith CU is defined as (Sun, 2021):

$$\zeta_t^i = \begin{cases} \frac{p^i g_t^{\mathrm{jB}}}{\sigma_N^2}, & if\ collision\ occurs\ or\ ith\ RB\ not\ selected \\ \frac{p^i g_t^{\mathrm{jB}}}{p_t^{Jl} g_t^{\mathrm{jB}} + \sigma_t^2} & otherwise \end{cases} \tag{1}$$

where p^i is denoted as the transmit power of the ith CU (assumed to be constant), p_t^{jl} is denoted as the lth transmit power level of the jth D2D-Tx at time t, and σ_N^2 is denoted as the additive white Gaussian noise power. The SINR of the jth D2D pair at time t is expressed as:

$$\xi_t^j = \begin{cases} 0, & if\ collision\ occurs \\ \frac{p^{jl} g_t^{\mathrm{j}}}{p_t^i g_t^{\mathrm{ij}} + \sigma_t^2} & otherwise \end{cases} \tag{2}$$

When a collision occurs, the conflicting D2D users will fail to transmit, that is, $\xi_t^j = 0$, since the model used here is a perfect collision model.

Optimization problem

This work also aims at maximizing the throughput in the system by choosing the RB i and controlling the D2D-Tx transmit power $p_t^{j,l}$ at time-slot t. Hence, for the overall throughput, the formulation of the online optimization problem is expressed as:

$$\max_{i \in x, g_t^{j,i}} \sum_{i \epsilon x} \sum_{j \epsilon J} W[\log_2(1 + \xi_t^i) + \mathbf{I}(i,j) \log_2(1 + \xi_t^j)] \quad ` \tag{3}$$

s.t

$$\xi_t^i \geq \xi_i^*, \ \forall_i \epsilon I, \forall_t \epsilon T \tag{3.1}$$

$$\xi_t^j \geq \xi_j^*, \ \forall_j \epsilon I, \forall_t \epsilon T \tag{3.2}$$

$$0 \leq p_t^{j,l} \leq p_{max}, \ \forall_j \epsilon I, \forall_t \epsilon T \tag{3.3}$$

$$\sum_j I\ (i,j) \leq 1,\ I\ (i,j)\ \epsilon\ \{0,1\}, \forall_i \epsilon I, \forall_t \epsilon T \tag{3.4}$$

$$\sum_i I\ (i,j) \leq 1,\ I\ (i,j)\ \epsilon\ \{0,1\}, \forall_j \epsilon I, \forall_t \epsilon T \tag{3.5}$$

where W denotes the channel bandwidth, ξ_i^* and ξ_j^* are the minimum SINR requirements of the CUs and D2D users respectively, p_{max} represents the maximum transmit power of D2D-Tx, I(i; j) denotes the resource reuse indicator function for CU i and D2D pair j, I(i; j) = 1 when the j-th D2D pair reuses the i-th RB at time-slot t; otherwise, I(i; j) = 0.

The constraint (3.1) represents the QoS requirement of CUs, while (3.2) denotes the QoS requirement of that of D2D users. In the system, the primary and secondary users are the CUs and D2D, hence, when both the CUs and D2D attain their SINR requirements, i.e., ξ_i^* and ξ_j^*j, are satisfied, only then will j-th D2D pair be set up over the i-th RB. The (3.3) constraint ensures that the D2DTx transmit power is within the maximum limit. The (3.4) constraints assure that each RB can be reused by only one D2D pair, and (3.5) indicates that each D2D-Tx can only reuse one RB.

Algorithm and Model Implementation

Algorithm

A multi-agent online distributed DRL (OD-DRL) algorithm is considered in the proposed work. The algorithm is based on Multi-Headed actor-critic method that ensures QoS for both D2D and CU users while also increasing overall performance in a D2D communication network. In the actor-critic method, the actor acts based on the current observed state and policy in the environment. As the environment reveals the next state, this is usually immediately, the critic gives a critique to actor by calculating the received reward from the environment. The critic uses a value function approximation to update its parameter, and the actor uses the critic's critique to update its parameter. The general framework of the actor-critic learning method is depicted in Figure 2 (Sun, 2021). For a two-headed output, the original policy output layer is replaced with two separate output layers. These layers give a probability distribution for channel selection as well as power level selection.

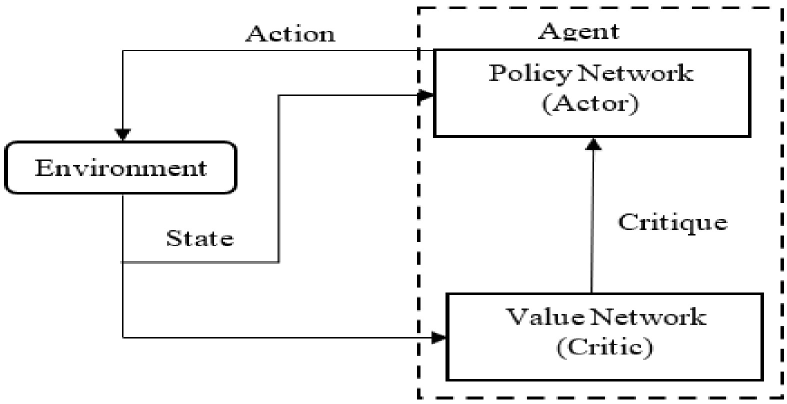

Figure 2: Structure of actor-critic learning method.

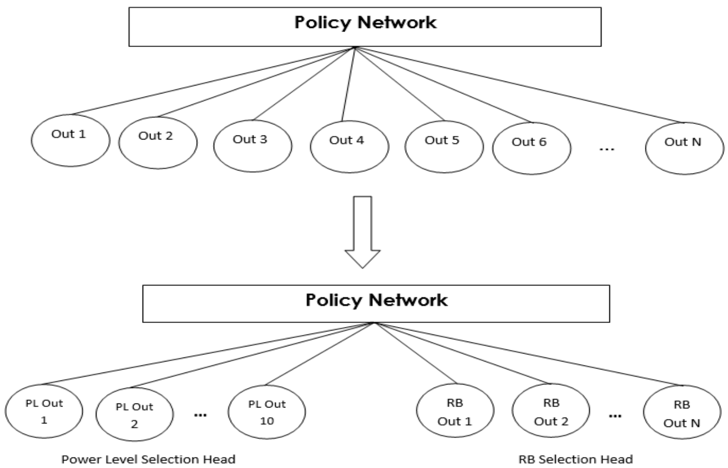

Figure 3: Structure of Multi-headed IAC

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The current observed policy and state determines how the actor acts in the environment. Subsequently, the next state is immediately revealed by the environment and the critic gives a critique to actor by calculating the received reward from the environment. The critic updates its parameter via a value function approximation, and the actor update its parameter based on the critique from the critic.

Performance Evaluation

3.2.1 Performance metrics

To evaluate the performance of the proposed method, we propose three metrics as seen in (Sun, 2021), they are;

D2D collision probability – gives the probability of collision between the D2D users. This implies $\psi(a_t^j)$ = 1 when a collision happens (multiple D2D users access the same RB at the same time) and $\psi(a_t^j)$ = 0 otherwise, the D2D collision can be denoted as:

$$\Psi_T = \frac{\sum_{t=0}^{T} \psi(a_t^j)}{T} \qquad (4)$$

D2D access rate - the D2D access rate is defined as the ratio of the number of accessed D2D pairs which meets both D2D users' and CUs' minimum SINR requirements, to the total D2D pairs over the time horizon *T*, as expressed below:

$$\Lambda_T = \frac{\sum_{t=1}^{T} J_t^a / J}{T} \qquad (5)$$

The time-average overall throughput: the overall throughput brought by the CUs and the accessed D2D users at time-slot *t* can be expressed as:

$$F_T = \frac{\sum_{t=1}^{T} f_t}{T} \qquad (6)$$

$$where\ f_t = \sum_{i \in X} \sum_{j \in J_t^a} W\ [log_2(1 + \xi_t^i) + I(i,j)\, log_2(1 + \xi_t^j)] \qquad (7)$$

J_t^a = the set of accessed D2D pairs at time-slot *t*.

3.2.2 Performance evaluation with previous algorithms

The performance of the developed scheme was benchmarked with four algorithms as follows.

1) DRL-based control approach which employed a joint power control and resource block (RB) scheduling scheme to improve the sum rate of the network (Budhiraja et al., 2021).

2) DRL-based distributed approach which used four DRL models for power control and RB allocation (Nguyen et al., 2019).

3) Deep Learning (DL) approach which employed deep neural network to mitigate the interference among the D2D pairs (Lee et al., 2019).

4) Random Selection (RS) approach in which RB was randomly selected from a pool of RBs by each pair (Chen et al., 2016).

Model implementation

The channel allocation and power control are implemented using deep reinforcement learning (DRL). The DRL technique is recently seen as a useful tool used to handle the computational complexity of a wireless network, especially when compared to other traditional techniques, which have a weakness of exponential growth (Sun, 2021). DRL is said to be effective in mitigating interference and as well as enhancing spectrum efficiency (Wang et al., 2021). DRL is a process where candidates, known as cellular users or D2D users search for a solution to the D2D problem; which is interference in our research. Every user has the ability to explore and ultimately improve its performance through trial-and-error complements; a setting where the goal is to find optimal control protocols based on the dynamics of the system. This is further solidified when considering the multi-user nature of the problem. The optimal RB selection and power level selection, at any time, for one D2D device is explicitly reliant on the state of all other devices in the network at that time. As such, it naturally follows that to fully exploit the nature of the problem set, one must consider the effect that other users have on the system.

The state space and the action space in reinforcement learning (RL) are denoted by *S* and *A*, respectively. At each time-slot *t*, the agent takes an action $a_t \epsilon A$ based on the current policy under the current state $s_t \epsilon S$ of the environment, and then the state of the environment transfers to the next state $s_{t+1} \epsilon S$ according to the transition probability $\Pr(s_{t+1}|s_t, a_t)$. The agent immediately receives a scalar reward denoted as r_t. Therefore, over time, a reinforcement learning agent learns its best policy from the rewards of trial-and-error interactions with the environment (Sun, 2021). In the system model, the agent, state, action and reward are identified as:

Agent: the D2DTx of the D2D pair is the agent

State: the state of the *i*-th CU at time-slot *t*, denoted as s_t^i and defined as

$$s_t^i = \xi_t^i, \forall_i \epsilon I \tag{8}$$

Therefore, the state s_t for D2D users is given as

$$s_t = [\, s_t^1, \ldots \, s_t^i, \ldots s_t^i]^T \tag{9}$$

Action: The action a_t^j of each D2D-Tx j at time-slot t is defined as

$$a_t^j = [i, p_t^{j,l}]^T \tag{10}$$

where *i* gives the selected *i*-th RB from *I* RBs and $p_t^{j,l}$ is the *l*-th transmit power level of the *j*-th D2D-Tx at time-slot *t*. We quantify the maximum transmit power p_{max} into *L* levels and define the transmit power level *l* as $l \epsilon [1, \ \ldots, L]$. Thus, the transmit power $p_t^{j,l}$ is given as:

$$p_t^{j,l} = \frac{p_{max}}{L} \, l \tag{11}$$

The action space *A* for each D2DTx *j* can be given as;

$$A = \{[1, p_t^{j,1}], \ [1, p_t^{j,2}], \ \ldots, \ [1, p_t^{j,l}], \ldots, [1, p_t^{j,L}]\} \tag{12}$$

Hence, each D2DTx *j* can select an action from *A* at the beginning of the time-slot *t*.

Reward: The agent *j* immediately receives the reward from the environment after taking an action. Let the reward function of the *j*-th D2D user over the *i*-th RB at time-slot *t* be denoted as r_t^j and expressed as:

$$r_t^j = \begin{cases} 0, \ if \ (3.1), \ (3.2) \ or \ (3.4) \ is \ violated \\ \sum_{i \epsilon X} (1+ \xi_t^i) + I(i,j)\,(1+ \xi_t^j), \ otherwise. \end{cases} \tag{13}$$

The reward for each agent consists of its own throughput and all CUs' throughput. The optimization of the system overall throughput in (3.3) can be achieved by maximizing each individual reward and this depend on a sequence of actions made over the time horizon *T*.

All implementation work was programmed using Python 3:6:9 in a Gym-D2D environment (Device-to-Device (D2D) communication (OpenAI Gym environment, 2021). The Gym-D2D environment is a device-to-device underlay evaluation platform that gives a framework for experimenting, simulating and evaluating system models (Cotton & Chaczko, 2021). Simulations parameters as seen in Table 1 were inputted into the Gym-D2D environment and the results obtained were compared with other models.

Results and Discussion

The proposed method utilizes online deep reinforcement learning which has an advantage of learning and updating its information real-time, hence, promising a better system throughput across varied number of D2D users. The simulation parameters employed are presented in Table 1 and the results are equally tabulated in Table 2.

Table 1: Simulation parameters

Number of_D2D	20-120
N_CU	60
D2D_distance	50m
Simulation Region	1000, #radius 500m
AWGN	-174, # -174dBm
W	5MHz (5*10**6)Hz
PLfactor	4
PL_k	0.01(10**-2)
CU_tr_Power	25,
CU_min_SINR	8
D2D_tr_Power_levels	10
D2D_tr_Power_max	25
D2D_min_SINR	8

NB: N_CU - Number of Cellular Users; W - Bandwidth; AWGN - Additive White Gaussian Noise.

Table 2: Results

D2D Varied	20	40	60	80	100	120
Throughput	57.8743	58.59678	66.66663	88.44297	77.08725	53.09419
Access_rate	0.985816	0.860429	0.639185	0.406064	0.27409	0.155303
Col_prob	0.040207	0.829996	1	1	1	1
Reward	58.87108	57.81222	58.18067	78.53263	65.24298	37.73971
Power loss	0.536561	0.772704	1.799118	2.213391	3.19379	2.976692
RB loss	0.501698	0.729742	1.755369	2.156549	3.14165	2.939301

NB: Col_prob – Collision Probability

Figure 4 gives the variation of access rate as the number of D2D users increases. The access rate, which is the ratio of the number of accessed D2D pairs that meets both D2D users' and CUs' minimum SINR requirements, to the total D2D pairs, reduced with increase in D2D devices. This implies that as the number of D2D pairs increases, there is a reduction of the rate at which the D2D pairs meets the SINR requirement as well as access the network.

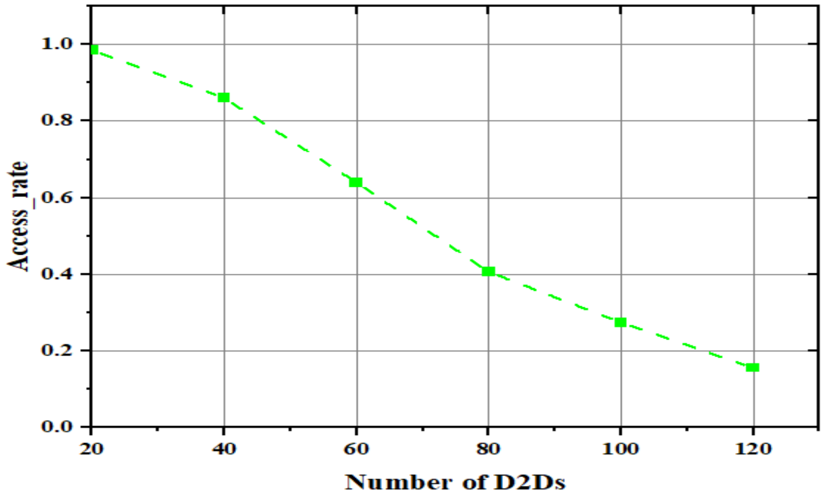

Figure 4: Access Rate Vs Number of D2Ds

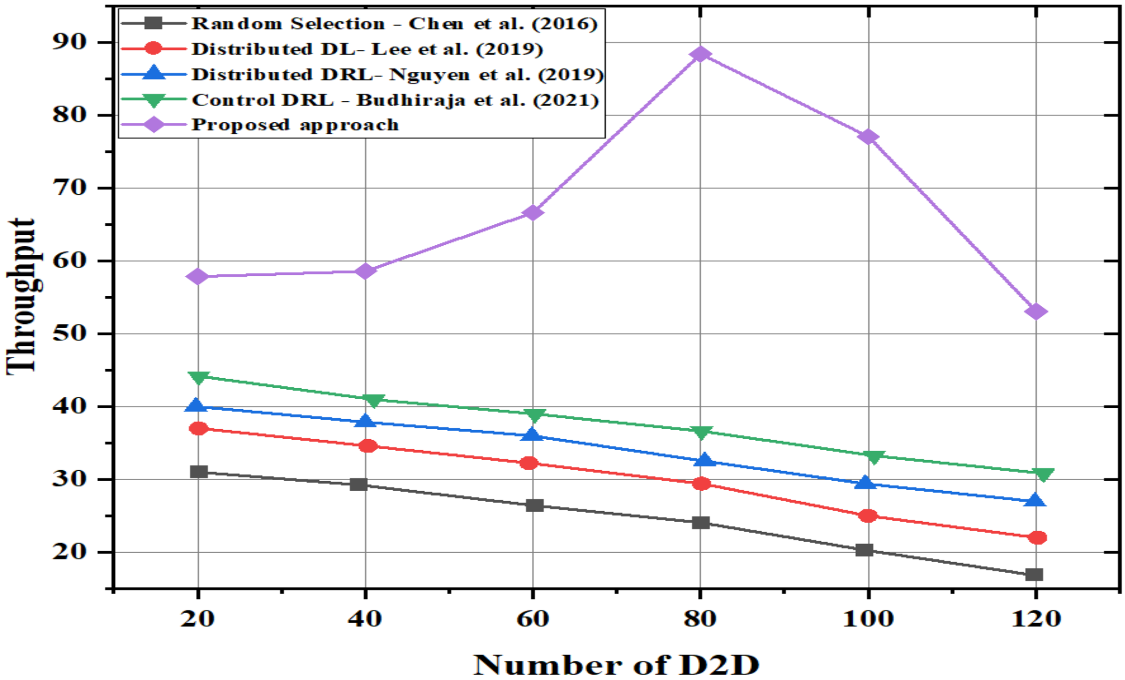

Figure 5: Throughput VS Number of D2Ds

Figure 5 shows the variation in the throughput of the network with respect to the number of D2D pairs as compared with results in four previous algorithms (section 3.2.2). The throughput, which is a function of the number of accessed D2D pair at a given time slot t and the SINR of the D2D pairs increased as the number of D2D pairs increased and reached a peak at number of D2D pairs = 80 and eventually decreased as the D2D pairs increased. This is because with an increase in the number of D2D pairs, there is also an increase in the co-channel interference among the D2D. The obtained result also implies that the proposed scheme achieved better throughput as compared to distributed DRL, distributed DL, and random allocation scheme in (Budhiraja et al., 2021) (Nguyen et al., 2019) (Lee et al., 2019) (Chen et al., 2016).

Specifically, the result showed that at 120 number of D2D pairs, the proposed approach achieved 72.22%, 59.30%, 48.15%, and 40.74% higher throughput compared with random selection, distributed DL, distributed DRL and, control DRL, respectively as our proposed algorithm has an advantage of updating real-time and resulting in optimal results.

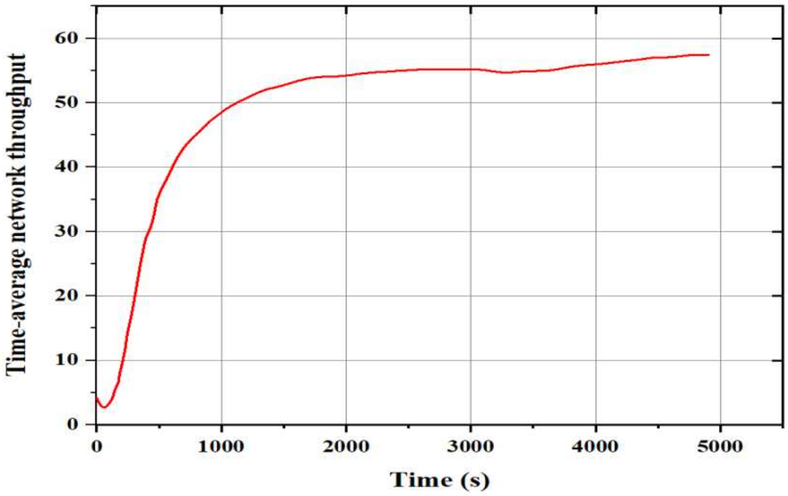

Figure 6: Time-averaged Network Throughput

Figure 6 shows the time-average network throughput F_T over time horizon T. The time average network throughput increased with more D2D pairs' throughput. It shows that the proposed algorithm effectively learns the power control and resources allocation reliably over time due to proper learning in selection of CUs and transmit power control for D2D users.

Conclusion

Reinforcement learning is a natural choice for a solution of scenarios that might seem impossible to automate. Reinforcement learning possesses the ability to learn solely through trial-and-error experience in an unknown system without need to expressly define and describe every unique facet and detail of that system. A novel deep reinforcement learning approach for the interference mitigation using Multi-Headed Individual Actor Critic (MHAIC) in D2D device through power control and resource allocation has been proposed in the current study. The network throughput was maximized while also ensuring QoS requirements of both D2D users and CUs were guaranteed under a dynamic environment. The proposed method also has an advantage of performing online, hence, real-time update was provided and better throughput achieved. Future works can focus on methods which can effectively accommodate more D2D devices while ensuring throughput is also maximized.

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SOCIAL ENGINEERING CYBER THREATS AND ATTACKS: A GROWING CONCERN AND CALL TO ACTION FOR ENGINEERS

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Abstract

The widespread of social engineering cyber threats and attacks caused by the Covid-19 pandemic was brought about by people having to work remotely without minding or checking the safety of their activities online. These cyber security threats and attacks are numerous and, on the increase, affecting individuals, businesses, and organizations. Social engineering based cyber threats and attacks are based on the use of psychological and systematic techniques to manipulate the target resulting in losses either financially or non-financially. The paper explores the concept of social engineering cyber threats and attacks with the aim of addressing phishing and its other forms used to track personal data like credit card numbers, bank accounts and other personal vital information of unsuspecting individual. It further explores the types and approaches and goals of social engineering. The social engineering based cyber solution considers research into cyber ethics and development to produce outcomes capable of instant incidence response in the case of unexpected and surprising cyber events. The paper seeks to emphasize the importance of ethics from an ethical perspective; compliance-based security which relies on regulations or standards to determine security implementation using training and awareness programs by relevant government agencies and other standard measures to mitigate social engineering cyber threats and attacks.

Keywords: *Social Engineering, Cyber-threat & attack, Phishing, Cyber Ethics, Mitigate.*

1.0 Introduction

Recently, the widespread and continued increase in social engineering attacks has a weakening effect in cyber security chain. It is used by hackers and cybercriminals to build strategies to deceive people to grant them access to system by by-passing security best practices and standards illegally or even without breaking the law. Social engineering can be defined as the act of manipulating human beings, most often with the use of psychological persuasion, to gain access to systems containing data, documents, and information that the social engineer should not have access to obtain (Mitnick & Simon, 2002; Tetri & Vuorinen, 2013; Heartfield & Loukas, 2015). It seeks to manipulate institutions and companies as well as individuals and try to disclose valuable and sensitive data for the benefit of cyber criminals (Kalniņš, R., J. Puriņš, and G. Alksnis, 2017). Various social engineering cyber-attacks are on the increase developing into a complex process due to the increasing use of technology in the world today cutting across every aspect of life. In fact, social engineering can be considered as one of the leading threats to information security today (Airehrour, Nair, & Madanian, 2018; Mitnick & Simon, 2002). It challenges network security regardless of the strength of its firewalls, intrusion detection systems, encryption methods and antivirus software systems (Salahdine, F. and N. Kaabouch, 2019). The social engineer performs their role as a fraudster, and making an effort to get access to computer networks, sensitive data, and information (K. Krombholz, H. Hobel, M. Huber, and E. Weippl, 2015). According to a CyberEdge (*CyberEdge Group, 2019*) report, "the number of