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An Improved Energy-Efficient Device-to-Device Communication in Overlaying Cellular Networks

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Abstract: This purpose of this paper is to design an energy efficient clustering protocol for device-device (D2D) in an overlay cellular networks. The protocol is also aimed at increasing the capacity of the cellular network. In order to achieve this, a clustering algorithm is proposed using a combination of Euclidean distance and the received signal to interference noise ratio for its design. These parameters are combined with Q-learning to define an energy efficient protocol for D2D communication. The protocol **C**lustering **A**lgorithm for **D**2D communication using **Re**inforcement **L**earning (CADREL) will reduce energy consumption in D2D communication in a co-located antenna system. It also improves the allocation of resources necessary for efficient data transmission as well as reduce the amount of data transmissions by intelligently electing cluster heads (CH) so as to minimize data collisions and enhance the lifetime of the network. A simulation experiment was conducted in order to compare the protocol with other state of the art clustering protocol using energy efficiency and channel capacity as the metrics. From the simulations carried out, it was observed that the proposed algorithm outperforms the other protocols by 23% and 34% respectively.

Keywords: Overlay, D2D communication co-located antenna system, clustering, cluster head, IoT

I.Introduction

D2D communication is an emerging technology that enables direct communication between two devices without the involvement of the Base Station (BS) or the evolved Node (eNB). This technology promises a lot of improvement over the cellular networks because (i) the small distance between D2D devices enables power saving as it doesn't need the long distance communication with the BS, (ii) reduced signal to interference noise ratio (SINR) because on non-existence of multi-path fading, path-loss and other communication impediments (iii) Improved energy efficiency as communication overhead is greatly reduced, (iv) increased throughput and (v) reduces delay. It can also reduce load on the conventional cellular network when many D2D communication occur without using the resources of the Base station.

The application of information and communication technology in Internet of Things (IoT) communication is helping in reducing global greenhouse gas emissions resulting from the communication of several millions of devices on the Internet. This is made possible by the reduction in the amount of data transmission that is done through careful and intelligent clustering of the devices on a global scale. Energy efficiency is of utmost importance in the transmission involving D2D communication. This is because of the memory and power constraint in their embedded systems used in data transmission. In this vein a multicast transmission instead of broadcast transmission has been used by researchers in the field of D2D communication in order to enhance the channel capacity [1], The use of D2D clustering algorithm will enhance the prospect of multicast communication in order to arrive at a better energy conservation technique. Researchers in literature has paid attention to the number of user equipment in a given cluster with respect to the size of the cluster. In these works it was verified that the use of D2D partitioning will result in reduction of average delay and transmission power required for data transmission as opposed to when flat topology is used [2],[3], [4]. It has also been confirmed that clustering of D2D network will lead to an increase in coverage area and channel capacity, (i.e. the ability of the network to admit more devices). However from these various researches there still exist the dearth of an efficient clustering algorithm that may lead to an optimal cluster size and optimum cellular capacity for D2D communication.

This paper proposes a protocol that is both energy efficient and capable of having optimum size for the cluster. The algorithm uses Q-learning to determine minimum energy requirement to aggregate data packet within the cluster while forwarding the aggregated data to the processing centre i.e. the co-located antenna. The contribution of this paper is in (i) determining the appropriate cluster size that will result in an energy efficient D2D communication, (ii) enhancing the capacity of the D2D network.

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The remaining part of this paper is organised as follows: section 2 outlines related works, section 3 presents the system model and the device power consumption and improved channel capacity algorithm, section 4 presents the simulation results and analysis while section 5 concludes the paper.

II. Related Works

THIS section presents works of researchers in the field of D2D communications. According to the works of [5], [6],[7], there are two types of D2D communication in a cellular network, these are out-band D2D and in-band D2D communication, this classification is based on whether frequency channels are shared or not shared with cellular networks. The D2D in-band underlying mode is that in which the D2D communication shares the spectrum and resources of the cellular network. The in-band overlay method occurs when the two devices involved in the D2D communication are directly connected to each other in which case they do not share the resources of the cellular network. In this mode data packets can be communicated directly between two or more devices separate from the cellular network. However the challenges which occur in the in-band communication is the need to completely eliminate communication interference with the cellular network, The out-band D2D communication uses unlicensed spectrum i.e. 2.4 GHz ISM band and the 38 GHz mm wave band while the cellular network uses its own dedicated licensed spectrum. The consequence of this is that there is no interference between D2D users and cellular users. The interference here occurs from other electronic wireless devices such as Bluetooth and Wi-Fi equipment operating in the same unlicensed band. The challenge in the out-band D2D communication is that the communication protocol required in controlling interference is complex.

According to the works of [8]), the results from the previously conducted work on the Quality of Service (QoS) on in-band communication shows that the possibility of intrusion on the cellular network spectrum from the unlicensed spectrum of the D2D network is of great concern for data throughput of the network [1]. Also from the analysis in the simulation experiments conducted by (He 2019), the D2D in-band communication does not have high resistance to interference from the cellular spectrum, this may lead to increased overhead in combating this problem. The shortcoming in their work is that no provision was made to address how data transmission from D2D network will transmit on the same channel been used by the cellular network. The approach used in the paper was to allocate specific resource to the competing network devices so that each network has specific mode of operation. The Qualcomm's FlashLinQ[9]project was the first implementation of the device to device (D2D) communication in cellular networks. These researchers employed the properties of (i) orthogonal frequency division multiple access in distributed scheduling for peer discovery, (ii) link management and (iii) synchronised timings to design a system capable of relieving some burden on the cellular network. In the work of [10], they designed a network that switches from cellular based network to D2D network. This they referred to as the next generation networks (NGNs). The main thrust of their work is on the optimal allocation of network resources by both the D2D users and the cellular network users. This they intend to achieve with the aid of sectored antennas at the base station. The contribution of this paper is to follow up on the work of this researchers by designing an energy efficient D2D network with co-located antennas at the base station using reinforcement learning. The aim here is to effectively serve the growing population of mobile networks users by optimally allocating the licensed frequency spectrum among the D2D users as well as that of the cellular network users, while also meeting the Quality of Service requirements of the network providers.

In the work of [11], an introductory study of D2D multicast clustering was provided with a predetermined number of D2D devices. Their work shows an improvement in data rate through cooperative multicast transmission for clustered D2D communication. Another work conducted by (Chen et al 2017), concentrated on reducing data transmission time in D2D communication. Their work presented an approach to mitigate against transmission failures by letting cluster heads (CHs) assist cluster members (CMs) in retransmitting the failed transmission [12] using game theory for collaborative communication among D2D clusters. A comprehensive study of D2D clustering was presented in [13] to determine the effect of varying data transfer rates on energy consumption. In the work of [14] they suggested that there will be an improvement in multicast performance through clustering. It was also shown that D2D multicast can yield better results when compared to non-cellular short-range technologies. An application of D2D communication which supports traffic safety in multi-hop architecture was designed in [15] to maximize transmission distance and minimize transmission delay. In [16] the transmission capacity and energy efficiency (EE) ofdevice-to-device (D2D) communication in co-located antenna system (CAS)was investigated. The researchers designed a clustering algorithm with a dedicated mode for communicating in a co-located antenna system. The shortcoming of their design is the use of separate protocol for the two parameters used in determining the cluster head among the UE. The use of a separate protocol leads to its complexity and longer duration necessary to elect the cluster head. This work is an improvement on the work of this researchers.

III.Methods/Experimentation

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The aim of this paper is to design an energy efficient Device-to-Device Communication in Overlaying Cellular Networks. This entails describing the network environment and the topology of the user equipment (UE), and designing an energy model for the system. The power consumption and the power model of the system is then derived. The subsections below describes the methods and experiments used in this paper.

3.1 Model of the System

A cellular communication system which consists of one omnidirectional BS positioned at the centre of a cell is shown in figure 1. It consists of L user equipment (UE) which are distributed randomly in the cells in the cluster. For easy analysis, the channels that are shared within the cells in the cluster are assumed to be orthogonal. This is to prevent interference among the UEs. It was also assumed that the BS has perfect channel state information (CSI) in which there will be no co-channel or adjacent channel interference. This enables the system to have proper schedule of resources which includes transmitted power and frequency spectrum.

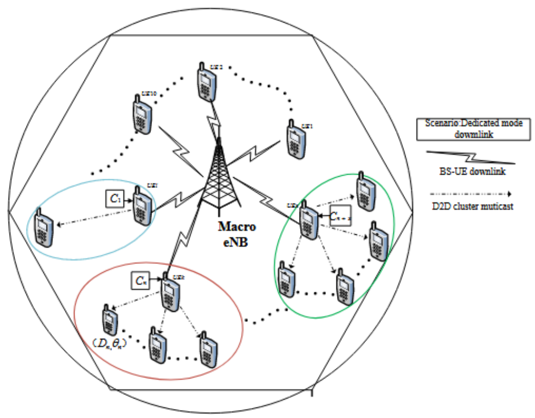

Figure 1. Model of the system

The total system bandwidth was denoted as BW, therefore the transmission rate of the L User Equipment for the downlink CAS can be given by equation 1

$$R_L^d = \frac{BW}{L} log_2(1 + \frac{P_L^d * h_{B,L}{}^2}{\sigma_L^2}) \qquad (1)$$

Where P_L^d represents the transmitted power of L User Equipment, in this model two channel disturbances of fast fading and shadowing are included as shown in [8], the gain in the channel power between the BS and user L is given by $h_{B,L}$ i.e. $c_0\zeta_{B,L}\beta_{B,L}d_{B,L}^{-\alpha}$and the gain in channel power between Cluster head (CH) L and cluster member (CM) M, as $c_0\zeta_{L,M}\beta_{L,M}d_{L,M}^{-\alpha}$ where c_0 and α denotes the path-loss constant and exponent respectively. $\zeta_{B,L}$ and $\beta_{M,M}$ are the gain due to fast fading with exponential distribution with slow fading gain and log-normal distribution respectively, while $d_{L,M}$denotes the distance between the transmitter L and the receiver M, σ represents the power of complex additive white Gaussian noise (AWGN). Therefore the average of the sum of the transmission rate of the co-located antenna system (CAS) is given by equation 2

$$R_{total}=\sum_{L=1}^{L} R_L^d \qquad (2)$$

From the equations given above, it can be seen that the total system capacity when the D2D cluster communication is added into the CAS is the sum of three components, The first component is a single user's capacity using the traditional cellular communication, the second component is the transmission capacity of the BS to the cluster heads. The transmission power of each cluster head is equal to the transmission power of the BS divided by the number of cluster heads, while the third and final component is the cluster head transmission capacity. Therefore the average capacity of the co-located antenna system which attaches with the D2D cluster can be given by equations

$$R_{BS-CH}^L = \frac{BW}{N} log_2(1 + \frac{\frac{P_t}{N} * h_{B,CH(L)}{}^2}{\sigma_N^2}) \qquad (3)$$

$$R_{CH-CM}^N = \frac{BW}{N} log_2(1 + \frac{\frac{D}{K} * h_{B,CH(CM(K))}{}^2}{\sigma_N^2}) \qquad (4)$$

$$R_{total\ D2D} = \sum_{L=1}^{U} R_L^d + \sum_{M=1}^{L} R_{Bs\ CH\ (L)}^{cluster} + \sum_{K=1}^{D} R_{CH\ CM(K)}^{cluster} \qquad (5)$$

Where U represents the number of users covered by the communication system, L represents the number of cluster heads, D represents the number of cluster members

3.2 Power Consumption Model

The energy model from two different models will be used in compliance with the work in [7, 8], the power consumption in our model comprises of three parts given by equation 6

$$P_{model} = \frac{P_{sum}}{\theta} + \gamma * P_{dy} + P_{st} \quad (6)$$

From the power model used in this paper, the first component θ represents the drain efficiency of the radio frequency of the power amplifier, The second part P_{dy} represents the dynamic powerconsumption of the signal component involved in the device transmission such as the frequency synthesizer, the filters and the mixers etc. this is of course independent ofthe actual ansmit power.The last part P_{st} is the static basic power consumption. This is independent of the numberof transmitter.

When the communication arising from the D2D communication is added to that of the co-located antenna system (CAS), the coefficient of P_{dy}isequal to numbers of transmitting antennas i.e. $\theta = \theta + 1$, otherwise it is equal to BS antenna number in CAS.i.e. $\theta = 1$. In idealistic scenario, only the first part of the model will be considered, thereby ignoring thedynamic and static power consumption components. Therefore in the ideal model the power consumption will be simplified to equation 7

$$P_{ideal} = \frac{P_{sum}}{\theta} \quad (7)$$

The transmission power P_{sum} of traditional CAS can be expressed as in equation 8

$$P_{sum} = \sum_{L=1}^{L} P_L^d \quad (8)$$

When the communication due to the D2D cluster is added, the transmitted power is given by equation 9.

$$P_{sum} = \sum_{L=1}^{U} P_L^d + \sum_{M=1}^{D} P_{CM}^{cluster} \quad (9)$$

From equation 8, $P_{CM}^{cluster}$ denotes the transmission power of the mth D2D cluster member i.e the sum of the transmission power of each cluster member is equal to the transmission power of the cluster head.

3.3 Energy Model

The energy consumption of a co-located antenna system is defined as the ratio of the sum of the transmission rate of its array of antennas divided by thetotal power consumption as shown in equation 10.

$$\vartheta_E = \frac{R_{sum}}{P_{sum}} \quad (10)$$

Where P_{sum} is the sum of the power transmission of the system. The total power consumption model is given by equation (6) under a reallife scenario, on the other hand, the model of an ideal system is given by equation (9).

3.4 Cluster Formation Algorithm

It has been established that the formation of D2D cluster is necessary for enhancing the performance of co-located antenna systems. This includes both increasing channel capacity as the direct communication between two UEs will remove some subscribers on the cellular network, thereby making it less congested. The reduced congestion also leads to less probability to data collision which ultimately results in reduced energy expenditure in the transmission of data packets.

In this paper we shall propose an algorithm which enable any user equipment within the co-located antenna system to form D2D clusters. The cluster formulation algorithm is modelled as an optimization problem comprising of two qualities of the D2D network. The first criteria is the distance of the UE from the co-located antenna system, while he second involves using the received signal to interference noise ratio from the Base station (BS).

This feature is achieved as follows: The cluster formed in the protocol is a variable size square cluster between 40 -60m. Each UE attempts to transmit its data packets directly to the BS in the network. In order to achieve this, a UE will either try to act as a cluster head or transmit its data packet to a better suited neighbour UE using the computation of the Q-value using equation 14 (to be defined later in this section). In the cluster-head routing scenario, every UE is an independent learning agent, and its actions includes energy efficient routing using different fit neighbours for the next hop toward the cluster-head. The cluster-head is defined as the node in the cluster with the best (lowest) routing cost to the sink. This cluster-head is elected based on the computation of Q-values described later in this section. The following provides the parameters used for the Q-learning clustering solution.

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The Q-learning model used in this paper consists of the following:

Agent states: This defines the states an agent (UEs) can be at any instance in time. This defines the location of the UE in the D2D network. For routing to the BS, the state of an agent is defined as a tuple {S_p, $routes_{S_p}^{N}$}, where S_p *is* the BS the packet must reach and $routes_{S_p}^{N}$ is the routing information about all fit neighbouring nodes N that will lead to the BS or the co-located antenna system..

Actions: This is the model of the transition from a state to the next available state. The WMN can take any of the following two actions, i.e. transit to a neighbour node with higher Q-values or elect itself as cluster head if it has higher Q-values than its neighbour..In the model, an action can include transmission of data packets to one or more different fit neighbours as next hops (as each node is expected to have more than one neighbour). The action is defined by *H*= (n_i, *S*) which defines a single fit neighbour n_i where i can be from 1 to 3 and the destinations *S* (Base station)indicating that neighbour $n_i$is the intended next hop for routing to destinations S. The value of action is as shown in equation 1

$$H = \left(\sum_S hops_S^{n_i}\right) \qquad (11)$$

where $hops_S^{n_i}$are the number of hops to reach the destination S using neighbour n_i, This translates to the transition equation shown in equation 2

$$E(s') = [p(s_{t+1}|\, s_t, A_s)] \qquad (12)$$

The number of alternate paths to the sink through a given neighbour node is given by equation 3

$$\sum_{s=1}^{k}[ps_{t+1}\,|s_{t,}A_s] \qquad (13)$$

where k is the number of neighbour nodes. In this paper, the upper bound for the number of neighbour nodes is three (3). The reason for this will be stated later in the section.

Q-Values. These represent the goodness of actions and the goal of the agent is to learn the *actual* goodness of the available actions. Here as opposed to the original Q-learning, which randomly initializes Q-Values, here Q-Values will be bound to represent the real cost of the routes, for example, in this paper the cost function is the combination of three parameters, the first criteria is the distance of the UE from the co-located antenna system, the second involves using the received signal to interference noise ratio from the Base station (BS) as defined in equation 14 while the third is the number of neighbour UE.

To initialize these values, a more sophisticated approach will be employed, which gives an estimate of the cost based on the individual information about the involved neighbours and sink (BS). This approach significantly speeds up the learning process and avoids oscillations of the Q-Values as is the case with most Q-learning model. The Q-value of an action is depicted by $Q(a_i)$ is as shown in equation 4

$$Q(a_i) = \left(\sum_S hops_S^{n_i}\right) + \lambda SINR(k) + \psi T \qquad (14)$$

where $hops_S^{n_i}$are the number of hops to reach a destination S using neighbour $n_i$or using itself and SINR(k) is the value of the signal to interference noise ratio of the Kth UE to the BS.

Equation 14 consists of three parts, the first part $(\sum_S hops_S^{n_i})$ of the equation accounts for energy efficiency, it defines the number of hops to reach the BS. In this model the first criteria in electing the CH is by comparing the number of hops of the UE to that of its neighbour, if the hop count is less than that of the neighbour, it elects itself as a cluster head, otherwise, it elects its neighbour as the cluster head. The minimum number of hops is selected after all neighbour paths to the sink have been computed, this results in minimizing data packet transmissions in the network. The second parameter is the selecting the UE with the highest signal to noise ratio. However a multiplier is combined with the SINR so that low value will be assigned to UE with high signal to interference noise ratio. The third parameter (T) consists of routing through UE with higher number of neighbour nodes as opposed to a node with just a single neighbour node. The importance of this is that routing through a WMN with higher number of neighbour node will improve transmission throughput as the alternative routes will enable alternate paths of transmission in the event of link or UE failure involving one of the neighbour nodes. In this paper, an upper limit has been placed on the number of neighbour nodes. The limit is set to three (3), this is important so as to limit the number of state-actions transitions that can be stored in the routing table. This is because an increase in the number of neighbour nodes to a UE leads to a polynomial increase in the state-actions, which lead to increase in delay.

These second and third elements of the equation are weighted with specific scalar values as explained in the next paragraph. The weighted values (WV) for each parameter grows exponentially with (i) decrease in the number of neighbour nodes and (ii) decrease in SINR. The consequence of this is that these parameters are weighted with different exponential functions. In the case

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of the number of neighbour nodes T, the exponential function ψ is $5^{(3-y)}$, where y is the number of neighbour nodes. The idea here is to fix the highest number of neighbour nodes attainable for a UE to three (3). This is necessary because an increase in the number of neighbour nodes increases polynomially the possible ways of routing data packets to the sink resulting in late convergence of the protocol in electing cluster heads. With this model, a UE having number of neighbours as three (3) will have the lowest weighted value of 1, i.e. 5^0. while the weighted value of a UE having one neighbour will be 25 (5^2). In the case of SINR, the weighted value function is given by $\lambda = 5^{\frac{50-t}{50}}$, where t depicts the value of the signal to interference noise ratio. It should be noted here that that range of the SINR used in the simulation is from 0 to 50dB, therefore a UE with SINR of 0dB will have the highest WV of 1 i.e. $5^{\frac{50-0}{50}}$, $5^1 = 5$ while a UE with speed of 50km/h will have the lowest weighted value of 1, i.e. $5^{\frac{50-50}{50}} = 5^0 = 1$ and a WMN with SINR of 35dB will have a weighted value of 1.62 i.e.$5^{\frac{50-35}{50}}$. = $5^{0.3}$= 1.62 This shows that the weighted value increase exponentially with a decrease in the signal to interference noise ratio. The reason why exponential function rather than a linear function was used is because the tendency here is to give high weighted value to parameters at the upper spectrum of the parameter range. This means that there will be a lower difference in weighted value (WV) for UE SINR of 50dB – 45dB than for SINR in the range 20dB – 15dB. In the first instance, the difference is (1.17 – 1) = 0.17, while in the second instance the difference is (3.09 - 2.63) = 0.46. The essence here is to make the WV skewed to the upper spectrum of the parameter value. This has the effect of electing UE in this upper spectrum in preference to those in the lower spectrum.

Q-Value Update. This denotes the reward values for each action taken in the environment for a particular state. In this case, after the BS sends the announcement control packet to the UEs in the network, each fit neighbour to which a data packet is forwarded sends the reward (Q-value) as feedback with its evaluation of the goodness to the sink. The new Q-Value of the action is as shown in equation 5

$Q_{new}(a_i) = Q_{old}(a_i) + \gamma(R(a_i) - Q_{old}(a_i))$ (15)

Where $R(a_i)$ is the immediate reward value and γis the learning rate of the algorithm. γ = 1 is used here because the initial Q-value represents an upper bound of actual value (i.e. maximum Q-values corresponds to UE with lowest energy as explained earlier in the section.This will be the initial Q-value to be used in the computation for the sink announcement to all UEs to reach selected destinations through all neighbours K and hence it is expected to reduce during learning. A lower learning rate (between 0 – 1) is usually used with randomly initialized Q-Values. This causes the Q-value to oscillate heavily in the beginning of the learning process. Therefore, with γ = 1, the formula is as shown in equation 16

$Q_{new}(a_i) = R(a_i)$ (16)

which directly updates the Q-Value with the reward.

Reward function. This is the downstream UEs (i.e. mobile nodes farther from the sinks) opportunity to inform the upstream neighbours of its actual cost for the requested action. Hence, when calculating this, the node selects its lowest (best) Q-Value for the destination node and adds the cost of the action itself. This is shown in **equation** 17**,**

$R(s,a_i) = c_{a_i} + \min_a(Q)(a)$(17)

where$c_{a_i}$is the action's cost, as shown in equation 18

$c_{a_i} = 1 + \lambda SINR(k) + \psi T$ (18)

This is because as the node transits to its neighbour, the downstream UE increment the hop count by 1 and subsequently update the action cost with the number of neighbour nodes and the SINR. The flowchart for the Q-value update procedure which is necessary for the election of cluster heads is shown in figure 2.

Policy (Model): The Q-learning model is then modified as shown in equation 19

$V(s) = \min[R(s,a_i) + \sum_{s' \in s} P(s'|s,a)V(s')]$ (19)

*w*here $R(s,a_i)$ is the current estimate i.e. current reward value, $V(s) = \min Q^*(a)$ i.e. the value function is the new estimate i.e the minimum Q-value of all routes (considering all alternate neighbour routes) starting from state (s) and action a to the destination, γ is the learning rate,γ = 1 here, hence it is omitted in the equation.

As said earlier, the first criteria used in the election of a cluster head from the UE is the distance of the UE from he co-located antenna system. In order to do this, we calculate the number of hops from the co-located antenna system to the farthest UE in the network. This is activated by the Base Station sending a sink announcement control packet to the nearest UE. As soon as this is done it increments the hop count by one. This process is repeated iteratively until the packet reaches the farthest UE from the

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Base station in which case there are no further neighbours down link. The next stage is the election of cluster heads by assigning the potential cluster head tag to those UEs whose number of hops from the co-located antenna is equal to or more than one-third the number of hops. These set of UE are combined with the second set of UEs where the received signal to interference noise ratio is used. Under the second criterion, a UE will be elected as a potential D2D cluster head if its SINR from the co-located antenna system is above a threshold value of 30dB. After which any UE having SINR < 20dB is included in the same cluster with the cluster head. The combination of these two criteria is used to elect the cluster heads while cluster members are joined to the cluster heads based on if their number of hops to the co-located antenna system is less or equal to one-fifth the number of hops in the D2D network. The pseudocode for this is shown in Figure 3

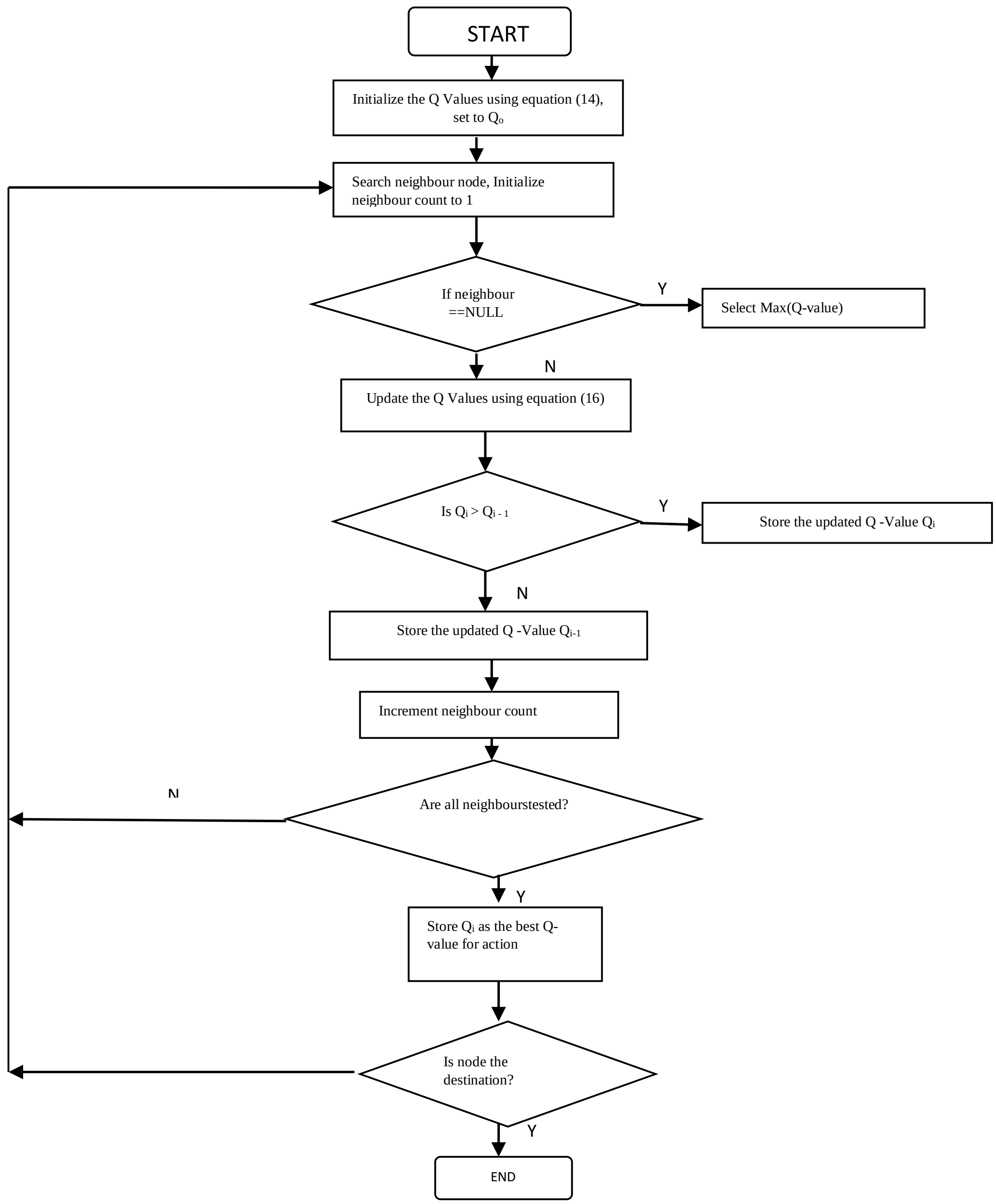

Figure 2 Flowchart Q-Value update procedure

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1: Initialization m UEs located randomly in the cell radius R,
user number t = 0, cluster number c = 0, user label tag1 = 0.

2: start_cost_procedure();

3: **send (DATA_REQ):**

4. // Compute number of hops of all UEs to BShop (m);
5. do (1)
6. for m =1 to m

7. incr_next_hop(loc.sinkBS,loc.nextUE)**;**

8. hop(m) = hop + 1;

9. ACK(data_packet p):

10. while next_UE != NULL

11 end do (1)

12. X = hop (m);

13 do (2)

14 for m = 1 to m

15. if hop (m) > X/3 , take m as the potential cluster head of UEs;

16. CH(j) = (m);

17. end do (2)
18. Compute SINR of all UEs to BS SINR(k);.

19. // formation of cluster head
20. do (3)
21. for k =1 to k – 1;

22. for m = k+ 1 to k
23. if SINR(m) + hop(m) >= 30dB + hop(k)

24. elect m as cluster head of UEs,

25 else elect m as cluster member

26 endif

27. end do (3)

Figure 3. Pseudocode of cluster formation based on distance from CAS and SINR

IV. Results And Discussions

In this section, results of the simulation experiments are provided to show the improvement of the **C**lustering **A**lgorithm on **D**2D network using **RE**inforcement**L**earning (CADREL). The parameters used in the simulation are listed in Table 1. The results of the simulation were calculated through 1200 iterations.

Table 1. Simulation Parameters.

Parameters	**Value**
The cellular radius R	1200m
Number of UEL	120
Size of bandwidth BW	1.5MHz
Path loss constant Co	0.015

Power of the noise μ_o^2	110dBm
Power consumption (dynamic) P_{dy}	22dBm
Power consumption P_{st}	32dBm
Maximum transmitted power P_t	5-50dBm
Path loss exponent λ	4
Efficiency of drain τ	40%

4.1. Result and Discussion of System Capacity

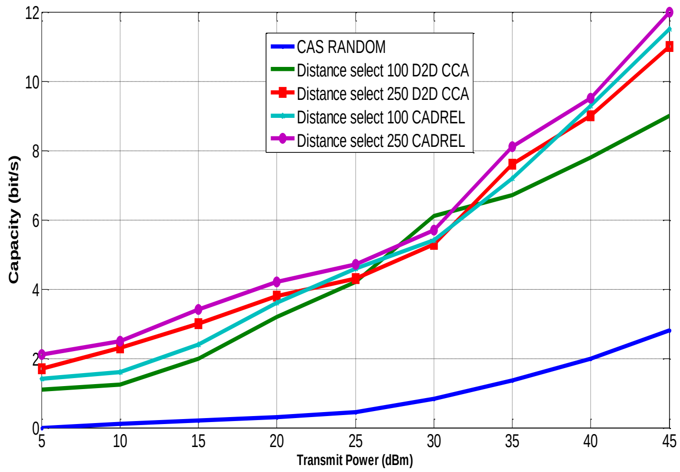

Fig 4 The BS transmitted power capacity

From the graph in figure 4 showing the total capacity achievable in the downlink (DL) cellular networks. It can be seen that the CADREL algorithm leads to considerable improvement over the compared protocols of cluster coalition algorithm (CCA) and the traditional cellularcommunications. From the figure, it can be seen that the CADREL algorithm outperforms the CCA algorithm by 12% and the Random CAS algorithm by 34%. This can be attributed to the intelligent resource allocation mechanism of the CADREL algorithm. It can also be seen that by increasing the distance between clusters, the capacity of the network is improved translating to higher bit rate due to lesser transmission in the network. This is due to reduced cluster numbers in the network as the size of cluster increase. This reduced cluster number will lead to lesser transmitted packets leading to reduced instances of collision.

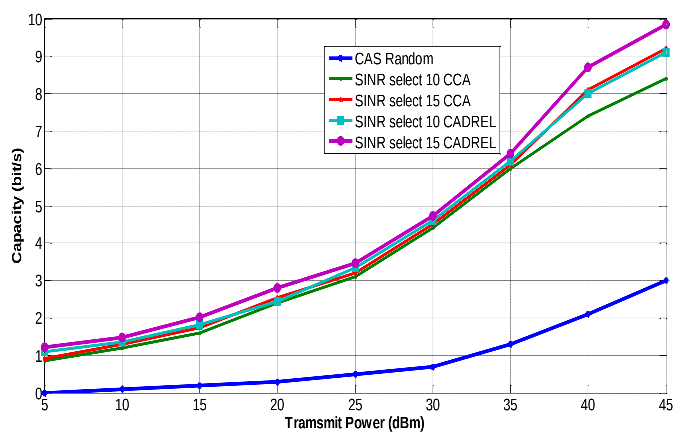

Figure 5. The BS Transmitted Power Capacity measured by SINR

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Figure 5 shows the transmission capacity for varying the transmitted power of the co-located antenna system. From the graph, it can be noticed that selecting more antenna for transmission to given cluster increases the transmission capacity. The proposed algorithm CADREL outperforms the CCA algorithm by 12% and the CAS random algorithm by 37%. The improvement of both CCA and CADREL algorithms over the CAS algorithm is due to the flexible selection of antenna distance from the clusters and the controlled signal to interference noise ratio rather than the random selection used in the CAS algorithm.

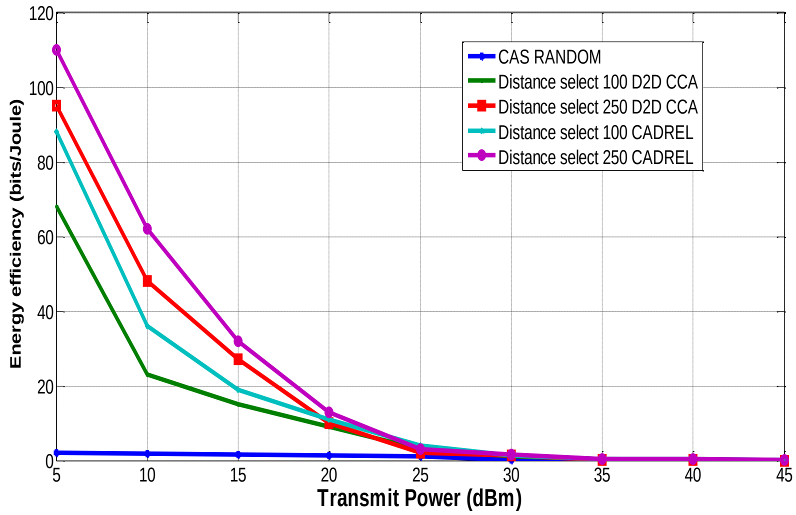

Figure 6. BS transmit power Vs Energy Efficiency in the energy model of distance factor

Figure 6 shows the energy consumption in the network for the downlink in relation to the transmit power of the co-located antenna system. From the graph it can be seen that the CADREL outperforms the CCS algorithm by 16% and the CAS random algorithm by 36%. The graph shows how the CADREL algorithm was able to improve the energy efficiency through intelligent resource allocation of the available channels in the spectrum. It can also be seen that energy efficiency in the system reduces with an increase in transmit power of the co-located antenna system.

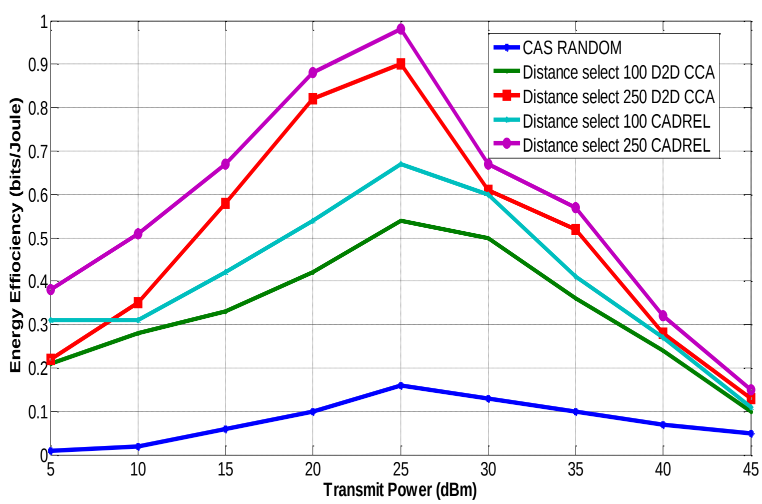

Figure 7. BS transmit power vs energy efficiency in the energy model of distance factor

Figure 7 shows the energy efficiency in relation to the transmit power of the co-located antenna system. It can be seen from the graph that the CADREL algorithm outperforms the CCS algorithm by 14% and the CAS random algorithm by 38% The reason for this is similar to that given in figure 5.

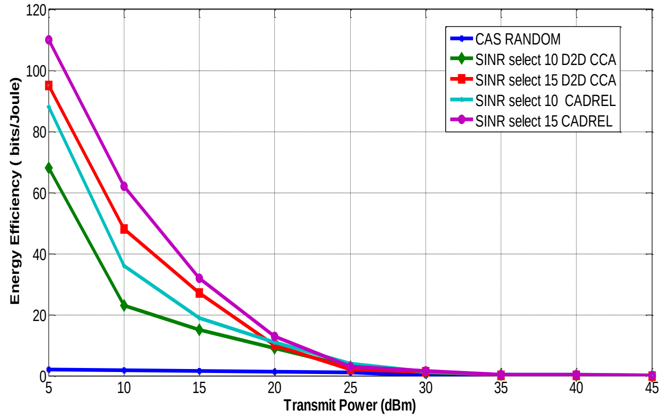

Figure 8. BS transmit power vs energy efficiency in the energy model of SINR factor

Figure 8 shows the energy efficiency in the system in relation to the transmitted power of the co-located antenna system. It can be seen that the energy of the system reduces with corresponding increase in transmit power at the BS. From the graph of figure 6 the CADREL algorithm outperforms the CCS algorithm by 12% and the CAS random algorithm by 32%.

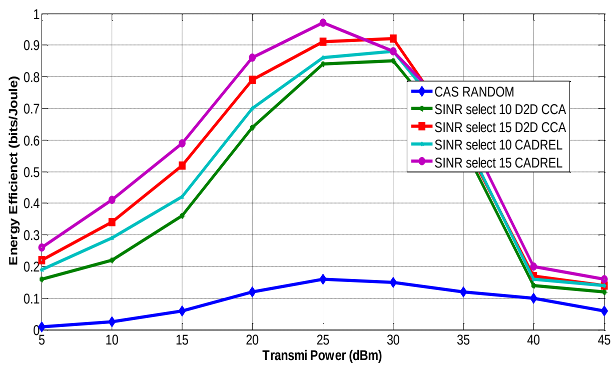

Figure 9. BS transmit power vs energy efficiency in the energy model of SINR factor

Figure 9 shows the average downlink energy consumption in relation to the transmitted power at the co-located antenna system (BS). From the graph in figure 7, the CADREL algorithm outperforms the CCS algorithm by 28% and the CAS random algorithm by 42%. It can also be seen that by slightly increasing the average energy in each cluster from 10 – 15 dB, the energy consumption was marginally reduced. This shows that a careful selection of the energy level in each cluster can lead to improvement in energy efficiency.

V. Conclusions

This paper proposed a reinforcement learning algorithm and in particular Q-learning in clustering of D2D communication involving co-located antenna system as the base station. Three parameters were used in formulating the Q-values, i.e. number of hops to the BS, number of neighbour nodes to the UE and the SINR. The results obtained through simulations shows a very promising prospect or the application of reinforcement learning in this scenario. In subsequent papers, this model will be scaled to more than one so that multi-hop routing will be obtainable n a cluster. This is hoped will further relieve the cellular network so that more resources will be available for increased capacity.

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Declarations

We the authors declare that the information contained in this paper is a result of our research findings and is a unique property.

Conflicting Interest

The authors are staff of Abia State University, Uturu,Abia State, Nigeria. They work together to unearth new frontiers in Electronic and communication engineering. They collaborate to foster their research interest and individual accomplishments.

Authors Contribution

The authors worked together for the successful completion of this work.

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