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Ant Colony Optimization-based Resource Allocation and Resource Sharing Scheme for V2V Communication

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The innovative architecture of Device-to-Device (D2D) underlying LTE/LTE-A networks is brought up to enable efficient discovery and communication between proximate devices. However, enabling D2D communications in a cellular network poses a major challenge that Quality of Service (QoS) requirements of D2D communications need to be guaranteed. Thus, synchronization between devices becomes a necessity and Radio Resource Management (RRM) becomes a key design aspect to enable D2D communication, where resource allocation phase is one of the most critical aspects. The problem of resource allocation in D2D communication system is a combinatorial optimization issue, difficult to obtain optimum solutions in polynomial time. In order to reduce complexity, it can be solved by using linear algorithms or by metaheuristic methods. In this paper an Ant Colony Optimization (ACO) based resource allocation and resource sharing scheme for Vehicle-to-Vehicle (V2V) based D2D communications in LTE-A networks is introduced. The swarm intelligence algorithm ACO, which is a typical algorithm of metaheuristic methods, is adopted to resolve the optimization problem of maximizing the network sum rate while considering the QoS requirements.

Keywords: V2V communication, radio resource allocation, sharing, ACO, QoS

1. INTRODUCTION

Internet of Things (IoT) is an integrated element of future internet containing existing and evolving network and Internet progress [1]. Conceptually, it could be defined as a global dynamic network infrastructure with self-management and self-configuration capabilities based on interoperable and standard communication protocols [2]. Device-to-Device (D2D) communication, introduced in Release 12 [3] to enable direct communications between devices, is an intrinsic part of the IoT. With D2D, devices autonomously communicate with each other, allowing spatial resource reuse that can cause significant performance improvements. LTE Release 14 [4] is thus expanding the concept of cellular network to specifically address Vehicle-to-Vehicle (V2V) and, in general, Vehicle-to-everything (V2X) communications [5]. In order to meet the increased requirements for D2D data services, the Radio Resource Management (RRM) plays a crucial role in handling limited radio resources to improve system's data rate and to ensure Quality of Service (QoS) provisioning [6]. LTE RRM introduced in the Third Generation

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Partnership Project (3GPP) TS 36.300 [7] includes a wide variety of procedures and techniques, such as packet scheduling and resource allocation. One of the main openly debated issues in LTE-V2V is the resource allocation. Several resource allocation mechanisms for V2V have been introduced in the literature where the efficient utilization of radio resources is fundamental to achieve the system performance targets and to ensure the QoS requirements. Authors in [8] aim maximize the overall network sum rate while guaranteeing the QoS requirements for both D2D users and Cellular Users (C-UEs). For this purpose, a sophisticated three stage resource allocation and power control algorithm was proposed. In [9], a heuristic algorithm has been developed where reliability and latency requirements of V2V links have been formulated into optimization constraints using only large-scale fading information. Likewise, authors in [10] proposed a two-step resource allocation and power control algorithm for V2V communication considering the QoS requirements of both vehicular users (V-UEs) and C-UEs. In [11], a proximity and load-aware resource allocation algorithm for V2V communication under slowly varying channel information is proposed, exploiting the spatio-temporal traffic patterns in terms of vehicles' physical proximity and service delay. Authors in [12] also adopt the strategy of location-based resource allocation for V2V communication. They proposed a resource allocation algorithm allocating resources based on the position, speed, direction, and density of vehicles, where two physically close Users Equipment (UEs) can directly communicate with each other. Three promising gains can thus be realized via resources sharing; reuse, hop, and proximity gains [13]. In [14], multiple Resource Block (RBs) are allowed to be shared not only between one V-UE and one C-UE but also among different vehicular users. In [15], the authors designed a centralized resource allocation strategy based on the position of the vehicles inside a single cell. Firstly, the proposed approach defines a spatial resource reuse strategy. Secondly, authors proposed two resource allocation schemes for both C-UEs and V-UEs. In [16], an Ant Colony Optimization (ACO) based resource allocation algorithm is proposed for C-UEs and V-UEs where two sets of RBs are adaptively assigned to each type of users.

In this paper, we propose an ACO based system model for resource allocation and resource sharing to maximize the overall network sum rate while satisfying the QoS requirements of users. The proposed algorithm consists of two main phases: resource allocation phase and resource sharing phase. In the first phase, the algorithm assigns RBs to C-UE based on user's outage probability and fairness index. In the second phase, it selects the suitable V-UE partner to each pair (C-UE, RB) to share the same resource, based on the interference link gain from the V-UE to the C-UE on this RB. This paper is organized as follows. Section 2 describes the proposed scheduling algorithm. Section 3 presents the simulation results and performance analysis. Finally, section 4 concludes this paper.

2. SYSTEM MODEL AND ALGORITHM DESCRIPTION

In this section, an ACO-based system model for the resource allocation between C-UEs and V-UEs is proposed to maximize the overall network sum rate under the constraint of satisfying the QoS requirements of both V-UEs and C-UEs.

2.1 Ant Colony Optimization

ACO is a typical algorithm of swarm intelligence which has become a new research hotspot. Its main idea is inspired from the behavior of seeking out food by colonies of ants [17]. Ants use a volatile chemical substance, called pheromone, a kind of biochemical smell, which is left behind them. Other ants are attracted by these pheromones and always follow the direction with the highest concentration of pheromone. Ants communicate with each other through pheromones. Their typical task is to look for the shortest path in a given graph. To each edge of the graph a certain preliminary pheromone value is assigned representing the desirability for choosing this edge. One single ant builds a complete path by choosing one edge after another according to the following equation:

$$p_{i,j}^{m} = \frac{[\tau_{i,j}]^{\alpha}[\eta_{i,j}]^{\beta}}{\sum_{l \in M_i^m}[\tau_{i,l}]^{\alpha}[\eta_{i,l}]^{\beta}}. \tag{1}$$

Eq. (1) describes the probability for selecting edge ij when starting from node i. $\tau_{i,j}$ is the pheromone value, $\eta_{i,j}$ is the heuristic information indicating the attractiveness of the move, and M refers to the neighborhood of node i. α and β are weighting parameters used to adjust the influence of heuristic information and pheromone. ACO is based on three phases: the pheromone evaporation, the update of local pheromone, and the update of global pheromone on the best path. The evaporation of the local pheromone is given as:

$$\tau_{i,j} = (1 - \rho)\,\tau_{i,j}. \tag{2}$$

Where $0 < \rho < 1$ is a parameter controlling the local pheromone evaporation. The ρ role is to make the system converge to a good solution by forgetting the bad routes. After building a complete path, pheromone values must be updated. Each ant deposits pheromone on the path it went through as follows:

$$\tau_{i,j} = \tau_{i,j} + \tau_0, \tag{3}$$

where τ_0 is the initial value of local pheromone. When all the ants have traversed all the edges, only the ant that generated the best path is allowed to update the concentration of pheromone on the edges, and the global pheromone is updated according to:

$$\tau_{i,j} = \tau_{i,j} + \Delta\tau_{i,j}^{best}. \tag{4}$$

Where $\Delta\tau_{i,j}^{best}$ indicates the pheromone on the best path.

2.2 ACO-based Resource Allocation

In this section, we introduce a resource allocation technique that can fulfill the QoS requirements for all users by prioritizing users with the lowest rate of outage probability and the best fairness index.

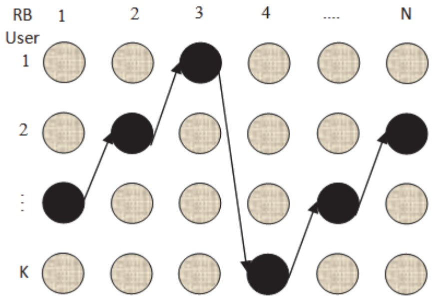

Fig. 1. ACO graph for RBs allocation.

In the proposed algorithm, each cell maintains a graphic for the ACO algorithm and ants choose users for the current RB with a certain probability. The chosen routes are saved in a matrix, as shown in Fig. 1. When node is chosen more times, more guidelines information will be offered and ants would like to select it next time.

The probability that RB n is allocated to user k is calculated according to Eq. (1), where the pair of nodes (i, j) is replaced by the pair of user and RB (k, n). This probability is calculated as follows:

$$p_{k,n}^{m} = \frac{[\tau_{k,n}]^{\alpha}[\eta_{k,n}]^{\beta}}{\sum_{l\in M_n^m}[\tau_{l,n}]^{\alpha}[\eta_{l,n}]^{\beta}}. \tag{5}$$

Where M_n^m represents the set of available users to select for ant m on RB n, which can be updated after each selection of a user. Recall that when an ant constructs a solution, each local pheromone is updated according to Eq. (3). After acquiring all solutions, the system evaluates, under different judge functions, the quality of the solutions and updates the corresponding pheromone. In the proposed algorithm, the heuristic information of user k on RB n is measured in terms of the number of bits that can be transmitted. The higher the transmission rate of user k on the RB n, the higher is the probability for the user to be allocated. This information is calculated as follows:

$$\eta_{k,n} = \delta \log_2(1+\gamma_{k,n}). \tag{6}$$

Where δ is the number of symbols per RB and $\gamma_{k,n}$ is the instantaneous Signal to Interference and Noise Ratio (SINR) of user k on RB n. $\gamma_{k,n}$ is calculated as follows:

$$\gamma_{k.n} = \frac{P_{k,n}H_{k,n}}{N_0 + \sum_{k'\in K/k}P_{k',n}H_{k',n}}. \tag{7}$$

Where $P_{k,n}$ and $H_{k,n}$ are the transmission power and the channel gain, respectively, of user k over RB n. N_0 represents the noise spectral density. The interference term in the denominator represents the aggregate interference at user k caused by the transmissions of other users $k'\in K\setminus\{k\}$ on same RB n.

The outage probability of users is an important metric that can improve the network QoS, so it is necessary to consider it in order to meet the users' communication quality requirements. The outage probability is defined as the probability that the immediate mutual information of the channel is under the transmitted code rate [18]. Thus, for N_k RBs allocated to user k, its outage probability (*i.e.* the probability that M_k error-free bits cannot be transmitted by any coding scheme) is defined as follows:

$$p_k^{out} = \Pr\left\{\sum_{n=1}^{N_k} \delta \log_2(1+\gamma_{k,n}) < M_k\right\}. \tag{8}$$

Where $\gamma_{k,n}$ is calculated according to Eq. (7) and M_k is the required number of bits of user k. Since our optimization problem is to maximize the network sum rate, we aim to maximize $\sum_{n=1}^{N_k} \delta \log_2(1+\gamma_{k,n})$ for all N_k RBs allocated to user k.

We define the judge function of users as the tradeoff between the outage probability and the fairness information of the user, User Fairness Index (UFI) [19, 20]. UFI is based on the throughput and it is calculated for each user in the cell as follows:

$$UFI_k = T_k / T_k^{req}. \tag{9}$$

Where T_k and T_k^{req} are the throughput and the throughput required by user k, respectively. Then, the judge function is defined as follows:

$$f_k = \mu * (1 - P_k^{out}) + (1-\mu) * UFI_k. \tag{10}$$

Where μ is a weighting parameter used to modulate the contribution of $(1 - P_k^{out})$ and UFI_k. Therefore, after acquiring all solutions, the user with the best tradeoff between the outage probability and the fairness index, has the best allocation. Note that the global pheromone is updated according to Eq. (4). Fig. 2 gives the flow chart of the proposed allocation algorithm.

ACO-based resource allocation algorithm

{Inputs}
$K_c \leftarrow$ Number of C-UEs;
$N \leftarrow$ Number of RBs;
$\Delta\tau_{k,n}^{best} \leftarrow$ The pheromone on the best path
Set_C-UE = {C-UE$_1$, C-UE$_2$, …, C-UE$_{Kc}$}
Set_RB = {RB$_1$, RB$_2$, …, RB$_N$}
$\tau_0 = 1$; % initial value of pheromone
$\alpha = 3$; $\beta = 1$; $\mu = 0.5$; % weighting parameters
$\rho = 0.1$; % parameter controlling the local pheromone evaporation
{Main}
Calculate $\eta(k_c, n)$, with $(k_c, n) \in$ Set_C-UE * Set_RB
Calculate $P(k_c, n)$, with $(k_c, n) \in$ Set_C-UE * Set_RB
Find $(k_c, n) = \max P(k_c, n)$, with $(k_c, n) \in$ Set_C-UE * Set_RB
Assign RB$_n$ to C-UE$_{kc}$
Update Set of RBs: Set_RB = Set_RB \ {n}
Update $\tau_{kc,n}$: $\tau_{kc,n} = \tau_{kc,n} + \tau_0$, with $n \in N_{kc}$
Update $\tau_{kc,n}$: $\tau_{kc,n} = \tau_{kc,n} - \rho\tau_{kc,n}$, with $n \in N_{kc}$

Calculate the judge function of C-UE$_{kc}$
Find(k_c) = max judge function(k_c), with $k_c \in$ Set_C-UE
Update $\tau_{k_c,n}$: $\tau_{k_c,n} = \tau_{k_c,n} + \Delta\tau_{k_c,n}{}^{best}$, with $n \in N_{k_c}$

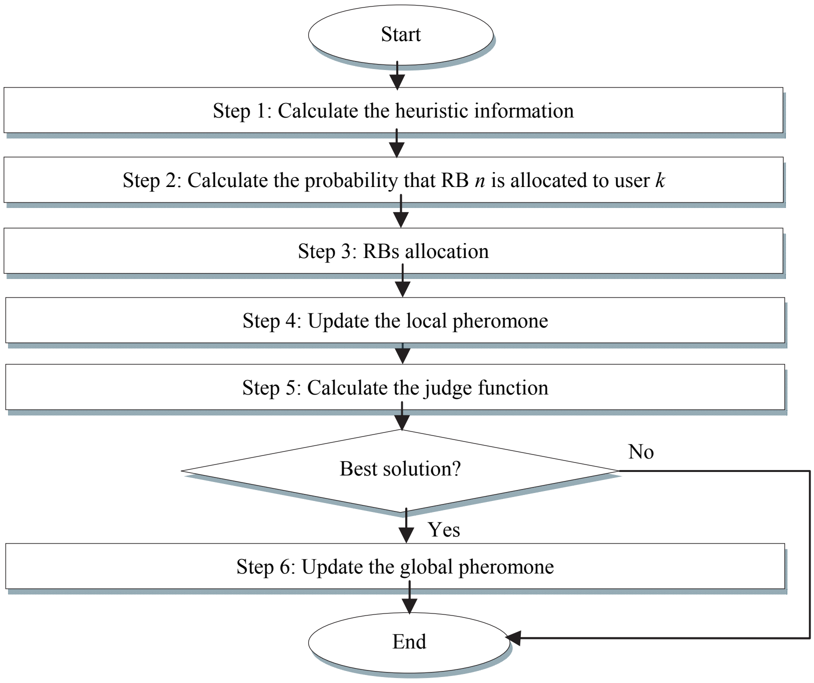

Fig. 2. Flow chart of the proposed algorithm.

2.3 Radio Resources Sharing

The sharing of resources between cellular and V2V connections is determined by the eNodeB so they are assumed capable of choosing the best resource sharing scheme for V2V and cellular connections. Three resource allocation modes are considered.

– Orthogonal sharing mode: V2V communication uses dedicated resources *i.e.*, V2V communication gets part of the resources and leaves the remaining part of resources to the C-UEs,
– Non-orthogonal sharing mode: both V2V and cellular traffics use the same resources,
– Cellular mode: V2V users communicate with each other via the BS that acts as a relay node.

Although orthogonal RBs sharing eases the task of interference management, better resource utilization may be attained by non-orthogonal RBs sharing. So, each V-UE can share the same RB with exactly one C-UE, and vice versa. In the proposed resources sharing algorithm, an ACO graphic is generated where ants choose users for sharing the same RB with a certain probability.

	$C\text{-}UE_1$	$C\text{-}UE_2$	…	$C\text{-}UE_c$
$V\text{-}UE_1$	$P_{1,1}$	$P_{1,2}$		$P_{1,c}$
$V\text{-}UE_2$	$P_{2,1}$	$P_{2,2}$		$P_{2,c}$
⋮				
$V\text{-}UE_v$	$P_{v,1}$	$P_{v,2}$		$P_{Kv,Kc}$

Fig. 3. ACO graph for RBs sharing.

The probability that V-UE k_v shares the same RB with the C-UE k_c is:

$$p^m_{k_v,k_c,n} = \frac{[\tau_{k_v,n}]^\alpha [\eta_{k_v,k_c,n}]^\beta}{\sum_{l \in M^m_{k_v}} [\tau_{k_v,n}]^\alpha [\eta_{k_v,l,n}]^\beta}. \tag{11}$$

Where $M^m_{k_v}$ represents the set of available C-UEs to select for ant m on V-UE k_v.

The heuristic value $\eta_{k_v,k_c,n}$ of users k_v and k_c on RB n is measured in terms of the aggregate interference at C-UE k_c caused by the transmission of V-UEs k_v on the RB n. So, the k_vth V-UE can share the nth RB with the k_cth C-UE only if the SINR $\gamma_{k_v,n}$ is higher than a defined SINR threshold ($SINR_{TH}$) as shown in Eq. (12):

$$\eta_{k_v,k_c,n} = \begin{cases} \gamma_{k_v,n} & \text{if } (\gamma_{k_v,n} \geq SINR_{TH}) \\ 0 & \text{else} \end{cases}. \tag{12}$$

$\gamma_{k_v,n}$ is calculated according to Eq. (7), where $k' = k_c$. The lower the interference the higher is the probability for the RB n to be shared between k_c and k_v. The probability of sharing an RB between a V-UE and a C-UE is calculated according to the heuristic and the pheromone values. In the heuristic information, we have considered the interference to fulfill the users' QoS requirements. In the global pheromone update, we consider the number of bits that can be transmitted by the V-UE on this RB in order to improve the network sum rate. Thus, the judge function is measured in terms of the number of bits that can be transmitted calculated in Eq. (6). After acquiring all solutions, the V-UE and C-UE pair with the lowest interference and best transmission capacity on an RB, has the best resource sharing, and the global pheromone is updated according to Eq. (4).

ACO-based resource sharing algorithm

{Inputs}
$K_c \leftarrow$ Number of C-UEs;
$K_v \leftarrow$ Number of V-UEs;
$N \leftarrow$ Number of RBs;
$\Delta\tau_{k_v,k_c,n}{}^{best} \leftarrow$ The pheromone on the best path
Set_C-UE = {C-UE$_1$, C-UE$_2$, …, C-UE$_{K_c}$}
Set_V-UE = {V-UE$_1$, V-UE$_2$, …, V-UE$_{K_v}$}
Set_RB = {RB$_1$, RB$_2$, …, RB$_N$}
$\tau_0 = 1$; % initial value of pheromone
$\alpha = 3$; $\beta = 1$; $\mu = 0.5$; % weighting parameters
$\rho = 0.1$; % parameter controlling the local pheromone evaporation
{Main}
Calculate η(k_v, k_c, n), with (k_v, k_c, n) ∈ Set_V-UE* Set_C-UE* Set_RB
Calculate P(k_v, k_c, n), with (k_v, k_c, n) ∈ Set_V-UE* Set_C-UE* Set_RB
Find (k_v, k_c, n) = max P(k_v, k_c, n), with (k_v, k_c, n) ∈ Set_V-UE* Set_C-UE* Set_RB

Share RB_n between C-UE_{k_c} and V-UE_{k_v}
Update Set of RBs: Set_RB = Set_RB \ $\{n\}$
Update $\tau_{k_v,k_c,n}$: $\tau_{k_v,k_c,n} = \tau_{k_v,k_c,n} + \tau_0$, with $n \in N_{k_c}$ and $n \in N_{k_v}$
Update $\tau_{k_v,k_c,n}$: $\tau_{k_v,k_c,n} = \tau_{k_v,k_c,n} - \rho\tau_{k_v,k_c,n}$, with $n \in N_{k_c}$ and $n \in N_{k_v}$
Find(k_v) = max judge function(k_v), with $k_v \in$ Set_V-UE
Update $\tau_{k_v,n}$: $\tau_{k_v,n} = \tau_{k_v,n} + \Delta\tau_{k_v,n}^{best}$, with $n \in N_{k_v}$

3. PERFORMANCE EVALUATION

In this section, we present the simulation results of our proposed resource allocation algorithm as well as the two resource allocation algorithms: position-based resource allocation [12] and location dependent resource allocation [15]. The position-based resource allocation algorithm allocates different time and frequency resources based on vehicle position, speed, direction, and density. The location dependent resource allocation defines a spatial resource reuse strategy to reuses the available resources, by separating between C-UEs and V-UEs using the same resources. Simulations were performed using a multi-user and multi-cell MATLAB simulator based on LTE-A network [21]. It implements the transmission in both downlink and uplink and supports both C-UEs and V-UEs. We consider a simulation model composed of a total number of C-UEs and V-UEs users varying between 100 and 500 where the number of V-UEs is 50% of the total number of users. C-UEs have random positions and random distribution inside the sector and V-UEs move in freeway scenario, the users' locations should be updated every 100ms during the simulation. The simulation parameters are presented in Table 1. The use cases implemented in vehicular traffic are presented in Table 2.

Table 1. Simulation parameters.

Parameter	Value
Cell Radius	1.5 km
Number of eNodeB	1
Carrier frequency	2 GHz
System bandwidth	5 MHz
Number of RBs	25 RBs
Traffic model for CUEs	VoIP, Video, and FTP
VoIP packet generation interval	20 ms
Video packet generation interval = Video delay threshold	100 ms
FTP packet generation interval	10 ms
Video delay threshold	150 ms
FTP delay threshold	300 ms
C-UEs speed	between 5 and 150 (km/hr)
V-UEs speed	between 30 and 150 (km/hr)
Maximum UEs transmit power	23 dBm
Total Number of V-UEs/C-UEs	100 -500
Simulation length	5000 TTI
TTI length	1 ms
Scheduling/Allocation resource	Per TTI
$SINR_{TH}$	10 dB

Table 2. Use cases of V2V services [22].

V2V service scenarios	Description	Maximum latency	Message size
Emergency Vehicle Warning	This service enables each vehicle to acquire the speed, location, and direction information of a surrounding emergency vehicle.	50 ms	50-300 Bytes
Emergency Stop	This service describes V2V communication used in case of emergency stop.	50 ms	50-300 Bytes
Pre-crash Sensing Warning	This service provides warnings to vehicles in imminent and unavoidable collision.	20 ms	50-300 Bytes

Figs. 4 and 5 respectively depict the influence of ACO parameters α and β. The choice of these parameters will indeed affect the performance of the proposed scheme. We note that when we increase β (*i.e.* the heuristic information influence) on the detriment of α, the network sum rate of C-UEs increases while the fairness index of C-UEs decreases. As shown in Figs. 4 and 5, when taking different values of α and β for C-UEs, the margin between the two curves is more important in the fairness index comparing with that the sum rate. Thus, we deduce that selecting $\alpha = 3$ and $\beta = 1$ provides the best tradeoff network sum rate/fairness index. Moreover, we also notice that increasing α improves considerably the network sum rate of V-UEs. Decreasing β does not imply that more C-UE RBs will suffer from interference caused by V-UEs. Furthermore, increasing β has a negligible importance as we always select the V-UE with condition (SINR > $SINR_{TH}$).

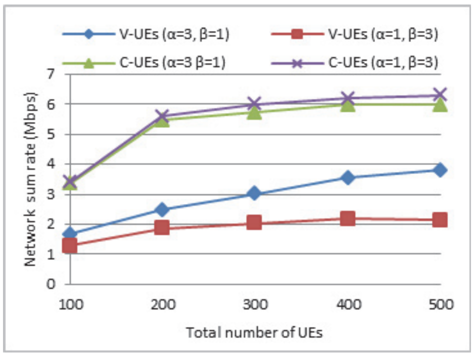

Fig. 4. Network sum rate in ACO-based resource allocation algorithm.

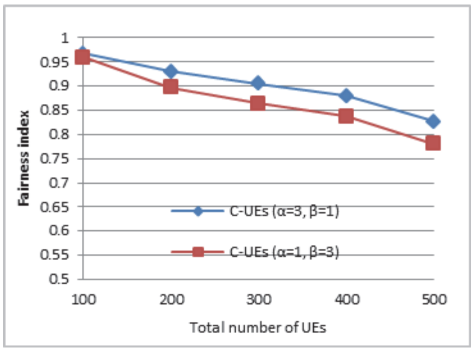

Fig. 5. Fairness index in ACO-based resource allocation algorithm.

Figs. 6 and 7 show the average user throughput of C-UEs and V-UEs inside the cell, respectively. Our algorithm reaches the best sum rate as it considers the channel state of both C-UEs and V-UEs. It utilizes efficiently the radio resource since it calculates the heuristic information based on the number of bits that can be transmitted. The higher the transmission rate of the user on the RB, the higher is the probability for the user to be allocated. As well in the judge function of C-UEs, user with the lowest outage probability has the best allocation. As expected, the position-based resource allocation provides the worst sum rate as it assigns statically a number of RBs to each set of UEs. Also, it does not implement the resource sharing between UEs.

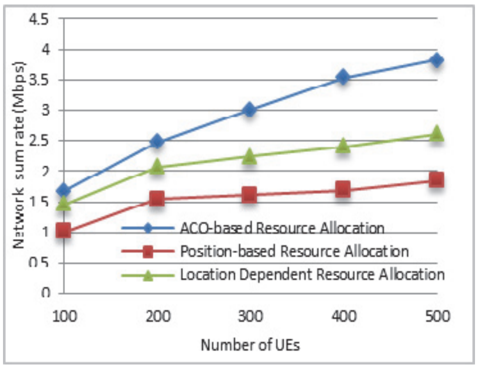

Fig. 6. Network sum rate of V-UEs.

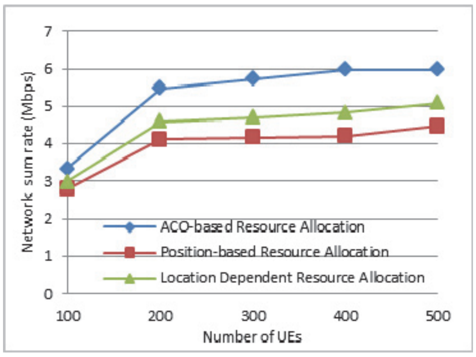

Fig. 7. Network sum rate of C-UEs.

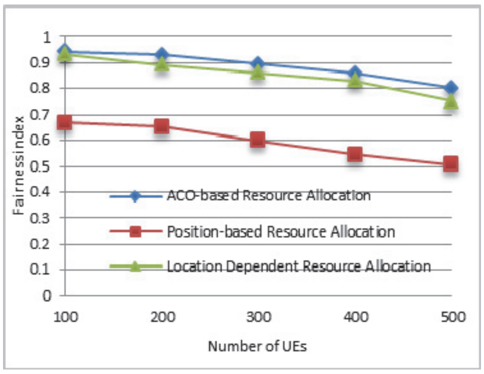

Fig. 8. Fairness index of V-UEs.

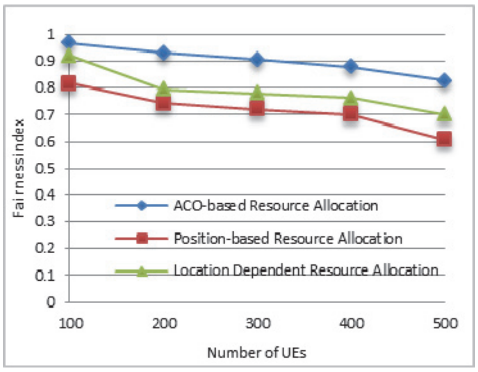

Fig. 9. Fairness index of C-UEs.

As shown in Figs. 8 and 9, the proposed algorithm gives the best fairness rates. The resources allocation process is triggered according to the channel state of all users in the network. It does not depend only on the previous state of the channel. In order to avoid discrimination between users with poor or strong channel quality, it considers all the variation in the channel state by using the global pheromone which brings more fairness.

In D2D communication, to assign a static number of RBs to each type of traffic or spatial area yields to a spectrum resource waste. As well, better resource utilization in the network may be reached by non-orthogonal RBs sharing. The proposed algorithm allocates RBs in adaptive way and implements the non-orthogonal RBs sharing. Thus, according to Fig. 10, the performance of our algorithm in terms of resource utilization ratio is the best. As well, according to Fig. 11, our proposed algorithm achieves the best PDR rate. In the one hand, the smart management of the BRs decreases the PDR rate. In the other hand, the high rate of outage probability may increase the PDR rate while our proposed algorithm assigns RBs to C-UEs with lowest outage probability.

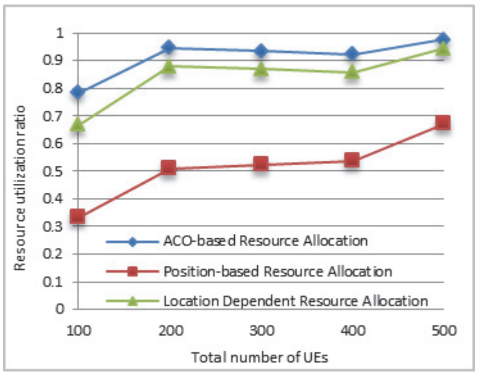

Fig. 10. Resource utilisation ratio.

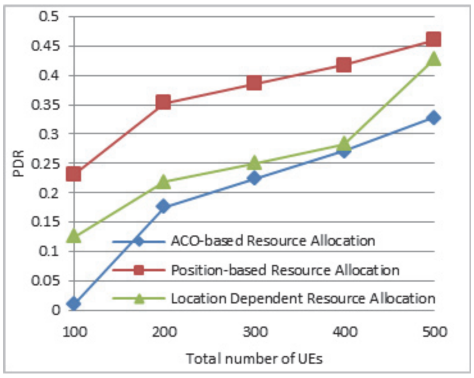

Fig. 11. Packet drop rate of UEs.

4. CONCLUSION

Maximizing the network sum rate is a target feature of resource allocation strategies. However, there are other important QoS requirements that must be considered. A trade-off between performance and QoS requirements when implementing resource allocation in wireless networks is a challenge. In this paper, an ACO-based system model for resource allocation between C-UEs and V-UEs was proposed to maximize the overall network sum rate under the constraint of satisfying the QoS requirements of both V-UEs and C-UEs. Using mathematical constraints, the resource allocation process has been formulated as an optimization problem, taking into consideration the requirements of both C-UEs and V-UEs and allowing them to share the same resources. The ACO is used in this algorithm to resolve this optimization problem.

The proposed algorithm is compared with other resource allocation algorithms from the literature. Simulation results indicate that our approach has significant performance gain. It yields not only better cellular and vehicular sum rates as well as fairness performance, but also improves PDR compared to the considered existing schemes. Furthermore, when analysing the runtime complexity of our algorithm as compared with other resource allocation algorithms, we found that our runtime complexity is much lower and thus optimized dueprimarily to the pheromone behaviour. In fact, the use of pheromone narrows considerably the search space for optimal solution by taking into account the optimal made allocations in the previous TTIs.

REFERENCES

1. S. Trabelsi, A. Belghith, F. Zarai, and M. S. Obaidat, "Performance evaluation of a decoupled-level with QoS aware downlink scheduling algorithm for LTE networks," in *Proceedings of International Conference on Internet of Things*, 2015, pp. 696-704.
2. B. Dorsemaine *et al.*, "Internet of Things: A definition & taxonomy," in *Proceedings of International Conference on Next Generation Mobile Applications*, *Services and Technologies*, 2015, pp. 72-77.
3. 3GPP TS V0.1.4, "Overview of 3GPP Release 12," 2014.

4. "Wireless technology evolution towards 5G: 3GPP release 13 to release 15 and beyond," white paper, 5G Americas, 2017.
5. S. H. Sun *et al.*, "Support for vehicle-to-everything services based on LTE," *IEEE Wireless Communications*, Vol. 23, 2016, pp. 4-8.
6. S. Feki, F. Zarai, and A. Belghith, "A Q-learning-based scheduler technique for LTE and LTE-advanced network," in *Proceedings of International Joint Conference on e-Business and Telecommunications*, 2017, pp. 27-35.
7. 3GPP TS 36.300, "Evolved UTRA and evolved UTRAN, overall description," 2008.
8. D. Feng, *et al.*, "Device-to-device communications underlaying cellular networks," *IEEE Transactions on Communications*, Vol. 61, 2013, pp. 3541-3551.
9. W. Sun, *et al.*, "Radio resource management for D2D-based V2V communication," *IEEE Transactions on Vehicular Technology*, Vol. 65, 2016, pp. 6636-6650.
10. W. Sun, *et al.*, "D2D-based V2V communications with latency and reliability constraints," in *Proceedings of IEEE Globecom Workshops*, 2014, pp. 1414-1419.
11. M. Ashraf, M. Bennis, C. Perfecto, and W. Saad, "Dynamic proximity-aware resource allocation in vehicle-to-vehicle (V2V) communications," in *Proceedings of the Globecom Workshops*, 2016, pp. 1-6.
12. J. Kim, J. Lee, S. Moon, and I. Hwang, "A position-based resource allocation scheme for V2V communication," *Wireless Personal Communications*, Springer US, 2017, pp. 1-18.
13. G. Fodor, *et al.*, "Design aspects of network assisted device-to-device communications," *IEEE Transactions on Communication Magazine*, Vol. 50, 2012, pp. 170-177.
14. W. Sun, D. Yuan, E. G. Strom, and F. Brannstrom, "Cluster-based radio resource management for D2Dsupported safety-critical V2X communications," *IEEE Transaction on Wireless Communication*, Vol. 15, 2016, pp. 2756-2769.
15. M. Botsov, M. Klugel, W. Kellerer, and P. Fertl, "Location dependent resource allocation for mobile device-to-device communications," in *Proceedings of IEEE Wireless Communications and Networking Conference*, 2014, pp. 1679-1684.
16. S. Feki, *et al.*, "Swarm intelligence-based radio resource management for D2D-based V2V communication," *International Journal of Communication Systems*, 2018, pp. 1-16.
17. S. Goss, S. Aron, J.-L. Deneubourg, and J. M. Pasteels, "Self-organized shortcuts in the argentine ant," *Naturwissenschaften*, Vol. 76, 1989, pp. 579-581.
18. G. Caire, G. Taricco, and E. Biglieri, "Optimum power control over fading channels," *IEEE Transactions on Information Theory*, Vol. 45, 1999, pp. 1468-1489.
19. A. Belghith, M. B. Mohamed, and M. S. Obaidat, "Efficient bandwidth call admission control in 3GPP LTE networks," in *Proceedings of IEEE Global Communication Conference*, 2016, pp. 1-6.
20. S. Feki and F. Zarai, "Cell performance-optimization scheduling algorithm using reinforcement learning for LTE-A network," in *Proceedings of IEEE International Conference on Computer Systems and Applications*, 2017, pp. 1075-1081.
21. A. Belghith, W. B. ElMabrouk, and S. Trabelsi, "Performance evaluation of mixed traffic scheduling algorithm in LTE," in *Proceedings of IEEE International Symposium on Network Computing and Applications*, 2015, pp. 43-46.
22. 3GPP TR 23.785 V14.0.0, "Study on architecture enhancements for LTE support of V2X services (Release 14)," September 2016.

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