

RESEARCH ARTICLE

Resource Management in LADNs Supporting 5G V2X Communications

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ABSTRACT Local access data networks (LADNs) are promising paradigms for reducing latency, decreasing energy consumption, and improving the quality of service (QoS) of fifth-generation (5G) radio access networks (RANs) that support vehicle-to-everything (V2X) communications. Remote radio heads (RRHs) that support V2X applications can be turned on or off depending on traffic demand to achieve optimal resource management and save energy by minimizing the activation of LADN servers in cloud-RANs (C-RANs). In this study, we investigated the problem of how to manage resources optimally in LADN while guaranteeing V2X QoS requirements. We formulated the resource allocation problem as an optimization problem to reduce the number of active RRHs subject to uplink bandwidth constraints. We calculated intercell interference (ICI) and uplink signal-to-interference-plus-noise ratio (SINR) to appropriately assign vehicles to RRHs. We solved the resource management problem by using an optimal algorithm and proposed heuristic algorithms to address the complexity of large-scale scenarios. The numerical results demonstrated that our model could efficiently utilize resources and provide optimal associations between vehicles and RRHs, thereby leading to energy savings. In particular, optimal associations could save up to 70% of energy in a scenario consisting of hundreds of vehicles. The computation time for a small-sized problem was approximately 60 ms, which means that the proposed model can be suitable for real-time control. Even on a large scale, the running time for a scenario with thousands of vehicles is still short. Therefore, the impact of vehicles' density is not harmful to the scalability of the whole approach.

INDEX TERMS 5G, local access data network (LADN), optimization, resource management, vehicle-to-everything (V2X) communications.

I. INTRODUCTION

The fifth-generation (5G) radio access networks (RANs) are expected to provide ultra-high data rate connectivity of user equipment (UE) with ultra-low latency. The third-generation partnership project (3GPP) specifies service requirements to enhance the quality of service (QoS) of 5G RANs in supporting vehicle-to-everything (V2X) scenarios that include vehicle platooning, remote driving, automated cooperative driving, collective perception of the environment, and collision avoidance [1].

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V2X communications enable information sharing and exchanging between a vehicle and any entity that may affect its functionality. Hence, vehicles can cooperate with other vehicles, pedestrians, devices, networks, and infrastructures. The goal is to improve road safety by reducing vehicular accidents using safety messages [2]. The society of automotive engineers (SAE) defines safety messages as basic safety messages (BSMs) that contain information about the vehicle's state which includes location, speed, acceleration, and direction. BSMs regularly sent ten times a second to enable V2X applications [3].

V2X communications also enhance the efficiency of traffic flows by using effective route planning and guidance.

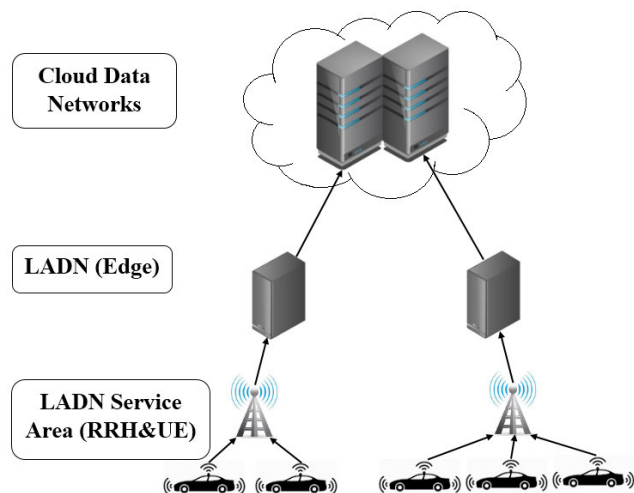


FIGURE 1. Overview of the architecture of LADN.

3GPP identifies four types of V2X communications: vehicle-to-network (V2N), vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), and vehicle-to-infrastructure (V2I), where infrastructure elements are, e.g., road-side units (RSUs) or traffic lights. The four types of V2X applications provide intelligent services to end users. These services encompass real-time traffic and routing, collision avoidance, traffic signal timing, priority, and safety alerts [4].

Local access data network (LADN) is a promising paradigm for providing high-efficiency V2X communications and meeting 5G V2X service requirements [1], i.e., the maximum latency should be 10 - 25 ms, and the minimum availability should be 90%–99.99%. LADN reduces latency, minimizes energy consumption, and improves the QoS for 5G networks. It achieves these service requirements by pushing the computing and networking services into proximity of UEs. LADN is defined as a multi-access edge computing (MAEC) paradigm that provides a distributed computing environment that brings network capabilities closer to UE, which leads to deploying services with minimum delays [5].

Fig. 1 illustrates an overview of LADN, where LADN is deployed near the edge and close to the UEs, while the UEs are located at the LADN service area. Furthermore, 5G new base stations (gNBs) are located at the network edge, RSUs are deployed closer to the UEs, and remote radio heads (RRHs) are identical to the remote antennas of RSUs.

Resource management is considered a challenge that plays a central role in minimizing the activation of LADN servers in Cloud-RAN (C-RAN), saving energy, and executing tasks that need ultra-low latency requirements [6]. In 5G RAN supporting V2X applications, the problem which affects the network functionality is how to efficiently allocate the available radio resources, i.e., resource blocks (RBs), in LADN [7]. Various tasks required by V2X applications have different resource requirements, including communication resources for task transmission [8]. Tasks completion of V2X applications can be realized as locally computed,

offloaded to neighboring vehicles, or offloaded to LADN. Task offloading depends on task data size, vehicle mobility, and latency [9].

RRHs could be turned off or activated subject to the traffic demand to optimize resource management and save energy [10]. To manage the resource efficiently, assignments between UEs and RRHs should be proper concerning inter-cell interference (ICI) and signal-to-interference-plus-noise ratio (SINR) management. The interference results not only from LADN but also from other terminals of the cellular network (e.g., other network slices) and could lead to performance degradation in the vehicular environment. ICI management plays a role in ensuring satisfactory link quality. SINR values determine the channel quality indicator (CQI) used to build a mapping table that associates UEs with RRHs. Optimal associations between UE and RRH produce less traffic in vehicular networks leading to a minimized number of active RRHs and optimized resource management.

In this work, we investigate the problem of how to perform an effective resource allocation in LADN to optimize resource utilization and save energy while guaranteeing the QoS requirements for V2X communications represented by uplink data rates, SINR values, and available uplink RBs. We focus on the resource management problem in V2X communications by analytically calculating the ICI and uplink SINR to minimize energy consumption subject to uplink bandwidth constraints. We propose a mathematical formulation of the resource management problem as an optimization problem with an objective function to reduce the number of active RRHs.

In particular, given the number of RRHs and vehicles, we need to determine the optimal assignments between vehicles and RRHs, and the state of specific RRHs to minimize the number of activated RRHs while satisfying the constraints on the number of RBs and data rates. We formulate the optimization problem as a 0-1 integer linear programming (ILP) problem. Then, we use the CPLEX suite [11] to solve our ILP problem and evaluate the proposed model. Moreover, to deal with the complexity of large scenarios (hundreds of RRHs and thousands of vehicles), we present solutions with heuristic algorithms [12] that produce near-optimal solutions without the guarantee of finding the optimal ones. Since our optimization problem is structurally matching the bin packing problem,¹ known to be \mathcal{NP} -complete, we apply the following heuristic algorithms: First-Fit (FF), Best-Fit (BF), First-Fit-Decreasing (FFD), and Best-Fit-Decreasing (BFD). The main contributions of this paper are summarized as follows:

- 1) We investigate the problem of how to realize effective resource management in 5G RAN supporting V2X communications and formulate it as an optimization problem to minimize the number of turned-on RRHs subject to uplink bandwidth constraints.

¹Where we have items with various volumes and the goal is to assign those items into a minimum number of bins of limited capacities.

- 2) We use the CPLEX suite to obtain optimal solutions to our resource allocation problem for small and medium scenarios. We suggest solutions with heuristic algorithms to deal with the complexity of large-scale optimization problems.
- 3) We confront the proposed heuristic algorithms using the theory of a fully polynomial time approximation scheme (FPTAS) class. We also compare our proposed algorithms with two meta-heuristic algorithms, particle swarm optimization (PSO) and genetic algorithm (GA), concerning the number of activated RRHs and computation time.
- 4) We compare optimal vs. strongest-signal vehicle associations and optimal vs. heuristic solutions to assess our proposed model by analyzing energy consumption. The results imply that our proposed model can efficiently allocate resources and save energy while guaranteeing the QoS requirements.
- 5) We analyze the impact of the required data rate and the density of vehicles on the number of active RRHs. We examine the effect of vehicle density on the computation time of optimal and heuristic solutions.

This paper is extended from an earlier version presented in IEEE 92nd VTC 2020-Fall [13], with extensions on SINR constraint, heuristic algorithms evaluation, and scalability analysis. The main differences are as follows:

- 1) The number of symbols is changed to 14 to realize 5G subcarriers. New obtained values of RB data rates and required RBs.
- 2) SINR's constraint is added to make the mathematical model practical and efficient.
- 3) New obtained optimal and heuristic solutions.
- 4) Evaluation of the proposed heuristic algorithms using FPTAS class and implementing PSO and GA algorithms.

The remainder of this paper is organized as follows. Section II summarizes the related studies on resource allocation for 5G V2X communications. Section III describes the configuration of the system model, including an example of V2X network topology. In Section IV we present the calculations of SINR, ICI, and required RBs, formulate the optimization problem, and propose the heuristic algorithms. The numerical results are presented in Section V. Conclusions are drawn in Section VI, and future work is pointed out therein.

II. RELATED WORK

Numerous research papers examined the resource allocation problem for 5G V2X communications and vehicular networks. Table 1 summarizes the objectives, constraints, decisions, and solutions covered in the references in this section.

In [14], the authors proposed two novel algorithms, the least delete (LD) algorithm, and the largest-first rounding with capacity constraints (LFRCC) algorithm, to achieve energy saving by minimizing the number of turned-on RRHs

while meeting the data requirement of vehicles and the available capacity of RRHs. LD algorithm efficiently allocated the resources and had a lower computation complexity than the LFRCC algorithm, which derived solutions closer to the optimal ones. The authors of [15] minimized the required number of RRHs in C-RAN while guaranteeing the QoS of each user by proposing a low-complexity algorithm based on the successive elimination of RRHs and simultaneously solving the optimal deployment problem. They adopted an abstraction of the average traffic demand in a small area, referred to as a traffic demand node (TDN). The authors of [16] conducted a resource allocation to maximize the sum ergodic capacity of V2X communication links while guaranteeing the latency constraint expressed by the latency violation probability. They decomposed the spectrum and power allocation problem into two sub-problems to obtain a global optimum solution in polynomial time. In [17], the authors investigated a modified switching cost model to jointly optimize a switching on/off strategy and user association policy with the consideration of the user's QoS, intended to maximize the energy efficiency (EE) of dense cellular networks with partial base stations (BSs). They proposed a two-step sub-optimal algorithm to optimize BSs' working states and user association policy. Authors of [18] introduced an approach to power allocation with EE optimization in a cellular device-to-device-based V2X communication network. The optimization problem is simplified to a power allocation problem by exploiting Lagrangian dual method and solved using a three-loop iterative algorithm.

The work of [19] aimed to investigate a joint spectrum sharing and power allocation scheme for a heterogeneous vehicular environment. These authors formulated a low-complexity resource allocation problem to maximize the sum rate of both cellular and vehicular UEs for a V2X communications scenario while guaranteeing a fair coexistence among all UEs. In [20], the authors proposed a two-stage scheme of centralized resource allocation and distributed power control to meet the requirement of the new radio (NR) V2X mode 1. They employed the non-orthogonal multiple access (NOMA) technologies in vehicle groups. The novel approach maximized the system capacity and minimized the power consumption of the 5G vehicular network. They proposed a graph-based matching approach to allocate the resources for the centralized method and a non-cooperative game to control the power of vehicle groups for the distributed one. The authors of [21] introduced a novel resource allocation strategy based on Cloud-V2X communications to enhance the reliability and latency of vehicular networks. The resource allocation problem is formulated as an optimization problem to minimize the overall latency by allocating the radio resource to the vehicular network.

The work in [22] proposed maximizing the EE of ultra-dense networks by optimizing the user association and small-cell BS on/off strategies. The optimization problem is formulated as a non-convex nonlinear programming problem and then decomposed into two sub-problems and resolved

individually as a user association strategy and a small-cell BS on/off strategy. In [23], the authors proposed a multi-level algorithm to solve the coordinated scheduling and power control optimization problem and improve the EE in C-RAN. The objective is to maximize the EE subject to constraints that provide full-frequency reuse among RRHs. The RRHs would be switched off or on according to the distribution of the users. The authors of [24] proposed the notion of a virtual BS formed by allocating virtualized network resources and formulated the energy-efficient optimization problem using an ILP to minimize the total energy consumption in C-RAN. They proposed novel energy-saving schemes for the network planning and traffic engineering stages, with a solution algorithm that minimized the number of active baseband process units (BBUs). The work in [25] formulated a joint computation and ultra-reliable and low-latency communication (URLLC) resource allocation strategy for MEC-based V2X communications, considering the significance of reliability and delay in vehicular networks. The authors formulated a joint power consumption optimization problem to reduce inter-cell interference and maximize the throughput while satisfying reliability and network stability. In [26], the authors proposed a BS switching and sleep mode optimization method intending to minimize the power consumption in wireless networks while ensuring that the arriving user traffic is sufficiently covered. They used the long-short-term memory (LSTM) prediction model and solved the Lyapunov optimization problem to obtain the optimal BS switching solution. The work in [27] formulated the energy-saving problem of BSs in cellular networks as a minimum energy cost problem. The authors developed the minimum cost flow algorithm to solve the optimization problem by choosing which BSs to be active during a period. They proposed a scheme in two steps to minimize the total energy cost of BSs: minimizing the energy cost of all BSs in a time unit independently without considering the cost of switching BS on/off and the switching cost of the state transitions for BSs over the entire period.

Although numerous studies have investigated the resource management problem in vehicular networks, the resource assignment between UEs and RRHs based on ICI and SINR has not been addressed extensively. These concern the calculations of ICI and uplink SINR since the management of ICI and SINR leads to optimal associations between vehicles and RRHs produces less traffic in the vehicular network and minimizes the number of active RRHs. These lead to optimized resource management. For example, although [15] and [23] proposed efficient resource management solutions, the work in [15] did not consider the interference from other RRHs, and the adopted abstraction could not precisely represent the traffic demands of users which led to failure in ensuring the QoS requirements of all TDNs. The work in [23] did not consider a constraint on the available capacity of the RRH. In addition, the proposed algorithm indicates all assignments, which might lead to immense

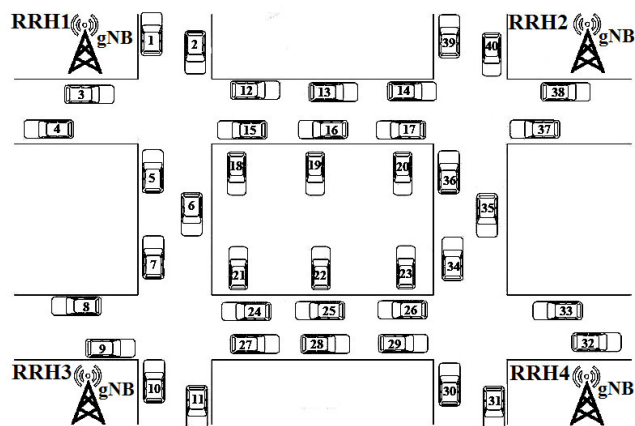


FIGURE 2. A small example of V2X network topology.

computational complexity when considering a large-scale scenario. Furthermore, previous works did not consider the QoS guarantee of all UEs in the optimization objectives. Only the work in [14] considers the allocation problem in the V2X environment, as this work does.

The differences between our work and [14] are in the interference model and the QoS requirement of each vehicle. Our work differs from [14] by finding the optimal solutions while guaranteeing the data rates of vehicles. Therefore, the main differences are summarized as follows: (1) We analytically calculate the values of ICI and uplink SINR. (2) We formulate the resource management problem as an optimization problem to minimize energy consumption. (3) We determine the optimal associations between UEs and RRHs according to the values of ICI and SINR. (4) We minimize the number of active RRHs subject to uplink bandwidth constraints represented by ICI and SINR.

III. SYSTEM MODEL

We consider a V2X computing infrastructure consisting of sets of UEs and gNBs, where the gNB is the 3GPP 5G next-generation BS which provides new radio communication capabilities towards the UEs. V2X computing infrastructure is C-RAN-based and constituted by densely deployed RRHs connected to a pool of BBUs, whereas the BBU provides signal processing, and RRH provides radio frequency processing. LADN can be deployed near the gNBs to execute the communication offloaded tasks, whereas the uplink traffic is sent to RRHs. To achieve optimal resource management and save energy, RRH, and its corresponding BBU can be turned on or off depending on the uplink traffic and under the constraint of uplink bandwidth requirement.

In our model of the system under study, as shown in Fig. 2, we consider a network topology consisting of LADN, RRHs (co-located with gNBs in crossroads), and vehicles (presented on a regular grid of streets). These vehicles need to send sensor information to LADN so that a local digital map can be constructed, which implies that the uplink traffic (i.e., the communication offloading) is offloaded to

TABLE 1. Comparison of research publications.

Lit.	Objectives	Constraints	Decisions	Solutions
[14]	Min. number of activated RRHs	RRH capacity and vehicle requirement	Vehicle-to-RRH associations and RRH turn-on	LD and LFRCC algorithms
[15]	Min. number of required RRHs	Network capacity	RRH deployment	Based on successive elimination of RRHs
[16]	Max. sum ergodic capacity	Spectrum reuse and latency	Latency violation probability	Decomposition into: power and spectrum allocations
[17]	Max. EE	BS capacity	BS state and user-to-BS association	Energy saving, two distance and QoS first maximum EE strategies
[18]	Max. EE	SINR threshold and energy harvesting target	Resource reuse and power allocation	Lagrangian dual method and three-loop iterative algorithm
[19]	Max. throughput	SINR	Allocation indicators and transmit powers	Kuhn-Munkres and Gale-Shapley algorithms
[20]	Max. network capacity and Min. power consumption	Transmission power and rate	RB and power allocation	Graph-based matching algorithm
[21]	Min. latency	SINR and latency	V2V links and latency reduction	Greedy link selection algorithm
[22]	Max. EE	SINR and load balancing	User-to-BS association and BS states (on/off)	User association and BS on/off strategies
[23]	Max. EE	Frequency reuse between RRHs	RRH turn-on and user assignment	Sub-optimal solution through heuristic algorithm
[24]	Min. number of active BBUs	Bandwidth	BBU and transceiver states (active or not)	Load balancing for overloaded BBU
[25]	Min. energy consumption	Transmission power and task stability	User-to-RB allocation and transmit power	Online Lyapunov method and game theory
[26]	Min. energy consumption	User QoS and queue stability	BS states and user traffic	Lyapunov optimization and long-short term memory prediction
[27]	Min. energy consumption	BS capacity and transmission power	BS switching on/off and UE-to-BS association	Minimum cost flow algorithm
Our work	Min. energy consumption	SINR, RRH capacity and guaranteed uplink data rate	Vehicle-to-RRH associations and RRH turn-on	Optimal solutions and Heuristic algorithms

RRH. In this model, we skipped modeling the mobility and considered snapshots of vehicles' positions. We neglect the influence of ICI by assuming a perfect orthogonal frequency-division multiplexing (OFDM) reception. The interference specified in this model occurred due to the cellular nature of LADN being a virtual part of a cellular network. So, the interference could happen from other terminals that belong to the vehicular environment and not necessarily being a part of LADN (e.g., other network slices).

In our model, we focused on turning the RRH on or off without specifying the energy model within the RRH

(e.g., energy consumption due to the use of RBs or energy consumption at BBU), which is not of the central concern, so the energy consumption occurs only when the RRH is turned-on. In particular, we investigate a scenario consisting of a set of RRHs ($n = 1, 2, \dots, N$) and a set of vehicles ($v = 1, 2, \dots, V$). Each RRH n has a number of available RBs per time slot, denoted by MRB_n . Each vehicle v , if it is associated with RRH n , will require several RBs per time slot for sending sensing data, denoted by $R_{n,v}$. The required RBs depend on SINR values and uplink data rates.

Table 2 summarizes the mathematical notations used in this paper.

TABLE 2. Mathematical notations used throughout the paper.

Symbol	Meaning
P_v	Transmission power of vehicle v
$d_{n,v}$	Distance between vehicle v and RRH n
α	Attenuation factor: calculated from the COST 231-Hata Model [28]
N_{OC}	Power spectral density of white noise source
I_{sum}	Aggregated uplink ICI representing interference power level of RRHs
I_i	Mean value of uplink ICI for RRH i
C	RRH coverage (in kilometers)
r	Distance from transmitter to receiver (in kilometers)
θ	Vehicle's angle to direct line connecting target RRH to interfering RRH
N	The number of RRHs
V	The number of vehicles
MRB_n	Available uplink RBs per time slot for RRH n
$R_{n,v}$	Required RBs per time slot for sending data
H	Threshold value for $SINR_{n,v}$
UL_DR_v	Required uplink data rate of vehicle v
x_n	Decision variable to turn on/off the RRH n
y_n^v	Decision variable indicating whether vehicle v is associated with RRH n or not

IV. PROBLEM FORMULATION

Given the number of RRHs with available uplink RBs and the number of vehicles with required RBs for sending data to RRHs, we need to decide whether to turn the RRHs on or off and determine the optimal associations of vehicles with RRHs. Our goal aims at reducing the number of turned-on RRHs depending on the required tasks and subject to the uplink bandwidth constraints exemplified by ICI and SINR.

SINR can be expressed as the signal power divided by the noise power plus the interference power of other signals in the network. SINR can be calculated from the transmission power of the vehicle and the interference power level of other interfering RRHs in the network. SINR values for the uplink transmission can be obtained as

$$SINR_{n,v} = \frac{P_v d_{n,v}^{-\alpha}}{N_{OC} + I_{sum}}, \quad (1)$$

where P_v is the transmission power of the vehicle v , $d_{n,v}$ is the distance between the vehicle v and the center of RRH n , α is the attenuation factor, i.e., the path loss, and calculated from COST 231-Hata Model [28], N_{OC} is the power spectral density of a white noise source, and I_{sum} is the aggregated uplink ICI.

Assuming that the network model is loaded fully with traffic, the usage of omnidirectional antennas, and the regular coverage pattern occurs, we could approximate the uplink ICI from the RRH n with a log-normal distribution by analytically determining the statistical parameters [29]. Therefore, the

aggregated uplink ICI, I_{sum} , is approximated with another log-normal distribution and calculated according to

$$I_{sum} = \sum_{i=1, i \neq n}^N I_i, \quad (2)$$

where I_i is the mean value of the uplink ICI of the interfering RRH i and for each RRH, only a single interference source is considered since only one vehicle is scheduled per RB. I_i is computed as²

$$I_i = \int_0^1 \int_0^{2\pi} \frac{P_v C^{-(\alpha+1)} r^{\alpha+1}}{\pi(\sqrt{r^2 + 4 + 4r \cos \theta})^\alpha} dr d\theta, \quad (3)$$

where C is the RRH coverage in kilometers, r is the distance from the transmitter to the receiver in kilometers, θ is the vehicle's angle to the directed line connecting the target RRH to the interfering RRH, and $(r^2 + 4 + 4r \cos \theta)^{1/2}$ denotes the distance between the target RRH and the interfering RRH [29].

After calculating SINR values for each vehicle, we need to calculate RB data rate according to SINR value, CQI index, and efficiency from the mapping table that determines various CQI indices based on different modulation orders, SINR ranges, and efficiencies [30]. We use this mapping to obtain the number of necessary RBs. For the sake of simplicity, we consider both UEs and gNBs forming the network working in single-input-single-output (SISO) mode [30]. The CQI index is calculated at the UE and reported to the gNB. We use the CQI to determine the efficiency and calculate the data rate of an RB. An RB per time slot of 1 ms consists of 12 subcarriers of 15 kHz wide in frequency, and each subcarrier consists of 14 symbols. Accordingly, the data rate of an RB is calculated as

$$RB_data_rate \text{ (bits/ms)} = 12 \times 14 \times \text{efficiency}. \quad (4)$$

After calculating the data rates of RBs, we can determine the number of RBs ($R_{n,v}$) requested by each vehicle to execute its uplink task. $R_{n,v}$ depends on the uplink and RB's data rates, i.e., UL_DR_v and RB_data_rate . We use the following formula.

$$R_{n,v} = \frac{UL_DR_v}{RB_data_rate}. \quad (5)$$

A. OPTIMIZATION TASK

Considering N RRHs with a number of available uplink RBs (namely MRB_n) and V vehicles with a number of required RBs per time slot for sending the sensing data from vehicle v to the RRH n (namely $R_{n,v}$), we need to determine y_n^v which denotes whether the vehicle v is associated with RRH n or not; and x_n which indicates whether to turn the RRH n on or off. The whole optimization problem minimizes the number of active RRHs while satisfying the constraints

²In this paper, we focus on the optimization problem rather than on the interference and SINR. For further details, we refer the reader to [29].

on $R_{n,v}$ and MRB_n . We formulate it as $\min \sum_{n=1}^N x_n$, subject to

$$\sum_{v=1}^V y_n^v R_{n,v} \leq MRB_n, \quad n = 1, \dots, N, \quad (6)$$

$$\sum_{v=1}^V y_n^v SINR_{n,v} \geq H, \quad n = 1, \dots, N, \quad (7)$$

$$\sum_{n=1}^N y_n^v = 1, \quad v = 1, \dots, V, \quad (8)$$

$$x_n \geq y_n^v, \quad n = 1, \dots, N; \quad v = 1, \dots, V, \quad (9)$$

$$x_n, y_n^v \in \{0, 1\}, \quad n = 1, \dots, N; \quad v = 1, \dots, V. \quad (10)$$

The above-mentioned objective function is subject to the following constraints: constraint (6) ensures that the number of required RBs per time slot to uplink data from vehicle v to the RRH n should not exceed the number of available uplink RBs at the RRH n , constraint (7) indicates that vehicle v can be assigned to RRH n if the predicted SINR is larger than the assumed threshold H , constraint (8) states that each vehicle v should be associated with one and only one RRH, constraint (9) ensures that vehicle v can be connected to RRH n only if RRH n is turned on, and constraint (10) indicates the lower and the upper bounds of the binary decision variables.

B. HEURISTIC ALGORITHMS

We apply heuristic algorithms to address the complexity of the ILP problem for the big-sized scenario. Heuristic algorithms produce competitive and fast but not necessarily optimal solutions. Since our ILP problem is structurally based on the bin packing problem, known to be \mathcal{NP} -complete, we apply the following heuristic algorithms (implemented in MATLAB): First-Fit (FF), Best-Fit (BF), First-Fit-Decreasing (FFD), and Best-Fit-Decreasing (BFD) [31].

We model the resource allocation problem as a bin-packing problem to efficiently associate vehicles with a set of RRHs and minimize the number of used RRHs. The resource allocation problem depends to a great extent on the size of the tasks requested by vehicles. Hence, it is necessary to determine if the problem is online or offline because the latter case, we can provide better assignments (we have an overall view and plan). In the online allocation problem, we obtain the tasks requested by the vehicles separately and assign vehicles to RRHs. We can apply FF and BF algorithms to deal with online allocation problems. In the offline management problem, we know the tasks requested by vehicles at the beginning of the assignment. We can use FFD and BFD algorithms to solve offline management problems [32].

The FF algorithm (Alg.1), being the basis for the other algorithms, works as follows: initially, all RRHs (counterparts of bins in bin packing problem) are empty. We start by assigning vehicles to the first RRH with sufficient capacity, i.e., available RBs. Then, we update the available RBs of RRH. If the RRH has no uplink RBs, we find a new RRH

Algorithm 1 First-Fit & First-Fit-Decreasing

```

for All ReqRB  $v = 1, 2, \dots, V$  do
  for All RRHs  $n = 1, 2, \dots, N$  do
    if First RRH  $n$  has a sufficient capacity then
      Assign ReqRB  $v$  to RRH  $n$ .
      Update RRH  $n$  remaining capacity.
    else
      Find a new RRH  $n$  and assign ReqRB  $v$  to it.
      Update RRH  $n$  remaining capacity.
  
```

For the First-Fit-Decreasing algorithm:

- 1- Sort ReqRBs in descending order.
 - 2- Apply First-Fit Algorithm to the sorted ReqRBs.
-

Algorithm 2 Best-Fit & Best-Fit-Decreasing

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for All ReqRB  $v = 1, 2, \dots, V$  do
  for All RRHs  $n = 1, 2, \dots, N$  do
    if RRH  $n$  has the minimum remaining capacity then
      Assign ReqRB  $v$  to RRH  $n$ .
      Update RRH  $n$  remaining capacity.
    else
      Find a new RRH  $n$  with remaining capacity that best match the size of ReqRB  $v$  and assign ReqRB  $v$  to it.
      Update RRH  $n$  remaining capacity.
  
```

For the Best-Fit-Decreasing algorithm:

- 1- Sort ReqRBs in descending order.
 - 2- Apply Best-Fit Algorithm to the sorted ReqRBs.
-

and repeat the procedure until all vehicles are assigned. For the FFD algorithm, we first sort the vehicles' required RBs in descending order then we apply the FF algorithm. In the BF algorithm, we find the RRH whose remaining capacity best matches the size of the required RBs, and then assign vehicles to that RRH (i.e., the best RRH with the least available RBs). For the BFD algorithm, we first sort the vehicles' required RBs in descending order then we apply the BF algorithm.

The complexity of the heuristic algorithms is analyzed as follows. In the worst case of the FF algorithm, a new RRH is turned on to serve each associated vehicle with its ReqRBs. Thus, the loops iterate over all ReqRBs and RRHs, and the time complexity is $\mathcal{O}(V^2)$. The FFD algorithm is influenced significantly by the execution time of the FF algorithm, so the time complexity of the FFD algorithm is $\mathcal{O}(V^2)$. For the BF algorithm, all RRHs are examined to determine the minimum remaining capacity that best matches the ReqRBs of each vehicle. Hence, the time complexity is $\mathcal{O}(V^2)$. Since the BFD algorithm is dominated by the running time of the BF algorithm, the time complexity of the BFD algorithm is $\mathcal{O}(V^2)$.

TABLE 3. Evaluation parameters.

Parameter	N_{OC}	α	C	r	θ	P_v	UL_DR_v	H
Value	-174	3.5	1	0 – 1	0 – 2π	23	1	-7
	dBm/Hz		km	km		dBm	Mb/s	dB

V. RESULTS AND EVALUATION

In this section, we evaluated our resource management problem under three scenarios of V2X network topologies with diverse sizes: 1)

- 1) A small-sized scenario (up to tens of RRHs and vehicles): we set the number of vehicles to 10, 20, 30, 40, and 50, and the number of RRHs to 4, and fixed locations.
- 2) A medium-sized scenario (tens of RRHs and hundreds of vehicles): we set the number of vehicles at 100, 200, 300, and 400, and the number of RRHs at 40, and random locations.
- 3) A big-sized scenario (hundreds of RRHs and thousands of vehicles): we set the number of vehicles at 1000, 2000, 3000, and 4000, and the number of RRHs at 400, and random locations.

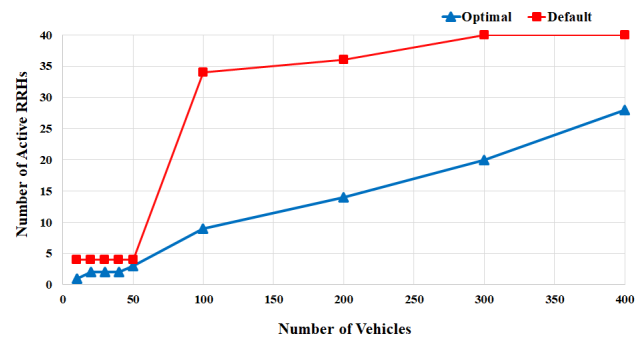
We compared the optimal and default associations of vehicles. We also compared the optimal solutions and the solutions obtained by implementing the above-mentioned heuristic algorithms. Furthermore, we analyzed the impacts of the required data rate and the density of vehicles on the number of turned-on RRHs. Finally, we examined how the vehicles' density impacts the computation time of the optimal and heuristic solutions.

First, we randomly generated the positions of vehicles and RRHs within the V2X network topology and calculated the SINR values of vehicles using (1) and depending on the vehicles' distances from each RRH. Then, we obtained the efficiency values from the mapping table [30] and calculated the data rate of RBs. Finally, we determined the number of required RBs to serve the requested uplink data rate by vehicles.

For simplicity and evaluation, we assumed that the vehicles have similar transmission power ($P_v = 23$ dBm), similar uplink data rates ($UL_DR_v = 1$ Mb/s), and the maximum number of RBs per each RRH equals 50 ($MRB_n = 50$ RBs). We chose these values according to the service requirements for 5G V2X services and to guarantee the QoS requirement for V2X communications expressed by SINR values and uplink data rates. Table 3 lists the parameter values used in the calculations and evaluations.

A. OPTIMAL VS. DEFAULT ASSOCIATIONS

In this subsection, we compared the optimal cf. strongest-signal associations of vehicles to investigate how much energy was saved by our proposed model. We obtained the optimal association from the optimal solution of our resource management problem. We got the strongest-signal association according to the default association, where the

**FIGURE 3. Comparison of optimal vs. strongest-signal associations.**

vehicles are associated with the serving RRH depending on their SINR values. Thus, in the strongest-signal association, the vehicle with the higher SINR value would be connected to the nearest RRH.

Fig. 3 shows the optimal association vs. the strongest-signal association. We observed that, as the number of vehicles increased, the optimal association was turning on fewer RRHs to serve the tasks of vehicles than the strongest-signal one, which led to energy savings. For the medium-sized scenario, the energy saved by the optimal assignment ranged from 30% to about 70%, according to the number of active RRHs. In addition, for the scenarios consisting of 20, 30, and 40 vehicles, the energy saved by the optimal association was 50%, and the number of turned-on RRHs was 2. Furthermore, for the scenario consisting of 10 vehicles, the energy saved by the optimal assignment was 75%. These imply that the optimal association turned on fewer RRHs than the default one, which led to saving energy.

Table 4 demonstrates the optimal vs. default associations in the number of activated RRHs and used RBs. We noticed that the default assignment turned on more RRHs than the optimal one but used fewer RBs. The default association consumed more energy than the optimal association, especially in the medium-sized scenario. For 100 vehicles with aggregated uplink data rate equal to 100 Mb/s, the strongest-signal association turned on 34 RRHs compared to 9 RRHs turned on by the optimal assignment. Furthermore, for the scenario consisting of 400 vehicles with aggregated uplink data rates equal to 400 Mb/s, we observed that the default assignment consumed about 70% more energy than the optimal association, depending on the number of activated RRHs. Both associations used almost the same number of RBs, i.e., the default association used only about 19% fewer RBs than the optimal assignment. Thus, the optimal association activated fewer RRHs than the default one and minimized energy consumption.

B. OPTIMAL VS. HEURISTIC SOLUTIONS

In this subsection, we compared the optimal vs. heuristic solutions for small and medium sizes scenarios. We obtained the optimal solution by solving the resource allocation problem using the CPLEX solver and the heuristic solution by

TABLE 4. Comparison of optimal vs. default associations.

Number of vehicles	Number of active RRHs		Number of used RBs	
	Optimal	Default	Optimal	Default
10	1	4	36	20
20	2	4	53	40
30	2	4	80	60
40	2	4	94	80
50	3	4	114	100
100	9	34	429	270
200	14	36	669	507
300	20	40	986	874
400	28	40	1350	1091

TABLE 5. Comparison of optimal vs. heuristic solutions.

Number of vehicles	Number of active RRHs		Number of used RBs	
	Optimal	Heuristic	Optimal	Heuristic
10	1	1	36	36
20	2	2	53	53
30	2	2	80	80
40	2	2	94	94
50	3	3	114	114
100	9	9	429	429
200	14	14	669	669
300	20	20	986	986
400	28	28	1350	1350

implementing the heuristic algorithms using MATLAB [33]. More precisely, we compared the number of turned-on RRHs, the number of served vehicles per each turned-on RRH, and the number of RBs used by each activated RRH. In addition, we analyzed the obtained heuristic solutions for the large-scale scenario. Furthermore, we evaluated the four heuristic algorithms using FPTAS to check the approximation level and implemented PSO and GA algorithms to analyze the number of active RRHs and the computation time.

Table 5 shows the number of activated RRHs and the RBs used by active RRHs. We observed that the number of RRHs turned on by the heuristic solutions was competitive compared to the ones provided by the exact solutions of the optimization problem. We obtained competitive results since we did not consider the constraints on SINR and vehicles' associations when we generated solutions based on the heuristic algorithms. Furthermore, we noticed that the results obtained from the heuristic and optimal solutions were similar only in the number of active RRHs, and the differences were in the number of vehicles served per each active RRH and in the capacity of the active RRHs, i.e., the number of RBs used by each active RRH.

Fig. 4 demonstrates the optimal vs. heuristic solutions concerning the number of vehicles served by each turned-on

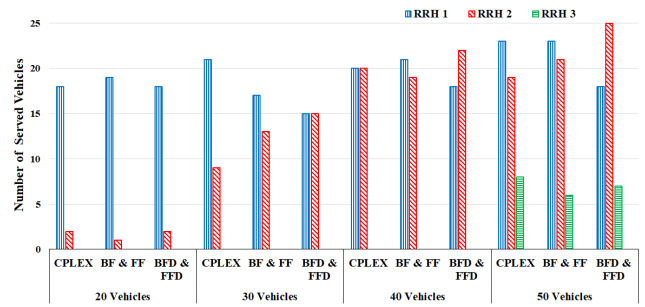


FIGURE 4. Served vehicles: optimal vs. heuristic for small size scenario.

RRH in the small-sized scenario. Although the heuristic algorithms turned on the same number of RRHs as the optimal results, we observed the differences in the number of served vehicles which varied among each activated RRH. For the 20 vehicles scenario, the optimal solutions associated 18 with the first active RRH and 2 with the second active RRH, while the FF and BF algorithms assigned 19 vehicles to one turned-on RRH and one to the second turned-on RRH, and the FFD and BFD results connected 18 with the first active RRH and 2 with the second active RRH. Also, for the scenario of 40 vehicles, we noticed that the optimal solutions scheduled the vehicles equally among the two activated RRHs, i.e., 20 per each turned-on RRH. Thus, the optimal associations of vehicles with RRHs led to efficient RRHs management and energy saving.

Fig. 5 compares the optimal and heuristic solutions for the number of RBs used per each active RRH to serve 100 vehicles. Even though the heuristic and the optimal solutions provided equivalent results in the number of active RRHs, we noticed a difference in the capacity of each activated RRH by applying various algorithms. We also saw that the number of used RBs obtained by applying the FF and BF algorithms was the same, and the results obtained by applying the FFD and BFD were the same. The heuristic algorithms performed similarly because the behavior of FF and BF did not depend only on the chosen strategy but also on the fact that they followed certain similar constraints. For instance, a new RRH is active only when a vehicle is not fit in any preactivated RRH. Furthermore, we observed that the optimal solutions provided a balanced utilization of the total number of RBs used among each active RRH, which led to efficient utilization of RRHs' capacity and dynamic management of the resource.

Table 6 shows the results of solving the optimization problem for the big-sized scenario by applying the above-mentioned heuristic algorithms. The maximum number of turned-on RRHs depended on the number of vehicles and their aggregated uplink data rate. The number of utilized RBs relied on the vehicles' density and associations with the serving RRHs. We noticed that the four heuristic algorithms produced comparable results related only to the number of activated RRHs, while the differences were in the number of vehicles served per each active RRH and in the capacity

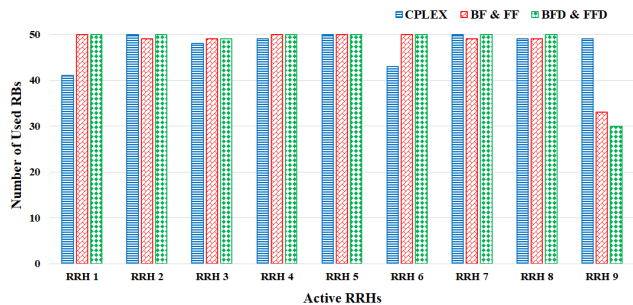


FIGURE 5. Number of RBs used per each RRH for 100 vehicles scenario.

TABLE 6. Number of active RRHs for big size scenario.

Vehicles	Uplink data rate	Number of active RRHs			
		FF	BF	FFD	BFD
1000	1000 Mb/s	42	42	41	41
2000	2000 Mb/s	82	82	82	82
3000	3000 Mb/s	123	123	122	122
4000	4000 Mb/s	164	164	163	163

of the active RRHs, i.e., the number of RBs used by each active RRH. We also observed that FFD and BFD algorithms turned on fewer RRHs for 1000, 3000, and 4000 vehicle scenarios, which implies that sorting of the vehicles yields better matching and fewer active RRHs, which led to energy saving.

We evaluated the proposed heuristic algorithms by checking the level of the approximations obtained using the results related to the [fully] polynomial time approximation algorithms (FPTAS) class, known for providing effective methods to solve the bin packing problem. Given an \mathcal{NP} -complete minimization problem with an objective function of f , algorithm \mathcal{A} belongs to FPTAS if, for any error parameter $\varepsilon > 0$, it is an ε -approximation scheme. That is, for any given input of the minimization problem, \mathcal{A} returns a solution s , such that $f(s) \leq (1 + \varepsilon)f(s^*)$, where: s^* is the optimum solution for the input of the minimization problem, and $(1 + \varepsilon)$ represents the approximation factor determining how good the approximation algorithm is [12].

Furthermore, \mathcal{A} 's running time depends polynomially on the input size of the minimization problem and on $\lceil 1/\varepsilon \rceil$ [12]. In our case, we let x be the number of RRHs obtained by the heuristic algorithms, and x^* be the optimal number of required RRHs. We say that the heuristic algorithms have an approximation factor $(1 + \varepsilon)$ if they provide the following upper bound: $x \leq (1 + \varepsilon)x^*$.

Fig. 6 shows the relationship between the optimal and heuristic solutions corresponding to the error parameter ε . Notice that the heuristic algorithms guarantee that the upper bound holds for $\varepsilon = 1$. This implies that the proposed heuristic algorithms are approximation schemes with $(1 + \varepsilon)$ -approximation factor.

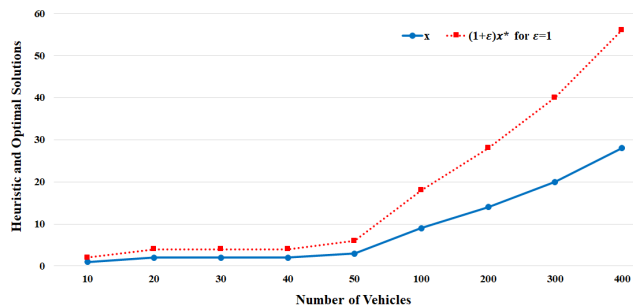


FIGURE 6. Optimal and heuristic solutions corresponding to ε .

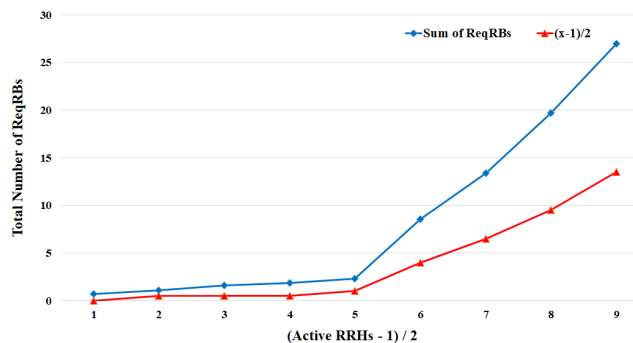


FIGURE 7. Total requested RBs vs. heuristic solutions.

In our resource allocation problem, given v vehicles with requested RBs $ReqRB_1, \dots, ReqRB_v \in (0, 1]$, noting that $ReqRB$ depends on which RRH the vehicle is associated with, we needed to find an assignment of unit-sized RRHs that minimized the number of used RRHs. If the proposed heuristic algorithms used x RRHs, then at least $(x - 1)$ RRHs are more than half full. Therefore,

$$\sum_{i=1}^v ReqRB_i > \frac{x - 1}{2}. \tag{11}$$

Fig. 7 illustrates the relationship between the heuristic solutions and the summation of the RBs requested by the vehicles. We noticed that the heuristic algorithms guarantee that (11) holds for all heuristic solutions, x RRHs, and any total number of requested RBs. Hence, the proposed heuristic algorithms are approximation schemes with an approximation factor. Since the summation of the requested RBs is a lower bound on the optimal number of RRHs x^* , $x - 1 < 2x^*$, i.e., $x < 2x^* + 1$ or $x \leq 2x^*$, and so the proposed heuristic algorithms have a 2-approximation factor.

We then compared the proposed heuristic algorithms with the following meta-heuristic algorithms; particle swarm optimization (PSO) and genetic algorithm (GA) implemented in MATLAB [34]. PSO is based on a swarm of solutions. A solution is called a particle that can follow its trajectory, a previous one, or the swarm's trajectory. GA is a stochastic search method using the mechanics of natural selection and

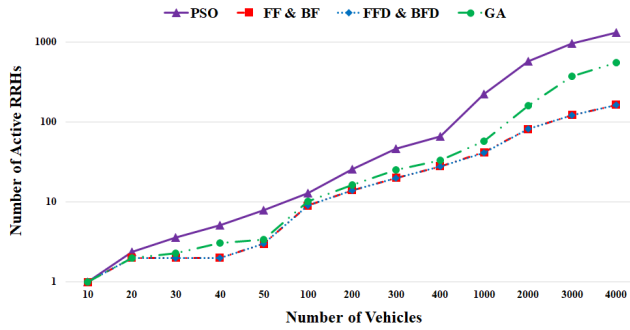


FIGURE 8. Comparison of active RRHs for PSO, GA, FF, BF, FFD, and BFD.

natural genetics. GA is based on a population of solutions and searches the solution space using the survival of the fitness-based strategy.

Fig. 8 and Fig. 9 show the comparison of active RRH and computation time, corresponding to the proposed heuristic algorithms and the implementation of PSO and GA. We set the population size to 40 and 50 for GA and PSO, respectively. We set the number of iterations to 100 for the small-sized problem and 1000 for the medium-sized and big-sized scenarios. For the small-sized problem, the four heuristic algorithms turned on the same number of RRHs as both PSO and GA, but the heuristic algorithms ran faster than PSO and GA. For the medium and large scenarios with hundreds and thousands of vehicles, the heuristic algorithms turned on fewer RRHs and ran faster than PSO and GA, which implies that the proposed heuristic algorithms outperformed PSO and GA in generating near-optimal solutions during a shorter time. The performance improvement is because the heuristic algorithms are problem-dependent and adapted to the bin packing problem, while GA and PSO are problem-independent algorithms that have difficulty in formulating the suitable fitness function and determining parameters such as the population size and crossover. Furthermore, GA turned on fewer RRHs and ran faster than PSO, which implies that GA performed better than PSO. PSO and GA needed more time to find near-optimal solutions compared to the performance of the four proposed heuristic algorithms.

C. IMPACT OF REQUIRED DATA RATES

In this subsection, according to the optimal results obtained using CPLEX, we analyze the impact of the data rate required by each vehicle on the number of active RRHs for the small and medium sizes scenarios. The number of active RRHs depended on the requested RBs needed to realize vehicle tasks and the vehicle associations with RRHs.

Fig. 10 shows the impact of the required uplink data rate on the number of turned-on RRHs. The labeled numbers above the curve indicate the number of turned-on RRHs. Intuitively, as the requested data rate increases, so is the number of active RRHs. We observed that 1 RRH turned on

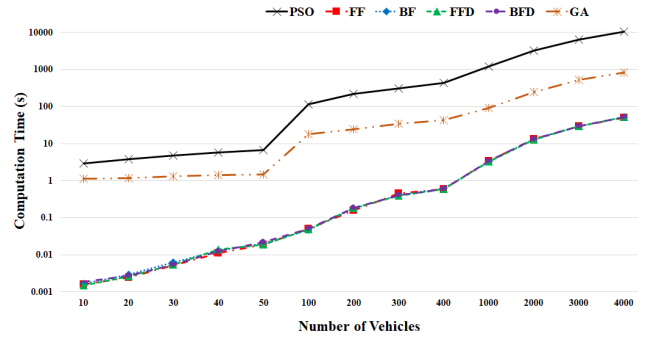


FIGURE 9. Comparison of computation time for PSO, GA, FF, BF, FFD, and BFD.

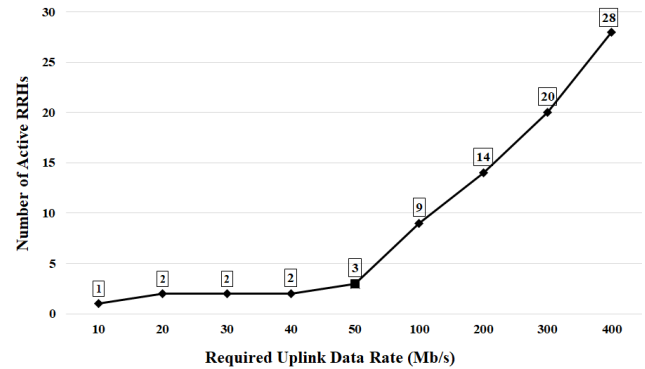


FIGURE 10. Required data rate vs. active RRHs.

to serve vehicles with aggregated uplink data rates equal to 10 Mb/s. We also noticed that 28 RRHs were activated to realize aggregated uplink data rates of 400 Mb/s. To serve vehicles with uplink data rates varied from 10 to 400 Mb/s, the number of activated RRHs varies from 1 to 28, which implies that the optimum resource allocation and vehicles' associations with the serving RRHs led to fewer active RRHs and saved energy.

D. IMPACT OF VEHICLES DENSITY

In this subsection, according to the optimal solutions to our resource management problem, we report the impact of the number of vehicles on the number of turned-on RRHs for network topologies of small and medium sizes. The number of turned-on RRHs relied on the vehicles' density per each RRH and assignments between vehicles and RRHs.

Fig. 11 shows the impact of the density of vehicles on the number of active RRHs. The labeled numbers above the curve indicate the number of active RRHs. Intuitively, as the vehicles' density increased, so was the number of turned-on RRHs. We observed that although the vehicles' density increased 40 times, the number of active RRHs increased 28 times, which implies that the optimal associations of vehicles with serving RRHs led to efficient resource utilization and energy saving by minimizing the number of turned-on RRHs.

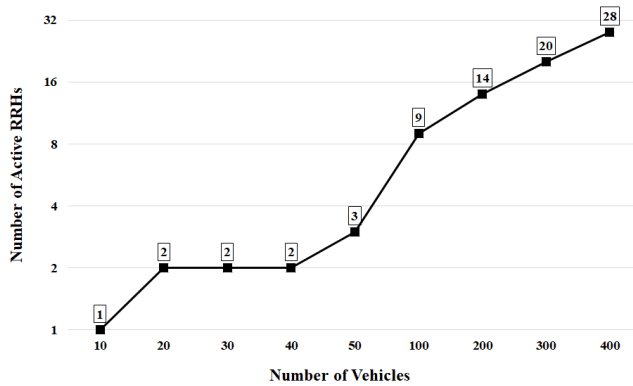


FIGURE 11. Number of vehicles vs. active RRHs.

TABLE 7. Elapsed time, measured in seconds, of solving the resource management problem.

Vehicles	CPLEX	FF	BF	FFD	BFD
10	0.022	0.002	0.002	0.002	0.002
20	0.030	0.003	0.003	0.003	0.003
30	0.036	0.005	0.006	0.006	0.006
40	0.085	0.011	0.013	0.014	0.012
50	0.104	0.019	0.020	0.019	0.022
100	1.136	0.050	0.046	0.049	0.050
200	5.369	0.158	0.180	0.183	0.185
300	169.192	0.462	0.406	0.393	0.399
400	193.768	0.601	0.607	0.599	0.606
1000	N/A*	3.354	3.315	3.337	3.388
2000	N/A*	13.105	13.162	13.064	13.120
3000	N/A*	29.083	29.479	29.516	29.286
4000	N/A*	50.774	51.698	51.521	51.764

* Values are not available due to memory shortage.

E. IMPACT ON COMPUTATION TIME

In this subsection, we compare the execution times of solving the optimization problem and running heuristic algorithms for the small, medium, and big sizes scenarios. We ran each implementation ten times and calculated the average elapsed time.

Table 7 shows the impact of the number of vehicles on the computation time measured in seconds. We compared the elapsed time of solving the resource management problem by implementing optimal and heuristic solutions. We obtained the optimal results for the small-sized problem in a reasonable execution time of around 60 ms. For the scenarios consisting of 300 and 400 vehicles, we observed that the elapsed time was too long because the CPLEX solver had a choice of algorithms for solving linear programming problems, and the execution time would depend not only on the problem size but also on the selected algorithm. In addition, the values of computation time for the big-sized scenario were not available because of memory shortage (a typical phenomenon for large instances). Furthermore, the heuristic algorithms provided competitive solutions to the optimal ones in a suitable implementation time.

TABLE 8. List of abbreviations.

Abbreviations	Definitions
3GPP	third-generation partnership project
5G	fifth-generation
BBU	base band unit
BF	best-fit
BFD	best-fit-decreasing
BSs	base stations
BSMs	basic safety messages
CQI	channel quality indicator
C-RAN	cloud radio access network
EE	energy efficiency
FF	first-fit
FFD	first-fit-decreasing
FPTAS	fully polynomial time approximation scheme
GA	genetic algorithm
gNBs	5G new base stations
ICI	inter-cell interference
LADNs	Local access data networks
LD	least delete
LFRC	largest-first rounding with capacity constraints
LSTM	long-short-term memory
MAEC	multi-access edge computing
NOMA	non-orthogonal multiple access
NR	new radio
OFDM	orthogonal frequency-division multiplexing
PSO	particle swarm optimization
QoS	quality of service
RANs	radio access networks
RBs	resource blocks
RRHs	remote radio head
RSUs	road-side units
SAE	society of automotive engineers
SINR	signal-to-interference-plus-noise ratio
TDN	traffic demand node
UE	user equipment
URLLC	ultra-reliable and low-latency communication
V2I	vehicle-to-infrastructure
V2N	vehicle-to-network
V2P	vehicle-to-pedestrian
V2V	vehicle-to-vehicle
V2X	vehicle-to-everything

VI. CONCLUSION

We investigated the problem of resource management in 5G LADN supporting V2X communications. The resource management problem was formulated mathematically as an optimization task based on ILP and solved using a professional solver. We applied heuristic algorithms to provide solution methods for large instances. We achieved the

optimal solutions for the small-sized scenario in appropriate implementation times. The proposed heuristic algorithms ran efficiently even with the big-sized problem and produced solutions that approximated the optimal ones in suitable acceptable execution times of seconds.

Our numerical results demonstrated that the proposed model is suitable for V2X applications and provides dynamic resource management depending on the uplink traffic while reducing energy consumption. Therefore, the proposed model could efficiently utilize resources and save energy while guaranteeing the QoS requirements of V2X communications. For the small-sized problem, the computation time was around 60 ms, which meant we could apply the proposed model in real-time applications. The energy saved by the optimal associations between vehicles and RRHs was up to 70%, which meant the proposed model provided efficient resource utilization leading to energy saving.

For future work and further research, additional constraints could be added to make the model more realistic (e.g., mobility of vehicles and latency). Communication and energy models could be considered to enhance the network performance (e.g., energy consumption due to using RBs or energy consumption at BBU). In addition, the impact of more factors on model performance could be investigated (e.g., CQI distribution and power of RRHs). Also, working with non-regular environments (e.g., existing town street networks) would be interesting. Furthermore, the situation when LADN is in the vicinity of both RSUs and gNBs could be analyzed with queuing modeling by determining the optimal ratio of the sensing data transferred to the gNB.

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