IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 February 2024, accepted 10 March 2024, date of publication 15 April 2024, date of current version 20 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3388891

RESEARCH ARTICLE

Resource-Optimized Vehicular Edge Networks With Fairness Constraints

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This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education under Grant 2021R1F1A1055408.

ABSTRACT Intelligent transportation systems (ITSs) have witnessed a rising interest from researchers because of their promising features. These features include lane change assistance, infotainment, and collision avoidance, among others. To effectively operate ITSs for these functions, there is a need for edge computing. One can install edge computing servers at the roadside units (RSUs). There must be seamless communication between the edge servers and the cars. Additionally, there will be some cars that experience higher delays and thus, are not preferable because they will highly degrade the performance. Therefore, in this work, we consider a vehicular network scenario and define a cost function that takes into account the latency that is determined by the car's computing frequency, association, and resource allocation while considering fairness constraints. Our cost function is to minimize the total latency (i.e., both local computing latency and transmission latency). The cost of the optimization problem is minimized by optimizing the car's local frequency allocation, resource allocation, and association. The problem is separable, therefore, we first compute the local frequencies of the cars using a convex optimizer. Next, we split the core problem into two separate problems: (a) the distribution of resources and (b) association, because the last defined problem (joint association and resource allocation) is NP-hard. We then suggest an iterative solution. In the end, we offer numerical findings to support the suggested solution.

INDEX TERMS Intelligent transportation systems, resource allocation, association, fairness.

I. INTRODUCTION

The constantly growing landscape of technological advancements in intelligent transportation systems (ITSs) will lead to many novel applications/functions [1], [2], [3]. These functions are lane change assistance, collision avoidance, congestion control, and infotainment [4], [5]. All of these applications/functions are based on emerging technologies and schemes: mathematical optimization, machine learning, graph theory, game theory, and matching theory [6], [7], [8]. Typically, a set of roadside units (RSUs) assisted by edge servers is installed to serve cars. Cars may have computing resource constraints, therefore, they must offload the traffic to the edge-empowered RSUs. The RSUs compute the car tasks and then send them back the outcomes. For the above tasks, the RSUs must be effectively deployed. Also, the RSUs must be connected using fast backhaul links.

Although edge computing-empowered cars will effectively enable various applications, there are many challenges associated with the design and deployment. These challenges are due to a number of limited RSUs and edge computing resources. Additionally, there will be a massive number of communication devices in the future networks, therefore, we must efficiently assign communication resources to the

The associate editor coordinating the review of this manuscript and approving it for publication was Shanying Zhu.

cars [9]. Other than communication resources, there must be an efficient allocation of car frequencies. For instance, if we consider deep reinforcement learning (DRL), where the agents are trained at cars and then aggregated using federated learning at the network edge (i.e., RSUs). In this case, all the agents' data should be received before the deadline. Therefore, we must have some deadline on the transmission latency of all cars (i.e., fairness constraint). Also, we must carefully associate the cars with RSUs to minimize the delay. Our work considers a cost function that accounts for overall latency (i.e., local latency and transmission latency) by optimizing cars operating frequencies, resource allocation, and association while considering fairness constraints. Our contributions are summarized as follows:

- We establish a cost function that takes into consideration delay in general (e.g., transmission latency and car computing latency). Next, we develop an optimization problem that optimizes the car's local operating frequencies, resource allocation, and association in order to minimize the cost.
- The problem is divided into two parts in order to be solved: the joint resource allocation and association problem (b) and the optimization of car operating frequencies (a). Convex optimization is used straight away to solve the first problem. An iterative approach based on decomposition-relaxation is used to tackle the second problem.
- Finally, the proposal is validated with numerical findings.

This is how the remainder of the paper will be structured: The most recent developments in resource allocation and association in automobiles are covered in Section II. In Section III, the system model and problem formulation are provided. Section IV presents the problem decomposition and analytical solution. In Section V, we finally draw the paper's conclusion.

II. RELATED WORKS

A. ASSOCIATION

In [10], the authors have discussed the shortcomings of federated learning, and a new structure is proposed for autonomous driving vehicles, namely, dispersed federated learning (DFL), in order to offer efficient utilization of resources, robust communication, and privacy-aware learning. The optimization problem is of Mixed integer non-linear programming (MINLP) kind that is expressed to cooperatively reduce the loss in accuracy for the federated approach of learning due to transmission latency and packet imperfections. The proposed solution for the non-convex and NP-hard problem is based on the Block Successive Upper-bound Minimization (BSUM). The effectiveness of proposed work is shown in the numerical results. In [11], the authors have solved the problem of association in vehicular networks to balance the load among various base stations. For achieving the feature of consistencies in the spatial-temporal dimension in vehicular connections, an online reinforcement learning approach (ORLA) is proposed. ORLA is a good connection solution verified through experiments on QiangSheng taxi movement with greater balancing quality of load compared with various well-known association methods. The issue of gateway association is discussed in [12]. A scenario is developed as a multiple knapsack problems with project limitations besides proposing two distinct effective association strategies for maximizing vehicles number assisted by gateways (Mobile). The results of simulation showed that the suggested schemes outclass the existing random and distance-based associations in numerous situations with diverse traffic bulks.

Authors in [13], debated on vehicle-to-everything (V2X) overview, where they have taken into consideration the issue of primary cars' control of entry and connection for secondary units in a single cell down-link vehicular system. The frequency of the network is 60 GHz which is millimeter wave communication. The objective of the study was to choose the most suitable topology connectivity for vehicles that enhances the quantity of acknowledged primary vehicles while ensuring coverage by associating all secondary vehicles. The problem was, however, treated in a combinatorial as well as NP-hard method. So, a sub-optimal and dual-stage algorithm was proposed for its solution. The suggested algorithm has achieved optimum performance.

In connection, an algorithm is presented for target association, followed by a radar sensor that is basically on board with the motion and position of data acquired from the VANET in [14]. The presented algorithm is a record-oriented multiple assertions tracker that is altered for integrating data comprised in the messages of VANET. The testing of algorithm is carried out, with the help of a real scenario using two vehicles for experiment and after that compared with further computational methods. One of computation method comprises of a modest single hypothesis technique for VANET messages association while the other is using the internal sensors only for the perception of the environment to quantify the benefits of employing wirelessly acquired information. For vehicular networks in an entirely distributed way was proposed in [15] based on a Bayesian positioning and data association scheme. Non-cooperative features are detected by jointly-connected vehicles followed by the association of local measurements of sensors to the properties for the growth of standalone GPS system. The proposed method performance showed significant improvement especially in severe situations with extremely denied or degraded GPS signals (e.g., urban tunnels or canyons).

The work in [16], provides the combination of radar measurements with deep neural network output using an inventive extended objects monitoring (EOM) strategy built on the hidden Markov models and random matrix model. With the aid of fusion methodology, high clutter-rated extended tracking in environments is shown to be possible. Instance Segmentation is enhanced. The tracking accuracy has been significantly improved with the inclusion of information regarding classification. Stationary objects are tracked by developing stop-and-go estimator. In [17], the examination of federated learning applications for vehicular networks is carried out in terms of significant autonomous vehicle mobility. Smooth connectivity amongst the end devices onboard the vehicles and the RSUs may not be approachable, which might cause standard federated learning useless. To address this problem, a dispersed federated learning (DFL) system for self-driving vehicles is proposed. A DFL cost minimization challenge is also presented through an iterative approach. The aforementioned proposal is supported by thorough simulation outcomes. In [18], a general framework was proposed for following multiple targets simultaneously, without linking detailed information with a uniform representation and predicting the dispersion of their upcoming motions or states. The technique used in [18] is, in fact a constrained mixture sequential Monte Carlo (CMSMC) scheme. It was also suggested to apply a general learning-based hierarchical time-series prediction model (HTSPM) in the previous Bayesian state estimate as an implicit proposal distribution. A numerical investigation and practical on-road vehicle surveillance and behavioral prediction challenge in highway-related situations were both conducted to judge the proposed structure and models. The outcomes reveal that the proposed CMSMC technique surpasses KF variants with regard to both mean and variance tracking accuracy.

B. RESOURCE ALLOCATION

Effective work related to resource allocation for vehicular networks is depicted in [19]. These works are listed in [20], [21], [22], [23], [24]. In [20], Kalsoom et al. proposed an architecture based on fifth-generation network technology for the Cooperative Driving System (CDS) that includes a resource allocation scheme based on D2D technology. It improves the quality of service for CDS and hence road traffic efficiency. The planned scheme is compared with the prevailing D2D approaches. The algorithm used for the implementation of the proposed scheme is the density-based scattered clustering algorithm with noise (DBSCAN) for vehicular clustering. The foremost motivation is an effective application for the wireless resources with increasing quality of service requirement for CDS with the constraint that requires devices in communication which must accomplish in a real-time scenario. In [21], Ashraf et al. have proposed a novel, dynamic load awareness and proximity-based allocation of resources from vehicle to vehicle (V2V) network. The approach guarantees periodic (or continuous) transmission prospects for vehicular applications like an independent safety facility in the V2V underlay while dropping control overhead as well as being interfered with other vehicles. The optimization problem is solved in two phases. First, the zoning of vehicles using a dynamic mechanism of clustering is proposed according to proximity data and traffic flow. Second, for the resource allocation of individual V2V pairs inside each zone, a matching game is proposed. The many-to-one matching game trick is cast-effective where resource blocks (RBs) and V2V pairs rank one another for their service delay reduction. The projected game is exposed to fit to matching games with an externalities type class. This game is resolved using a distributed algorithm so that RBs and V2V pairs collaborate to attain stable matching.

In [22], Liu et al. have focused on the improvement of traffic efficiency and travel safety under multi-vehicle cooperation scenarios. The three main scenarios summarized are (i) Formation control (ii) Convey driving and (iii) Intersection management. A generalized solution for resource allocation is formulated for multi-vehicle cooperation in which a couple of resource allocation schemes are formulated for intersection management. Finally, the anticipated performance structures are compared and evaluated. In [23], He et al. have grounded on an architecture of heterogeneous type containing both cellular base stations (BSs) for extensive exposure and roadside infrastructure of cognitive-radio-enabled. A resource-sharing arrangement based on a semi-Markov decision process (SMDP) is planned to enable the utilization of video transmission in peak signal-to-noise ratio (PSNR) terms and even playback. The optimum resource allocation, targeting improving the standard of streaming video and assuring the user's call-level efficiency in the background, is attained by mentioning two interconnected combinations comprising of Call Admission Control (CAC) as well as channel allotment issues for cellular networks and roadside network infrastructure. The authors in [24] have emphasized on effective control and power spread allocation that guarantees an anticipated data rate for individual pairs of V2V communication with an ideal transmit power. Hence, a power spread allocation model by means of game theory is proposed in a vehicular wireless network of C-V2X mode. A generalized Nash equilibrium (GNE) game model is presented to allocate and regulate the convey strength of V2V combinations over devoted channels. The introduced game intended to find a reliable power source that assurances a minimized transmit power and essential data rate for the individual user. In [25], the main objective is to put forward a V2V offloading technique which improves resource utilization and user experience. In order to optimize the use of self-driving vehicles–as determined by a weighted average of operation time and cost of computation–the issue of employing offloading of mobility activities in VEC systems was investigated. Unlike previous efforts, the decisions about unloading were made while considering both the opportunity and challenges presented by the automobile's mobility. A pair of hop client vehicles were used along with one hop, to speed up job processing subject to feasibility. To solve the stated offloading problem, a semidefinite relaxation technique and an adaptive adjustment algorithm were used. The simulation findings have revealed that the suggested V2V unloading method has significantly improved the performance delay in comparison to advanced designs.

Different from the existing works [10], [11], [12], [13], [14], [15], [16], [18], [20], [21], [22], [23], [24], our

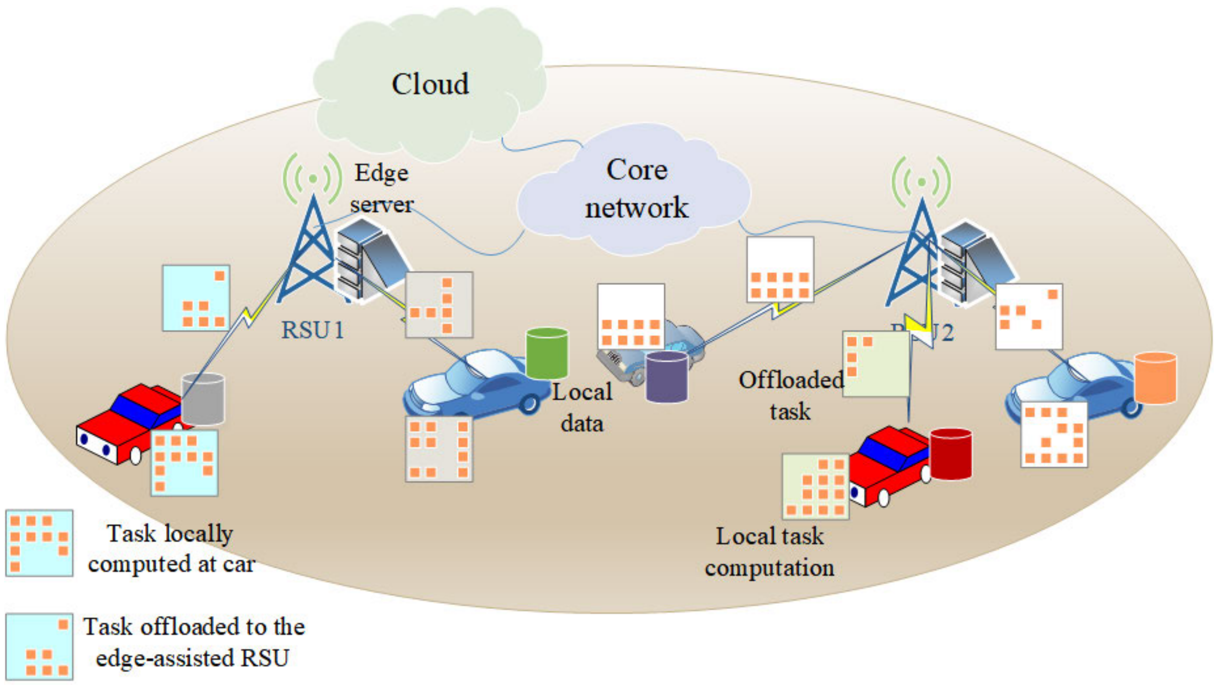

FIGURE 1. System model.

work considers cost optimization issue in cars with fairness constraints. The cost takes into account the transmission latency and local computing latency that is minimized by optimizing local devices operating frequencies, resource allocation, and association. Next, we discuss our system model in detail along with problem formulation.

III. SYSTEM MODEL

Consider a system that consists of a set $\mathcal{C}$ of C cars. A set $\mathcal{B}$ of B roadside units (RSUs) assisted by edge computing servers are used to serve cars. Every car c has a task $\mathcal{T}_c(a_c, b_c, d_c)$, where a_c, b_c, and d_c denote the task size (i.e., bits), computing resource (i.e., CPU-cycles/sec) for processing a single point, and the computing deadline, respectively. Table 1 lists the key parameters. Every car computes a partial task due to computing resources constraints and the remaining task is offloaded to the RSU for further computation. Note that are many RSUs and cars, therefore, there is a need for an efficient association of cars with the RSUs. Additionally, the communication resources must be efficiently utilized to minimize the delay. On the other hand, there must be an efficient computing resource allocation for cars. For instance, if the local task is the partial local model for split federated learning. In this case, the edge servers at RSUs will wait for learning data from cars. Therefore, we must allocate local computing resources to cars. Similarly, for traditional federated learning, the edge servers wait for a certain deadline before receiving the local models from the cars. Therefore, we must efficiently allocate local computing resources. On the other hand, an increase in local computing resources causes an increase in energy consumption. Therefore, we must make a tradeoff between the local computing resources assignment and energy consumption. Next, we discuss the local task computing model.

TABLE 1. Summary of key notations.

Notation	Description
$\mathcal{B}$	Set of RSUs assisted by edge servers
B	Total number of RSUs
W	Bandwidth of a resource block
$\mathcal{C}$	Set of cars
C	Total cars
$\mathcal{F}$	Computing power (i.e., frequencies) set
f_c	Computing power (i.e., frequency) assigned to car c.
$\mathcal{P}$	Transmit power set
P_{MAX}	Maximum allowed transmit power for all cars in a system
p_c	Transmit power assigned to car c
$\mathcal{R}$	Set of wireless resource blocks
R	Total number of available wireless resource blocks
$x_{c,m}$	Binary association variable
$\boldsymbol{X}$	Association matrix
$y_{c,r}$	Binary resource block allocation variable
$\boldsymbol{Y}$	Resource allocation matrix
ζ_c	Throughput of autonomous car c

A. COMPUTATION MODEL

To compute the local task at car c with operating frequency f_c for the task $\mathcal{T}_c(a_c, b_c, d_c)$, one can use the following equation.

$$t_{\text{local}} = b_c \left(\frac{a_c}{f_c}\right) \tag{1}$$

(1) shows that an increase in frequency will minimize the local computing time, but at the cost of an increase in local energy consumption. The set $\mathcal{F}$ of F computing resources (i.e., frequencies) will be used to denote frequencies of all cars. The local energy consumption for a device c with CPU-dependent constant ρ_c can be given by:

$$e_{\text{local}} = \rho_c b_c a_c (f_c)^2, \tag{2}$$

(2) shows that energy consumption varies with the square of the operating frequency. Therefore, there is a need for efficient utilization of local devices' frequency selection. The frequencies assigned to all devices must not exceed the maximum limit.

$$\sum_{c=1}^{C} f_c \leq F_{\max} \tag{3}$$

Other than the total local computing frequencies constraint, there must be some range of frequencies, each car can take.

$$f_{\min} \leq f_c \leq f_{\max}, \; \forall c \in \mathcal{C} \tag{4}$$

Next, we discuss the communication model.

B. COMMUNICATION MODEL

In this case, our focus is on the use of orthogonal frequency division multiple access (OFDMA) for car-to-RSU communication. To do so, we consider a set $\mathcal{R}$ of R resource blocks. These resource blocks are owned by cellular users and reused for efficient reuse of the limited communication resources. This will make efficient use of communication resources for serving more users. In our system model, a single car should not get more than a maximum allowed (e.g., 3) resource blocks.

$$\sum_{r=1}^{R} y_{c,r} \leq r_{\text{n, max}}, \tag{5}$$

where $r_{\text{c, max}}$ denotes the maximum number of resource blocks that a car c can take. There can be many ways to select the number of resource blocks for cars. Generally, an increase in the number of resource blocks for a car will improve the signal-to-noise-plus-interference ratio (SINR). However, there are limitations on the availability of resource blocks, therefore, there is a need for efficient management of resource blocks while maintaining the car's performance in terms of SINR or throughput. To do so, there must be a mechanism that allows to allocation least possible resources to cars to fulfill their minimum throughput requirements. Some of the devices have very poor SINR performance for a single resource block, therefore, there is a need for the upper limit of resource blocks assigned to cars to avoid extra usage of communication resources. As a result, the total number of resource blocks allocated to every automobile should either be fewer than or equal to the entire amount of resources that are accessible.

$$\sum_{c=1}^{C} y_{c,r} \leq R_{\text{MAX}}, \tag{6}$$

Now, we define a binary variable $x_{c,b}$ (i.e., $x_{c,b} = 1$ if car c is associated with an RSU b and otherwise $x_{c,b} = 0$) that shows the association of a car c with an RSU b. The throughput of a car c using resource block R with bandwidth W can be given by:

$$\zeta_c = W \log_2 \left(1 + \left(\frac{p_c h_{c,b}}{\sum_{l=1}^{L} p_l h_{l,b} + N_o^2} \right) \right), \; \forall c \in \mathcal{C} \tag{7}$$

where p_c and $h_{c,b}$ denote the transmit power of cars and channel gain between gain c and RSU b, respectively. Where $\sum_{l=1}^{L} p_l h_{l,b}$ is interference due to cellular users on the resource block R used by the car. Note that cars with poor SINR performance will induce more delays in transferring the offloaded task, and thus might not be desirable. To avoid such delays, there is a need for a fairness constraint, such as the latency of every device should not be more than a certain threshold, as follows.

$$\frac{u_c}{W \log_2 \left(1 + \left(\frac{p_c h_{c,b}}{\sum_{l=1}^{L} p_l h_{l,b} + N_o^2} \right) \right)} \leq \phi_{\max}, \; \forall c \in \mathcal{C}, \tag{8}$$

where $\phi_{\max}$ denotes the minimum allowed value of SINR. Every device's transmission power needs to be within a certain range.

$$p_{\min} \leq p_c \leq p_{\max}. \; \forall c \in \mathcal{C} \tag{9}$$

There are limitations on the available backup power of cars. Therefore, there should be constraint on the transmit power allocation. The total power allocated to all devices must not be more than the total available power.

$$\sum_{c=1}^{C} p_c \leq P_{\text{MAX}}. \tag{10}$$

On the other hand, note that there are computing capacity limitations of RSUs to serve cars. A particular RSU must not serve the maximum limit of RSUs.

$$\sum_{c=1}^{C} x_{c,b} \leq L_b, \forall b \in \mathcal{B} \tag{11}$$

On the other hand, a car must not be associated with more than one RSU.

$$\sum_{b=1}^{B} x_{c,b} \leq 1, \forall c \in \mathcal{C} \tag{12}$$

Note that (12) there might be cars that are in the middle of coverage areas of the RSUs. In our scenario, we will deploy RSUs whose coverage will overlap to avoid this issue. The transmission taken by cars for transferring the offloaded data to the RSU can be given by:

$$t_{\text{trans}}^{n} = \frac{u_c}{\zeta_c}, \tag{13}$$

where u_c denotes the size of the offloaded information to the RSU by the car c. Similarly, the energy required for transmission can be given by:

$$e^n_{\text{trans}} = \frac{u_c p_c}{\zeta_c}, \tag{14}$$

The total cost that accounts for local latency and transmission latency can be given by:

$$\mathcal{T}(\boldsymbol{f}, \boldsymbol{x}, \boldsymbol{y}, \boldsymbol{p}) = \left(\sum_{c=1}^{C} t^c_{\text{local}}(\boldsymbol{f})\right) + \left(\sum_{n=1}^{C} t^c_{\text{trans}}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{p})\right), \tag{15}$$

C. PROBLEM FORMULATION

Our problem is to minimize the cost associated with latency (i.e., both local computing and transmission) and energy (i.e., transmission).

$$\mathbf{P}: \underset{f,x,y,p}{\text{minimize}} \left(\sum_{c=1}^{C} t^c_{\text{local}}(\boldsymbol{f})\right) + \left(\sum_{n=1}^{C} t^c_{\text{trans}}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{p})\right) \tag{16}$$

$$\text{subject to: } p_{\min} \le p_c \le p_{\max}. \ \forall c \in \mathcal{C}, \tag{16a}$$

$$\sum_{c=1}^{C} p_c \le P_{\text{MAX}}, \tag{16b}$$

$$\sum_{c=1}^{C} f_c \le F_{\max}, \tag{16c}$$

$$f_{\min} \le f_c \le f_{\max}, \ \forall c \in \mathcal{C}, \tag{16d}$$

$$\sum_{r=1}^{R} y_{c,r} \le r_{\text{n, max}}, \tag{16e}$$

$$\sum_{c=1}^{C} y_{c,r} \le R_{\text{MAX}}, \tag{16f}$$

$$\frac{x_{c,b} y_{c,r} u_c}{W \log_2\left(1 + \left(\frac{p_c h_{c,b}}{\sum_{l=1}^{L} p_l h_{l,b} + N_o^2}\right)\right)} \le \phi_{\max}, \quad \forall c \in \mathcal{C}, \tag{16g}$$

$$\sum_{c=1}^{C} x_{c,b} \le L_b, \quad \forall b \in \mathcal{B}, \tag{16h}$$

$$\sum_{b=1}^{B} x_{c,b} \le 1, \quad \forall c \in \mathcal{C}, \tag{16i}$$

$$x_{c,b} \in \{0, 1\}, \quad \forall l \in \mathcal{L}, r \in \mathcal{R}, \tag{16j}$$

$$y_{c,b} \in \{0, 1\}, \quad \forall r \in \mathcal{R}, c \in \mathcal{C}, r \in \mathcal{R}. \tag{16k}$$

Problem **P** is a non-convex problem and therefore, one cannot simply apply convex optimization schemes. Constraint (16a) shows the lower and upper limit of the transmit power. Constraint (16b) limits the total transmit power

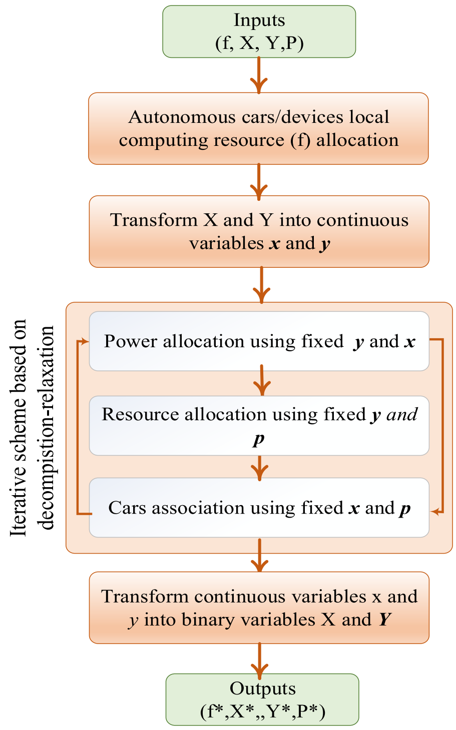

FIGURE 2. Solution approach.

of devices. Constraint (16c) denotes that the frequencies assigned to all devices should not exceed the maximum allowed limit. (16d) sets the upper and lower limits of the car operating frequencies. (16e) shows the total resource blocks assigned to a particular car must not be more than the allowed resource block for one car. (16f) limits the allocation of resource blocks to all cars. (16g) is the fairness constraint that shows the delay encountered for a car must not be more than the maximum deadline. (16h) denotes that number of cars associated with a certain RSU must not be more than its serving capacity. (16i) shows that a single car not be assigned to more than one RSU. Finally, the constraints (16j) and (16k) show their binary nature.

IV. PROPOSED SOLUTION

An NP-hard problem **P** like this renders it hard to solve using a convex optimization. As a result, we divide this main problem into three smaller problems: the resource allocation problem, the association problem, and the local computing resource optimization problem. The local computing sub-problem can be written as:

$$\mathbf{P-1}: \underset{f}{\text{minimize}} \ \mathcal{T}(\boldsymbol{f}) \tag{17}$$

$$\text{subject to: } \quad (16c), (16d) \tag{17a}$$

Convex optimizers can be used to solve problem (P-1) since it is a convex optimization problem.

Lemma 1 (Convexity of Sub-problem ***P-1****):* Here, the convexity of **P-1** is demonstrated for every possible value of the variable c using a hessian matrix. The following formula can be used to calculate the Hessian matrix values for **P-1** [26], [27].

$$\gamma_{i,j} = \frac{\partial^2 \mathcal{T}(\boldsymbol{f})}{\partial f_i \partial f_j}, \ \forall i = 1, 2, \ldots, C, \ j = 1, 2, \ldots, C \quad (18)$$

A summation of terms with f_i $i = 1, 2, \ldots, C$ makes up $\boldsymbol{f}$. 0 will be obtained by taking a double derivative of the terms that are not diagonal terms. With each diagonal element $\left(\frac{2b_c a_c}{f_n^3}\right)$, from (18), we derive a $C \times C$ diagonal matrix $\boldsymbol{\gamma}$, where f_n denotes the computational resources allotted to car n. The following is the form for the positive semidefinite.

$$C^T \boldsymbol{\gamma} C \geq 0, \quad (19)$$

It is evident that (19) is satisfied for all conceivable positive values (i.e., between c_{min} and c_{max}) of the variable c. This demonstrates that **P-1**'s objective function is a convex function. The constraints are also based on linear inequality. Thus, sub-problem **P-1** is an optimization problem that is convex.

For a fixed local computing resource allocation, the sub-problem (**P-2**) can be rewritten as:

$$\mathbf{P-2}: \underset{x,y,p}{\text{minimize}} \ \mathcal{T}(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{p})$$
$$\text{subject to:} (16a) - (16b), (16e) - (16k). \quad (20)$$

Sub-problem (**P-2**) has a non-convex nature due to the presence of two binary variables $\boldsymbol{x}$ and $\boldsymbol{y}$. Also, solving the problem (P-2) is difficult due to the constraint (14d). Constraint (14d) is about ensuring fairness such that every user should get minimum throughput so that their delay should not exceed the maximum allowed limit. To solve **P-2**, one can use a heuristic scheme that suffers from high complexity. Therefore, one can use decomposition-relaxation-based schemes to solve **P-2**. To do so, there is a need to transform the binary resource allocation and association variables into continuous variables. Problem **P-2** can be rewritten as:

$$\mathbf{P-3}: \underset{\widehat{x},\widehat{y},p}{\text{minimize}} \ \mathcal{T}(\widehat{\boldsymbol{x}}, \widehat{\boldsymbol{y}}, \boldsymbol{p}) \quad (21)$$
$$\text{subject to: } p_{\min} \leq p_c \leq p_{\max}. \ \forall c \in \mathcal{C}, \quad (21a)$$
$$\sum_{c=1}^{C} p_c \leq P_{\text{MAX}}, \quad (21b)$$
$$\sum_{r=1}^{R} \widehat{y}_{c,r} \leq r_{\text{n, max}}, \quad (21c)$$
$$\sum_{c=1}^{C} \widehat{y}_{c,r} \leq R_{\text{MAX}}, \quad (21d)$$
$$\frac{\widehat{x}_{c,b}\widehat{y}_{c,r}u_c}{W \log_2\left(1 + \left(\frac{p_c h_{c,b}}{\sum_{l=1}^{L} p_l h_{l,b} + N_o^2}\right)\right)} \leq \phi_{\max}, \forall c \in \mathcal{C}, \quad (21e)$$
$$\sum_{c=1}^{C} \widehat{x}_{c,b} \leq L_b, \forall b \in \mathcal{B}, \quad (21f)$$
$$\sum_{b=1}^{B} \widehat{x}_{c,b} \leq L_b, \forall c \in \mathcal{C}, \quad (21g)$$
$$0 \leq \widehat{x}_{c,b} \leq 1, \forall c \in \mathcal{C}, r \in \mathcal{R}, \quad (21h)$$
$$0 \leq \widehat{y}_{c,b} \leq 1, \forall r \in \mathcal{R}, c \in \mathcal{C}, r \in \mathcal{R}. \quad (21i)$$

Algorithm 1 BCD Algorithm

1: **Initialization Phase:** Set $k = 0$, $\epsilon_1 > 0$. Then, compute the initial feasible solutions, $(\widehat{X}^{(0)}, \widehat{Y}^{(0)})$.
2: **repeat**
3: Use index set $\mathcal{I}^k$;
4: For a fixed $\widehat{X}$ and $\widehat{P}$, compute $\widehat{Y}$ using convex optimizer, such as $\widehat{\boldsymbol{Y}}_i^{(k+1)} \in \min \mathcal{T}_i(\widehat{\boldsymbol{Y}}_{\boldsymbol{i}}^{(\boldsymbol{k}\mathcal{C}\mathbf{1})})$;
5: For a fixed $\widehat{Y}$, and $\widehat{P}$ compute $\widehat{X}$ using convex optimizer, such as $\widehat{\boldsymbol{X}}_i^{(k+1)} \in \min \mathcal{T}_i(\widehat{\boldsymbol{X}}_{\boldsymbol{i}}^{(\boldsymbol{k}\mathcal{C}\mathbf{1})})$;
6: For a fixed $\widehat{Y}$ and $\widehat{X}$, compute $\widehat{P}$ using convex optimizer, such as $\widehat{\boldsymbol{P}}_i^{(k+1)} \in \min \mathcal{T}_i(\widehat{\boldsymbol{P}}_{\boldsymbol{i}}^{(\boldsymbol{k}\mathcal{C}\mathbf{1})})$;
7: **until** $\| \frac{\mathcal{T}_i^{(k)} - \mathcal{T}_i^{(k+1)}}{\mathcal{T}_i^{(k)}} \| \leq \epsilon_1$
8: Then, set $\left(\widehat{X}_i^{(k+1)}, \widehat{P}_i^{(k+1)}, \widehat{Y}_i^{(k+1)}\right)$ as the desired solution.

To solve **P-3**, we decompose the main problem **P-3** into two sub-problems and then solve the individual problems iteratively, as depicted in Fig. 2. For a fixed association, one can write the resource allocation problem as follows.

$$\mathbf{P-4}: \underset{\widehat{y}}{\text{minimize}} \ \mathcal{T}(\widehat{\boldsymbol{y}})$$
$$\text{subject to:} \quad (21c) - (21e), (21i). \quad (22)$$

*Lemma 2 (Convexity of Sub-problem **P-4**):* Initially, we examine the constraints and the objective function across the entire range of the optimization variable $\widehat{\boldsymbol{y}}$. The function $\mathcal{T}(\widehat{\boldsymbol{y}})$ is a linear function of the variable $\widehat{\boldsymbol{y}}$. We can now see the constraints. Since there are only linear inequality constraints, the problem **P-4** can be classified as a convex optimization problem.

Like sub-problem **P-4**, an association problem for resource allocation of fixed type can be written as follows.

$$\mathbf{P-5}: \underset{\widehat{x}}{\text{minimize}} \ \mathcal{T}(\widehat{\boldsymbol{x}})$$
$$\text{subject to:} \quad (21e) - (21h). \quad (23)$$

*Lemma 3 (Convexity of Sub-problem **P-5**):* The objective function and constraints are explained below for the optimization variable $\widehat{\boldsymbol{x}}$ along its whole range. The function $\mathcal{T}(\widehat{\boldsymbol{x}})$ is a linear function of the variable $\widehat{\boldsymbol{x}}$. We can now perceive the limitations. It is possible to classify the problem **P-5** as a convex optimization problem because all of the constraints are linear inequality constraints.

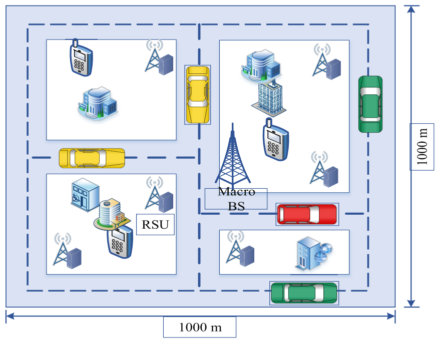

FIGURE 3. Simulation scenario overview.

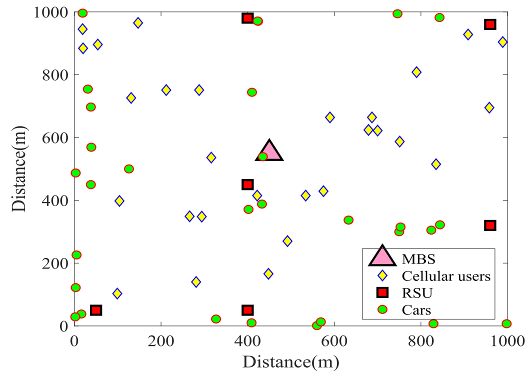

FIGURE 4. Sample scenario overview.

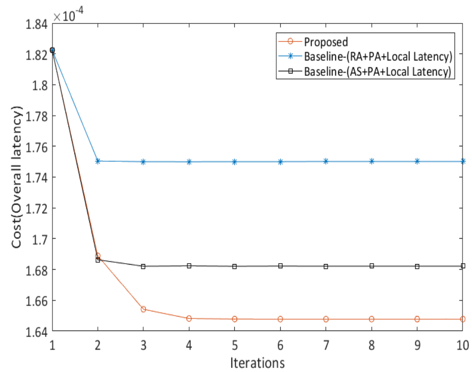

FIGURE 5. Cost vs. iterations for different schemes.

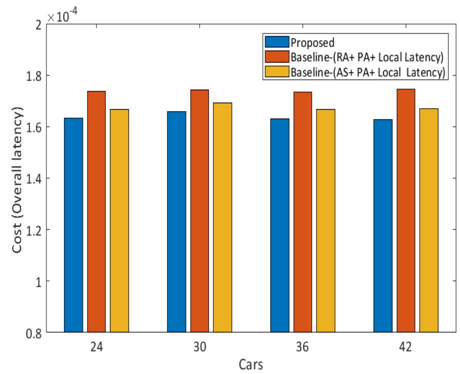

FIGURE 6. Cost vs cars for various schemes.

Now, we write the transmit power allocation problem as

$$\mathbf{P-6}: \underset{p}{\text{minimize}} \ \mathcal{T}(\boldsymbol{p}) \quad \text{subject to:} \quad (21a) - (21b). \tag{24}$$

Problem **P-6** has a convex nature that can be proved using the following lemma.

*Lemma 4 (Convexity of Sub-problem **P-7**):* The objective function and constraints are tested below for the optimization variable $\boldsymbol{p}$ along its whole range. The function, $\mathcal{T}(\boldsymbol{f})$ is convex for $\boldsymbol{p}$. By taking the derivative twice and comparing its values to every possible value of input $\mathbf{p}$, this may be demonstrated. We can now perceive the constraints. It is possible to classify the problem **P-6** as a convex optimization problem because all of the constraints are linear inequality problems.

We are going to discuss the complexity of the proposed strategy. The proposed scheme has two parts: (a) convex optimization to solve operating frequencies and (b) joint resource allocation, association, and power allocation. Our proposed scheme for joint resource allocation, association, and power allocation uses iterative approach that further uses convex optimizer. A Convex optimizer converges fast (i.e., within less iterations). Therefore, one can say that the proposed scheme has a reasonable complexity. To run the proposed scheme, one can use edge severs or cloud server. Furthermore, the complexity is low and it will not significantly affect performance of other applications/schemes.

V. NUMERICAL RESULTS

Here, we present numerical results for validating the performance of our proposed model with the solution. An area of $1000 \times 1000\ m^2$ is considered for simulation, as shown in Fig. 3. The locations of RSUs are fixed, whereas, the locations of cars are randomly changed for different simulation runs. To implement vehicular networks, one can use two approaches, such as LTE-based implementation and dedicated short-range communication-based implementation. Similar to many works [10], we use the LTE-based implementation of vehicular networks. The sample scenario is shown in Fig. 4. To show the effectiveness of our scheme compared to existing schemes, two baselines, such as (a) baseline-(RA+PA+Local latency)) (i.e., resource allocation, power allocation and cars' local frequency allocation) and (b) baseline-(AS+PA+Local latency) (i.e., association, power allocation, and cars' local frequency allocation) are considered.

Fig. 5 shows the performance comparison of various schemes for different iterations. It is evident from Fig. 5 that our scheme outperformed different baselines. The main cause of this performance improvement is due to the fact that the proposed scheme considers car frequency allocation, wireless resource allocation, power allocation, and

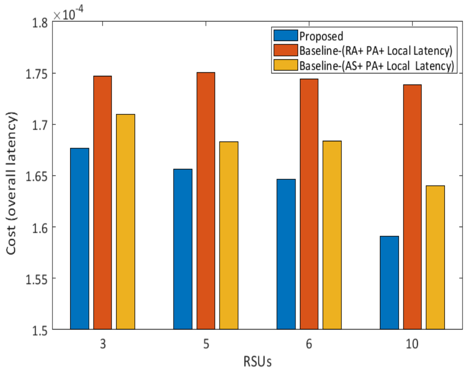

FIGURE 7. Cost vs RSUs for various schemes.

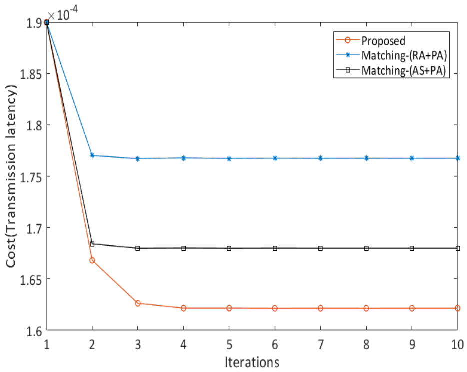

FIGURE 8. Cost vs RSUs for proposed and matching-based schemes.

association. On the other hand, baseline-(RA+PA+Local latency) considers only local car frequency allocation, power allocation, and resource allocation, whereas baseline-(AS+PA+Local latency) performs cars' local frequency allocation, power allocation, and association. If we see the performance trends, Fig. 5 follows the trend from best to worsts as proposed, baseline-(AS+PA+Local latency), and baseline-(RA+PA+Local latency). According to this performance trend, the cost for resource allocation for the specified scenario and settings is less dependent compared to association. The cost of the recommended approach for cars for a fixed number of RSUs for different schemes is displayed in another figure, 6. Figure 6 makes it evident that the suggested approach functions fairly for a range of car counts. This demonstrates the proposal's viability for modified real-time applications. Similar to Fig. 6, Fig. 7 shows the cost for a proposed scheme for different numbers of RSUs using a fixed number of cars. It is clear from Fig. 7 that the proposed scheme performs reasonably for various numbers of RSUs. All the above Figs. 5, 6, and 7 shows that proposed scheme outperforms all others.

Fig. 8 shows the performance comparison of the proposed scheme with matching based schemes. Two variant of matching-based schemes are considered, Matching (RA+PA) and Matching (AS+PA). Matching (RA+PA) considers proposed power allocation and matching game-based resource allocation [28]. Matching (AS+PA) considers proposed power allocation and matching game based association [29].

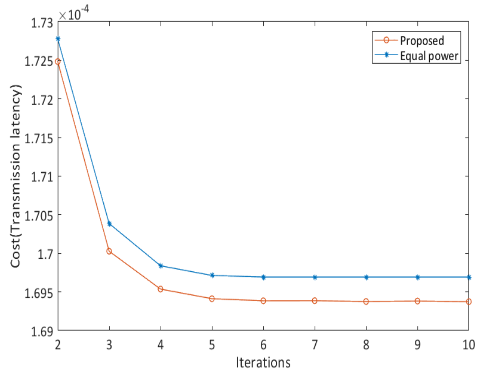

FIGURE 9. Proposed vs. equal power for proposed scheme.

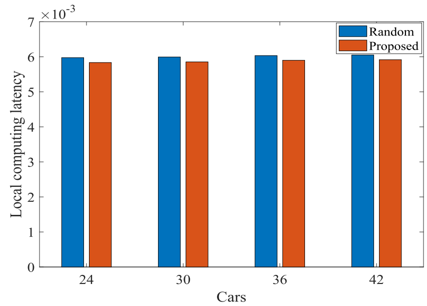

FIGURE 10. Local computing latency vs cars for different schemes.

Fig. 8 demonstrates that proposed scheme outperforms the matching based schemes. Finally, we discuss Fig. 10 that compares proposed vs random local computing frequencies allocation. It is clear from Fig. 10 that proposed scheme outperforms the random scheme.

VI. CONCLUSION

We have investigated a vehicle network with computational workload offloading in this paper. We establish a cost function that takes into account the total latency, which includes the latency from task offloading and local processing. To minimize the cost, we proposed a decomposition-relaxation-based scheme, that enables cars' local frequency allocation, resource allocation, and association problem. Finally, numerical results are provided to reveal the effectiveness of the proposed solution. Our proposed scheme outperformed other baselines. We concluded that our proposal can be used effectively as a guideline for future works with fairness constraints. Although the proposed system model and solution offer many benefits, there is still a room for more work to further improve the performance. For instance, one can propose another novel solution to further minimize the approximation errors caused in BCD-based solution due to approximation (e.g., approximation error in conversion of the binary resource allocation variable into continuous for solution and then transformation back to binary after finding a solution). Additionally, one can add more constraints (e.g., reliability constraints in terms of outage probability and mobility constraints).

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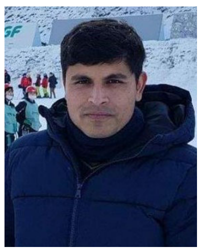

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