Abstract—In this paper, a dynamic spectrum management framework is proposed to improve spectrum resource utilization in a multi-access edge computing (MEC) in autonomous vehicular network (AVNET). To support the increasing communication data traffic and guarantee quality-of-service (QoS), spectrum slicing, spectrum allocating, and transmit power controlling are jointly considered. Accordingly, three non-convex network utility maximization problems are formulated to slice spectrum among base stations (BSs), allocate spectrum among autonomous vehicles (AVs) associated with a BS, and control transmit powers of BSs, respectively. Through linear programming relaxation and first-order Taylor series approximation, these problems are transformed into tractable forms and then are jointly solved through an alternate concave search (ACS) algorithm. As a result, the optimal spectrum slicing ratios among BSs, optimal BS-vehicle association patterns, optimal fractions of spectrum resources allocated to AVs, and optimal transmit powers of BSs are obtained. Based on our simulation, a high aggregate network utility is achieved by the proposed spectrum management scheme compared with two existing schemes.

Index Terms—Multi-access edge computing, NFV, spectrum resource allocation, QoS-guaranteed service, autonomous vehicles.

I. INTRODUCTION

RECENT advances in automobiles and artificial intelligence technology are promoting the developing of autonomous vehicles (AVs), which are becoming a reality [1] and are expected to be commercialized and appear on the roads in the coming years [2]. However, salient challenges in computing and communication remain to be addressed to support AV applications. From the computing perspective, various computing tasks need to be carried out on board for real-time environment sensing and driving decision making [3]. Moreover, enabling cooperative driving among AVs, such as platoon-based driving [4]–[7] and convoy-based driving [3], [8], also requires extra computing tasks. From the communication perspective, the vehicular network enables inter-AV information exchanging and provides high definition (HD) maps [9] to AVs to support vehicular safety and non-safety related applications [10], [11]. For example, cooperative driving requires inter-AV communications for sharing position, velocity, acceleration, and other cruise control information [5], [12]. All these required information exchanges among AVs increase the communication data traffic and are with differential quality-of-service (QoS) requirements.

Some achievements have been made to overcome the challenges in computing and communication in vehicular networks. Edge computing has been regarded as an effective technology to enhance computing and storing capabilities in vehicular networks while alleviating traffic load to the core network [13]–[15]. Via moving computing and storing resources to servers placed at the edge of the core network, vehicles can offload its computing tasks to edge servers. Another potential method to address the computing issue is enabling collaborative computing among vehicles [3], [16], [17]. In the scenarios with light computing task load, the on-board computing resource utilization can be improved through offloading computing tasks to the adjacent vehicles with idle computing power [3]. To address the communication issues in vehicular networks, interworking of multiple wireless access technologies has been widely accepted, such as the interworking of cellular network and dedicated short-range communications (DSRC) technologies [18]. To simultaneously address both computing and communication issues in vehicular networks, multi-access edge computing (MEC) has recently been considered in some existing works [19], [20].

Inspired by existing works, a new architecture combines MEC with network function virtualization (NFV) and software defined networking (SDN) to address the challenges in computing and communication in autonomous vehicular networks (AVNETs) [21]. Via the MEC technology, 1) AVs with limited on-board computing/storing resources can offload the tasks requiring high computing/storing requirements to the MEC servers, such that a shorter response delay can be guaranteed through avoiding the data transfer between the core network and MEC servers; 2) multiple types of access technologies are permitted, thus moving AVs can access MEC servers via different base stations (BSs), such as Wi-Fi access points (Wi-Fi APs), road-side units (RSUs) [22], White-Fi infostations, and evolved NodeBs (eNBs). Moreover, by integrating SDN and NFV concepts in each MEC server [23]–[25], global network control is enabled, and therefore, the computing/storing resources placed at MEC servers can be dynamically managed.

1In 2017, mobile edge computing has been renamed to multi-access edge computing by the European Telecommunication Standards Institute (ETSI) to better reflect the growing interest and requirements in edge computing from non-cellular operators.

and various radio spectrum resources can be abstracted and sliced to the BSs and then be allocated to AVs by each BS.

Efficient management for computing, storing, and spectrum resources is of paramount importance for the MEC-based AVNET. However, it is challenging to simultaneously manage the three types of resources while guaranteeing the QoS requirements for different AV applications, especially in the scenario with a high AV density. In this paper, we focus on spectrum resource management which can be extended to multiple resource allocation as our future work. The main contributions of this work are summarized as follows:

1) By considering the tradeoff between spectrum resource utilization and inter-cell interference, we develop a dynamic two-tier spectrum management framework for the MEC-based AVNET, which can be easily extended to other heterogeneous networks.
2) Leveraging logarithmic and linear utility functions, we formulate three aggregate network utility maximization problems to fairly slice spectrum resources among BSs connected to the same MEC server, optimize BS-vehicle association patterns and resource allocation, and control the transmit power of BS.
3) Linear programming relaxation and first-order Taylor series approximation are used and an alternate concave search (ACS) algorithm is designed to jointly solve the three formulated optimization problems.

The remainder of this paper is organized as follows. First, the MEC-based AVNET is introduced in Section II, followed by the dynamic spectrum management framework and the communication model. In Section III, three optimization problems are formulated to slice and allocate spectrum resources among BSs and among AVs and control the transmit power of BS. Then, the three problems are transformed to tractable problems and are jointly solved in Section IV. In Section V, extensive simulation results are presented to demonstrate the performance of the proposed spectrum management framework. Finally, we draw concluding remarks in Section VI.

II. SYSTEM MODEL

In this section, we first present an MEC-based AVNET architecture and a dynamic spectrum management framework, and then describe the communication model under the considered AVNET.

A. MEC-Based AVNET Architecture

Based on a reference model suggested by the MEC ETSI industry specification group [19], we consider an MEC-based AVNET with one MEC server to support AV applications, as shown in Fig. 1. The MEC server allows AVs to access the edge computing/storing resources through different wireless access technologies.

To improve the cost efficiency of MEC server placement and provide short response delays to the AVs, the MEC server should be placed close to the edge of the core network but not directly at each BS [21]. The communication hops between an MEC server and an AV is assumed to be two. Thus, a large number of AVs within the coverages of several neighboring BSs can be served by the same MEC server and the enlarged service area of the MEC server can better overcome the challenges caused by high AV mobility. The total coverages of BSs connected to an MEC server is defined as the service area of this server. To realize the resource virtualization process, including computing, storing, and spectrum resources, we consider a virtual wireless network controller at the MEC server. Through collecting information from the BSs and the AVs in the service area, resource management functions can run at the controller to adjust the virtual computing and storing resources to different AV tasks and to coordinate wireless access over the wide range of spectrum resources for AVs.

B. Dynamic Spectrum Management Framework

Due to the high AV mobility and heterogeneous AV applications, AVNET topology and QoS requirements change frequently, and therefore, resource allocation should be adjusted accordingly. To improve spectrum resource utilization, a dynamic spectrum management framework is developed for downlink transmission. Taking a one-way straight road with two lanes as an example in Fig. 2, two wireless access technologies, cellular and Wi-Fi/DSRC [26]–[29], are available to the AVs. Wi-Fi APs/RSUs and eNBs are uniformly deployed on one side of the road, where the $i$th Wi-Fi AP and the $j$th eNB are denoted by $W_i$ and $S_j$, respectively. The transmit power of each eNB, $P$, is fixed and high enough to guarantee a wide-area coverage, such that all AVs can receive sufficient strong control signal or information signal from eNBs. Denote $P'$ as the transmit power of Wi-Fi AP $W_i$, which is lower than $P$ and is dynamically adjusted by the controller. For AVs within the overlapping area of two BSs, only one of the BSs is associated for downlink transmission.

Fig. 1. An MEC-based AVNET model.
We divide the eNBs into two groups, denoted by $B_1$ and $B_2$, where eNBs in the same group share the same spectrum resources and are not neighbored to each other. ENBs $S_1$ and $S_2$ shown in Fig. 2 are the two target eNBs from the two different sets, where $S_1 \in B_1$ is adjacent to $S_2 \in B_2$. Set of Wi-Fi APs under the coverage of eNB $S_1$ is denoted by $A_j$. Denote the total available spectrum resources for AV applications to be $R^{\text{max}}$. After collecting the application requests from AVs via BSs, the controller performs dynamic spectrum management for downlink transmission. The procedure can be divided into two tiers as the following.

1) **Spectrum slicing among BSs:** The controller slices the spectrum resource, $R^{\text{max}}$, into three slices with ratio set $\{\beta_1, \beta_2, \beta_w\}$ with $\beta_1 + \beta_2 + \beta_w = 1$, and allocates them to eNBs in $B_1$, eNBs in $B_2$, and Wi-Fi APs, respectively.

2) **Spectrum allocating among AVs:** Once the spectrum is sliced, each BS allocates its available spectrum resources to AVs associated to it. By allocating an appropriate amount of spectrum resources to each AV, the QoS requirements of various AV applications can be satisfied and the sum of transmission rates over the whole AVNET can be maximized.

Spectrum slicing among BSs, spectrum allocating among AVs, and transmit power controlling for Wi-Fi APs are updated once the traffic load of each eNB fluctuates, which is in a large time scale compared to network dynamic due to AV mobility. The traffic load of an eNB is defined as the average arrival traffic for AVs in the coverage of the eNB.

**C. Communication Model**

Assume the three slices of spectrum resources are mutually orthogonal, therefore, there is no inter-slice interference. To improve the spectrum resource utilization, two levels of spectrum reusing are considered. The first level is reusing the spectrum resource $\beta_w R^{\text{max}}$ among all the Wi-Fi APs as long as with an acceptable inter-cell interference. Moreover, we assume that the Wi-Fi APs with no overlapping coverage area with an eNB can reuse the spectrum allocated to that eNB. Thus, the interference to eNBs caused by the Wi-Fi APs can be controlled by adjusting the transmit powers of the Wi-Fi APs while the spectrum resource utilization can be further improved by allowing each Wi-Fi AP to reuse either the spectrum resource $(\beta_w + \beta_1) R^{\text{max}}$ or $(\beta_w + \beta_2) R^{\text{max}}$.

According to the dynamic spectrum management framework presented in Section II-B, all the eNBs in $B_1$ reuse the spectrum resource $\beta_1 R^{\text{max}}$ for downlink transmission. Denote $\mathcal{M}_j / \mathcal{M}_j$ as the set/number of AVs within the coverage of eNB $S_j$. Then AV $k$, under the coverage of eNB $S_1$ (i.e., $k \in \mathcal{M}_1$), experiences two kinds of interference to the corresponding downlink: from transmissions of other eNBs in $B_1$ and of Wi-Fi APs in the coverage of eNBs in $B_2$. Thus, the spectrum efficiency at AV $k$ ($k \in \mathcal{M}_1$) from eNB $S_1$ can be given by

$$r^{\text{k}}_{1} = \log_2(1 + \frac{P \cdot G^{\text{k}}_{1}}{\sum_{j \in \mathcal{B}_1, j \neq 1} P \cdot G_{j}^{\text{k}} + \sum_{j \in \mathcal{B}_2} \sum_{i \in A_j} P \cdot G_{i}^{\text{k}} + \sigma^2}),$$

where $G^{\text{k}}_{1} (G^{\text{k}}_{j})$ is the channel power gain between eNB $S_j$ (Wi-Fi AP $W_i$) and AV $k$, and $\sigma^2$ is the power spectrum density of the additive white Gaussian noise (AWGN). Similarly, the spectrum efficiency at AV $k$ ($k \in \mathcal{M}_2$) from eNB $S_2$, $r^{\text{k}}_{2}$, can be obtained. Let $R^{\text{k}}_{1}$ be the amount of spectrum allocated for AV $k$ from eNB $S_1$. Then, the achievable transmission rates of AV $k$ associated with eNBs $S_1$ (or $S_2$) can be expressed as

$$\gamma^{\text{k}}_{1} = \frac{R^{\text{k}}_{1} r^{\text{k}}_{1}}{g^{\text{k}}_{1}} \quad \text{or} \quad \gamma^{\text{k}}_{2} = \frac{R^{\text{k}}_{2} r^{\text{k}}_{2}}{g^{\text{k}}_{2}}.$$

Denote $N_1 / N_2$ as the set/number of AVs within the coverage of Wi-Fi AP $W_i$. Let $R^{\text{k}}_{1}$ and $R^{\text{k}}_{2}$ be the amount of spectrum allocated to AV $k$ from $\beta_2 R^{\text{max}}$ and $\beta_w R^{\text{max}}$, respectively, by Wi-Fi AP $W_g$ under the coverage of eNB $S_1$ (i.e., $W_g \in A_1$). Then the spectrum efficiencies at AV $k$ from Wi-Fi AP $W_g$ include the following two parts,

$$r^{\text{k}}_{2,g} = \log_2(1 + \frac{P \cdot G^{\text{k}}_{2,g}}{\sum_{i \in A_1, i \neq g} P \cdot G_{i}^{\text{k}} + \sum_{j \in \mathcal{B}_2} P \cdot G_{j}^{\text{k}} + \sigma^2}),$$

$$r^{\text{k}}_{w,g} = \log_2(1 + \frac{P \cdot G^{\text{k}}_{w,g}}{\sum_{i \in \{A_1 \cup A_2\}, i \neq g} P \cdot G_{i}^{\text{k}} + \sigma^2}).$$

And the achievable transmission rate of a tagged AV $k$ associated with Wi-Fi AP $W_g$, i.e., $k \in \{W_g \in A_1, N_1\}$, can be expressed as

$$\gamma^{\text{k}}_{g} = \frac{R^{\text{k}}_{2,g} r^{\text{k}}_{2,g} + R^{\text{k}}_{w,g} r^{\text{k}}_{w,g}}{g^{\text{k}}_{g}}.$$

Let $R^{\text{k}}_{1,h}$ and $R^{\text{k}}_{w,h}$ be the amount of spectrum allocated for AV $k$ from $\beta_1 R^{\text{max}}$ and $\beta_w R^{\text{max}}$, respectively, by Wi-Fi AP $W_h$ under the coverage of eNB $S_2$ (i.e., $W_h \in A_2$), and $r^{\text{k}}_{1,h}$ and $r^{\text{k}}_{w,h}$ be the spectrum efficiencies at AV $k$ from Wi-Fi AP $W_h$. Similarly, the achievable transmission rate of a tagged AV $k$ associated with Wi-Fi AP $W_h$, i.e., $k \in \{W_h \in A_2, N_2\}$, can be given by

$$\gamma^{\text{k}}_{h} = \frac{R^{\text{k}}_{1,h} r^{\text{k}}_{1,h} + R^{\text{k}}_{w,h} r^{\text{k}}_{w,h}}{g^{\text{k}}_{h}}.$$

**III. RESOURCE MANAGEMENT SCHEME**

We consider two kinds of traffic for each AV: delay-sensitive traffic and delay-tolerant traffic. Examples of AVs’ delay-sensitive traffic include real-time collision avoidance.
and platooning/convoying. The delay-tolerant traffic can be HD map information downloading and infotainment services. Denote \( p \) as the probability that an AV generates a delay-sensitive request. To accommodate the large amounts of data traffic generated by AVs while guaranteeing different QoS requirements for AV applications, designing efficient resource management schemes are very important.

For downlink transmission to accommodate AVs’ delay-sensitive requests, the transmission delay from eNB \( S_j \) or Wi-Fi AP \( W_i \) should be guaranteed statically. Let \( D_s \) and \( \lambda_s \) be the size and the arrival rate of the delay-sensitive packet. From [30], the maximum delay requirement, \( D_{\text{max}} \), can be transformed to a lower bound of the required transmission rate to guarantee that the downlink transmission delay exceeding \( D_{\text{max}} \) at most with probability \( \varrho \), which can be expressed as

\[
\gamma_{\text{min}} = \frac{D_s \log \varrho}{D_{\text{max}} \log (1 - \log(1/(D_s D_{\text{max}})))}.
\]

A. Spectrum Resource Allocation

To address complicated resource allocation, we will introduce a two-tier approach, including spectrum slicing among BSs and spectrum allocating among AVs, as following.

1) Spectrum Slicing Among BSs: Based on the dynamic spectrum management framework, the total available spectrum resources are sliced according to the ratio set \( \{\beta_1, \beta_2, \beta_w\} \) for different BSs. The main concern for spectrum slicing is fairness among BSs. To this end, a logarithmic utility function, which is concave and with diminishing marginal utility [30], is considered to achieve a certain level of fairness among BSs.

For AV \( k \) within the coverages of Wi-Fi APs, binary variables \( x^j_k \) and \( x^k \) represent the BS-vehicle association patterns, where \( x^j_k = 1 \) (or \( x^k = 1 \)) means AV \( k \) is associated with eNB \( S_j \) (or Wi-Fi AP \( W_i \)), \( x^j_k = 0 \) (or \( x^k = 0 \)) otherwise. Denote \( \overline{M}_j / M_j \) as the set number of AVs within the coverage of eNB \( S_j \) while outside of Wi-Fi APs. Then, the utility for AV \( k \) associated to eNBs or Wi-Fi APs is

\[
\begin{align*}
  u^k &= \begin{cases} 
    \log(\gamma^k_j), & \text{if } k \in \overline{M}_j \cup \{k|x^j_k = 1\} \\
    \log(\gamma^k_2), & \text{if } k \in M_2 \cup \{k|x^j_k = 1\} \\
    \log(\gamma^k_N), & \text{if } k \in N_N \cap \{k|x^j_k = 1\} \\
    \log(\gamma^k_h), & \text{if } k \in N_h \cap \{k|x^j_k = 1\}. 
  \end{cases}
\end{align*}
\]

The aggregated network utility is defined as the summation of utility of each individual AV. Let \( R = \{R^1_j, R^2_k\} \) and \( R^w = \{R^w_1, R^w_2, R^w_{s,w}, R^w_{h,w}, R^w_{h,w,h}\} \) be the matrices describing spectrum allocated to AVs by eNBs and by Wi-Fi APs, respectively. For given BS-vehicle association patterns with fixed transmit power of each Wi-Fi AP, a network throughput maximization problem can be formulated as

\[
\begin{align*}
  \text{P1 : } \max_{\beta_1, \beta_2, \beta_w} & \quad \sum_{k \in \overline{M}_1} u^k + \sum_{W_i \in N_N} \sum_{k \in N_N} (x^j_k u^k_{1} + x^k u^k_{2}) + \sum_{W_h \in N_h} \sum_{k \in N_h} (x^j_k u^k_{1} + x^k u^k_{2}) \\
  \text{s.t.} & \quad \beta_1 + \beta_2 + \beta_w = 1, \\
  & \quad \sum_{k \in \overline{M}_1} R^1_k + \sum_{W_i \in N_N} \sum_{k \in N_N} x^j_k R^1_k = \beta_1 R^\text{max}, \\
  & \quad \sum_{k \in \overline{M}_2} R^2_k + \sum_{W_i \in N_N} \sum_{k \in N_N} x^j_k R^2_k = \beta_2 R^\text{max}, \\
  & \quad \sum_{k \in N_N} x^j_k R^w_{1,k} = \beta_1 R^\text{max}, \quad l \in \{2, w\}, \\
  & \quad \sum_{k \in N_h} x^j_k R^w_{1,k} = \beta_1 R^\text{max}, \quad l \in \{1, w\}, \\
  & \quad R^1_k, R^2_k, R^w_{1,k}, R^w_{2,k}, R^w_{s,w}, R^w_{h,w}, R^w_{h,w,h} \geq 0. 
\end{align*}
\]

In problem (P1), the objective function is to maximize the aggregated network utility. Since \( \beta_1, \beta_2, \) and \( \beta_w \) are the only three slicing ratios, constraints (8a) and (8b) are considered in (P1). Constraints (8c)-(8g) indicate that spectrum resources allocated to AVs by a BS should be constrained by its available spectrum resources. According to problem (P1), each BS equally allocates the spectrum resources to AVs associated to it (will be discussed in detail in the next section). However, the downlink transmission rate required by an AV depends on its application request. For a BS with a fixed amount of available spectrum resources, equally allocating spectrum to AVs associated to it and simultaneously guaranteeing their heterogeneous QoS requirements will reduce the number of accommodated AVs. Thus, QoS constraints on \( R \) and \( R^w \) are not considered in problem (P1) and the optimal \( \{\beta^*_1, \beta^*_2, \beta^*_w\} \) is regarded as the only output to slice the total spectrum resources among BSs.

2) Spectrum Allocating Among AVs: To accommodate situations with high density AVs, a linear network utility function is considered in allocating spectrum among AVs associated to the same BS. For given slicing ratios \( \beta_1, \beta_2, \) and \( \beta_w, \) and transmit power of each Wi-Fi AP, a network throughput maximization problem can be formulated as

\[
\begin{align*}
  \text{P2 : } \max_{\beta_1, \beta_2, \beta_w} & \quad \sum_{k \in \overline{M}_1} \gamma^k_1 + \sum_{W_i \in A_{E}} \sum_{k \in N_N} (x^j_k \gamma^k_1 + x^k \gamma^k_2) + \sum_{W_h \in A_{H}} \sum_{k \in N_h} (x^j_k \gamma^k_1 + x^k \gamma^k_2) \\
  \text{s.t.} & \quad \beta_1 + \beta_2 + \beta_w = 1, \\
  & \quad \sum_{k \in \overline{M}_1} \gamma^k_1 = \gamma^\text{min}, \quad l \in \{2, w\}, \\
  & \quad \sum_{k \in \overline{M}_1} \gamma^k_2 = \gamma^\text{min}, \quad l \in \{2, w\}, \\ & \quad x^j_k \gamma^k_1 + x^k \gamma^k_2 \geq 0, \quad k \in W_i N_N, \\
  & \quad x^j_k \gamma^k_1 + x^k \gamma^k_2 \geq 0, \quad k \in W_h N_h. 
\end{align*}
\]

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where \( X = \{ x_1^k, x_2^k \} \) and \( X' = \{ x_2^k, x_2^k \} \) are the association pattern matrices between eNBs and AVs, and between Wi-Fi APs and AVs, respectively; \( L_{a} \) and \( j_{aw} \) are the corresponding packet size and the arrival rate for delay-tolerant service requests; \( \mathcal{M}_1/M_j \) or \( \mathcal{M}_2/M_j \) are the set/number of AVs only within the coverage of eNB \( S_j \) and requesting for delay-sensitive (or delay-tolerant) services; \( \mathcal{N}_r^g/N_r^g \) (or \( \mathcal{N}_r^g/N_r^g \)) are the set/number of AVs within the coverage of Wi-Fi AP \( W_i \) and requesting for delay-sensitive (or delay-tolerant) services.

In problem (P2), the first five constraints are same with problem (P1) and used to demonstrate the required spectrum for each AV allocated by its associated BS. Constraints (9b)-(9d) indicate that each AV is associated with either the eNB or the Wi-Fi AP closed to it. Constraints (9e)-(9f) ensure the service rates from eNBs and Wi-Fi APs to guarantee the delay requirements of delay-sensitive services. For AVs with delay-tolerant requests, constraints (9g)-(9i) indicate that the service rate from an eNB or a Wi-Fi AP should be not less than the periodic traffic arrival rate at that eNB or Wi-Fi AP. Via solving problem (P2), the optimal association pattern matrices \( X^* \) and \( X'^* \), and local spectrum allocation matrices \( R^* \) and \( R'^* \) can be obtained, which maximize the network throughput with guaranteed QoS for different AV applications.

**B. Transmit Power Control**

In addition to spectrum slicing and allocating among BSs and among AVs, controlling the transmit power of Wi-Fi APs to adjust the inter-cell interference would further improve the spectrum utilization. Denote \( \mathbf{P}' = \{ p'_w | W_i \in \{ A_1 \cup A_2 \} \} \) as the transmit power matrix of Wi-Fi APs. Equations (1) and (3) indicate that the received signal-to-interference-plus-noise (SINR) [31] by AVs from either an eNB or a Wi-Fi AP change with Wi-Fi APs’ transmit powers, and therefore, impacting the achievable transmission rates of the corresponding downlink. To obtain optimal transmit powers of Wi-Fi APs, the linear utility function is considered in this part similar to problem (P2). For a given slicing ratio set \( \{ \beta_1, \beta_2, \beta_w \} \), BS-vehicle association pattern matrices \( X \) and \( X' \), and local spectrum allocation matrices \( R \) and \( R' \), the network throughput maximization problem focusing on transmit power control can be formulated as

\[
P3: \max_{\mathbf{P}} \sum_{k \in \mathcal{M}_1} \gamma_1^k + \sum_{w \in A_1, k \in \mathcal{N}_r^g} (x_1^k y_1^k + x_2^k y_2^k) + \sum_{k \in \mathcal{M}_2} \gamma_2^k + \sum_{w \in A_2, k \in \mathcal{N}_r^g} (x_2^k y_2^k + x_2^k y_2^k) \tag{10}
\]

\[
s.t. \left\{ \begin{align*}
(9e) - (9f), \quad & (10a) \\
\mathbf{P}' \in [0, \mathbf{P}_{\text{max}}], \quad & (10b)
\end{align*} \right.
\]

where \( \mathbf{P}_{\text{max}} \) is the maximum transmit power allowed by each Wi-Fi AP. In problem (P3), the first eight constraints in (10a) are same with problem (P2) and used to ensure the QoS requirements for delay-sensitive and delay-tolerant services. Constraint (10b) indicates that transmit power of each Wi-Fi AP is less than \( \mathbf{P}_{\text{max}} \). Then the optimal transmit power for each Wi-Fi AP can be determined by solving problem (P3). From the above discussion, variables considered in problems (P1), (P2), and (P3) are coupled, thus the three problems should be solved jointly.

**IV. PROBLEM ANALYSIS AND SUBOPTIMAL SOLUTION**

In this section, we first analyze each problem and then transform (P2) and (P3) to tractable forms before we jointly solving these three problems for the final optimal solutions.

**A. Problem Analysis**

Let \( \mathcal{N}_r^g \) be the set of AVs within and associated with Wi-Fi AP \( W_i \), i.e., \( \mathcal{N}_r^g = \{ k \in \mathcal{N}_r^g | x_1^k = 1 \} \) for \( W_i \in \{ A_1 \cup A_2 \} \), and \( \mathcal{N}_r^g \) \( \mathcal{N}_r^g \). Then, the objective function of (P1) can be transformed into,

\[
\sum_{k \in \mathcal{M}_1 \setminus \{ W_i \}} \log(R_1^k r_1^k) + \sum_{w \in \mathcal{N}_r^g} \log(\gamma_2^k) + \sum_{k \in \mathcal{M}_2 \setminus \{ W_i \}} \log(R_2^k r_2^k) + \sum_{w \in \mathcal{N}_r^g} \log(\gamma_2^k) \tag{11}
\]

where mathematical symbol, \( \setminus \), describes the relative complement of one set with respect to another set. According to the constraints of (P1), the sets of spectrum allocation variables, \( \{ R_1^k \}, \{ R_2^k \}, \{ R_2^k \}, \{ R_w^k \}, \{ R_w^k \}, \{ R_2^k \}, \) and \( \{ R_w^k \}, \) are independent with uncoupled constraints. Thus, similar to proposition 1 in [30], we can decompose problem (P1) into six subproblems and obtain the optimal fractions of spectrum allocated to AVs from the associated BSs as follows.

\[
R_1^k = R_1^k = \frac{\beta_1 R_{\text{max}}}{M_1 - \sum_{w \in A_1 \setminus \{ W_i \}} N_r^g} \\
R_2^k = R_2^k = \frac{\beta_2 R_{\text{max}}}{M_2 - \sum_{w \in A_2 \setminus \{ W_i \}} N_r^g} \\
R_2^g = R_2^g = \frac{\beta_2 R_{\text{max}}}{N_r^g} \\
R_w^g = R_w^g = \frac{\beta_w R_{\text{max}}}{N_r^g} \\
R_1^h = R_1^h = \frac{\beta_1 R_{\text{max}}}{N_r^h} \\
R_w^h = R_w^h = \frac{\beta_w R_{\text{max}}}{N_r^h} \tag{12}
\]

Equation (12) indicates that each BS equally allocates spectrum to AVs associated to it. By replacing the spectrum allocation variables with Equation (12), problem (P1) can be transformed into

\[
P1': \max_{\beta_1, \beta_2, \beta_w} \sum_{k \in \mathcal{M}_1 \setminus \{ W_i \}} \log(\frac{\beta_1 R_{\text{max}} r_1^k}{M_1 - \sum_{w \in A_1 \setminus \{ W_i \}} N_r^g}) + \sum_{w \in A_1 \setminus \{ W_i \}} \log(\frac{\beta_1 R_{\text{max}} r_1^k}{M_1 - \sum_{w \in A_1 \setminus \{ W_i \}} N_r^g}) \tag{13}
\]

\[
+ \sum_{k \in \mathcal{M}_2 \setminus \{ W_i \}} \log(\frac{\beta_2 R_{\text{max}} r_2^k}{M_2 - \sum_{w \in A_2 \setminus \{ W_i \}} N_r^g}) + \sum_{w \in A_2 \setminus \{ W_i \}} \log(\frac{\beta_2 R_{\text{max}} r_2^k}{M_2 - \sum_{w \in A_2 \setminus \{ W_i \}} N_r^g}) \tag{13a}
\]

s.t.\{ (8a) - (8b). \tag{13a} \}
Due to the binary variable matrices $X$ and $X'$, using the brute force algorithm to solve problems (P2) and (P3) is with high complexity. To address this issue, we allow AVs within the overlapping area of a Wi-Fi AP and an eNB to associate to one or both of the Wi-Fi AP and the eNB [32]. Thus, binary matrices $X$ and $X'$ are relaxed into real-valued matrices $\tilde{X}$ and $\tilde{X}'$ with elements $\tilde{x}_i^k \in \{0, 1\}$ and $\tilde{x}'_i^k \in \{0, 1\}$, respectively. And then, we can transform problem (P2) into

$$\textbf{P2'}: \max_{X, X'} \sum_{i \in M_1} \sum_{k \in N_i} \gamma_i^k + \sum_{W \in A_1 \cap A_2} \sum_{k \in N_{W}} (\tilde{x}_i^k \gamma_i^k + \tilde{x}'_i^k \gamma_i^k)$$

$$+ \sum_{i \in M_2} \gamma_i^k + \sum_{k \in N_{W}} \sum_{W \in A_2} \sum_{k \in N_{W}} (\tilde{x}_i^k \gamma_i^k + \tilde{x}'_i^k \gamma_i^k) \quad (14)$$

$$\sum_{k \in N_i} R_i^k + \sum_{k \in N_{W}} \tilde{x}_i^k R_i^k = \beta_1 R_{\text{max}}, \quad l \in \{2, w\} \quad (14c)$$

$$\sum_{k \in N_{W}} \tilde{x}_i^k R_i^k = \beta_1 R_{\text{max}}, \quad l \in \{1, w\} \quad (14d)$$

s.t. $R_i^k, R_i^k, R_{w, g}, R_{w, h}^k, R_{w, h}^k, R_{w, h}^k \geq 0 \quad (14e)$

$\tilde{x}_i^k + \tilde{x}_i^k = 1, \quad k \in N_i \quad (14f)$

$\tilde{x}_i^k + \tilde{x}_i^k = 1, \quad k \in N_{W} \quad (14g)$

$\gamma_i^k \geq \gamma_{\min}, \quad l \in \{1, 2\}, k \in \{M_1, M_2\} \quad (14h)$

$\tilde{x}_i^k y_i^k \geq 0, \quad k \in N_i \quad (14j)$

$\tilde{x}_i^k y_i^k \geq 0, \quad k \in N_{W} \quad (14k)$

$\tilde{x}_i^k \gamma_i^k \leq \gamma_{\min}, \quad k \in \{W_{W} \cup A_2\} \quad (14l)$

$\gamma_i^k \geq \lambda_{n} L_n, \quad l \in \{1, 2\}, k \in \{M_1 \cup M_2\} \quad (14m)$

$\tilde{x}_i^k y_i^k \geq 0, \quad k \in N_i \quad (14n)$

$\tilde{x}_i^k y_i^k \geq 0, \quad k \in N_{W} \quad (14o)$

$\tilde{x}_i^k \gamma_i^k \leq \gamma_{\min}, \quad k \in \{W_{W} \cup A_2\} \quad (14p)$

To analyze the concavity property of problems (P1') and (P2'), three definitions about concave functions [33, 34] and two concavity-preserving operations [33] are introduced in Appendix A. The following propositions, proved in Appendix B and Appendix C, summarize the concavity property of problems (P1') and (P2'), respectively.

**Proposition 1:** The objective function of problem (P1') is a concave function on the three optimal variables $\beta_1, \beta_2$, and $\beta_w$, and problem (P1') is a concave optimization problem.

**Proposition 2:** The objective function of problem (P2') is a biconvex function on variable set $[X, X'] \times [R, R']$, and problem (P2') is a biconvex optimization problem.

Even though the integer-value variables in problem (P3) can be relaxed to real-value ones by replacing constraint (10a) by (14i)-(14p), the non-concave or non-biconcave relations between the objective function and decision variable of problem (P3) makes it difficult to solve directly. Thus, we use the first-order Taylor series approximation, and introduce two new variable matrices, $C = \{C_i^k, C_i^k\}$ and $C' = \{C_i^k, C_i^k, C_i^k, C_i^k\}$ with elements that are linear-fractional function of $P_i^k$, to replace the received SINR on AVs within each BS's coverage. Then, the downlink spectrum efficiency on an AV associated to a BS can be re-expressed as a concave function of $C$. For example, using $C_i^k$ to replace the SINR received on AV $k$ associated to eNB $S_i$, we can rewritten equation (1) as

$$P_i^k = \log_2 (1 + C_i^k). \quad (15)$$

Therefore, problem (P3) can be transformed into

**P3':** $\max_{\beta, C'} \sum_{k \in N_{i}} R_i^k \log_2 (1 + C_i^k)$

$$+ \sum_{k \in N_{i}} R_i^k \log_2 (1 + C_i^k) \quad (16a)$$

$$\sum_{W \in A_1} \sum_{k \in N_{W}} (\tilde{x}_i^k R_i^k \log_2 (1 + C_i^k))$$

$$\sum_{W \in A_2} \sum_{k \in N_{W}} (\tilde{x}_i^k R_i^k \log_2 (1 + C_i^k)) \quad (16b)$$

s.t. $P_i^k \in [0, P_{\text{max}}], \quad W_i \in \{A_1 \cup A_2\}$

$C_i^k \leq C_k \quad (16c)$

$C_i^k \leq C_k \quad (16d)$

$C_i^k \leq C_k \quad (16e)$

$C_i^k \leq C_k \quad (16f)$

where $C_k$ (or $C_k$) are the received SINRs on AV $k$ from its associated eNB (or Wi-Fi AP). The six additional constraints (16c)-(16h) are biaffine on $[P'] \times [C, C']$ and are considered in problem (P3') to ensure the equivalent with problems (P3).

**B. Algorithms Design**

To jointly solve the three problems (P1'), (P2'), and (P3'), we first design an alternate algorithm for (P3') and then an alternate concave search (ACS) algorithm is applied to jointly solve these three problems. For simplicity, the objective functions for the three problems are denoted by $U(P_1'), U(P_2')$, and $U(P_3')$, respectively.

The objective function of problem (P3'), $U(P_3')$, is concave on $[C, C']$, while constraints (16c)-(16h) are biaffine on $[P'] \times [C, C']$. Through maximizing $U(P_3')$, optimal $[C, C']$ can be obtained for given $P'$ with constraints (16c)-(16h). Moreover, through maximizing 0 with constraints (16a)-(16h), the feasible set of $P'$ can be obtained. Thus, we first separate problem (P3') into two subproblems as follows

**P3' SP1:** $\max_{C'} U(P_3')$

s.t. (16c) – (16h)
and

\[ P3_{.SP2} : \max_{P^*} 0 \]  
\[ \text{s.t.} \ (16a) - (16h). \]

It is obvious that there must be a solution to subproblem (P3_{.SP1}). Moreover, since subproblem (P3_{.SP2}) is a feasibility problem and the initial value of \( P^* \) is always the solution for (P3_{.SP2}). Thus, problem (P3') converges and can be solved by iteratively solving subproblems (P3'_{.SP1}) and (P3'_{.SP2}).

To jointly solve (P1'), (P2'), and (P3') and obtain the final optimal decision variables, the ACS algorithm is summarized in Algorithm 1. \( \{\hat{X}^{(t)}, \tilde{X}^{(t)}\} \) and \( P^{(t)} \) are the values of \( \{\hat{X}, \tilde{X}\} \) and \( P \) at the beginning of the \( t \)th iteration, and \( U^{(P1)}_{(P2)} \) is the maximum objective function value of problem (P2') with optimal decision variables \( \{\beta_1^{(t)}, \beta_2^{(t)}, \beta_w^{(t)}\}, \{\tilde{R}_1^{(t)}, \tilde{R}_2^{(t)}\}, \{\tilde{X}^{(t)}, \tilde{X}'^{(t)}\}, \) and \( P^{(t)} \). To enhance the convergence speed of Algorithm 1, the output at the \( (t-1) \)th iteration is regarded as a feedback to the input at the \( t \)th iteration [35], such as, the \( t \)th input \( P^{(t)} \) is defined as

\[ P^{(t)} = P^{(t-1)} + \theta(P^{(t)} - P^{(t-1)}) \]  
(17)

where, \( \theta \) is the feedback coefficient. Moreover, considering that a larger \( \theta \) may result in missing optimal output at each iteration while a small \( \theta \) reduces the convergence speed, two coefficients \( \theta_1 \) and \( \theta_2 \) are considered in Algorithm 1.

According to the analysis of each problem in subsection IV-A, Algorithm 1 converges since:

(i) The output of problems (P1') and (P2'), \( \{\beta_1, \beta_2, \beta_w\}, \{\hat{X}, \tilde{X}\}, \) and \( \{\tilde{R}, \tilde{R}\} \), are closed sets;

(ii) Both (P1') and (P2') are concave/biconcave optimization problems such that the optimal solution for each problem at the end of the \( k \)th iteration is unique when the input of the algorithm is the optimal results obtained from the \( (k-1) \)th iteration;

(iii) Problem (P3') is always solvable.

V. SIMULATION RESULTS

To show the effectiveness of our proposed spectrum resource management framework, extensive simulation is carried out. We compare the proposed spectrum resource management scheme with two existing resource slicing schemes, i.e., the maximization-utility (max-utility) based resource slicing scheme proposed in [30], and the maximization-SINR (max-SINR) based resource slicing scheme proposed in [32].

The BS-vehicle association patterns and spectrum slicing ratios are optimized with objective of maximizing the aggregated network utility in max-utility scheme while AVs choose to associate with the BS providing higher SINR and only spectrum slicing ratios are optimized in max-SINR scheme.

We consider two eNBs (eNB \( S_1 \in \mathcal{E}_1 \) and eNB \( S_2 \in \mathcal{E}_2 \)) and four Wi-Fi APs (AP 1 and AP 2 in \( \mathcal{A}_1 \), and AP 3 and AP 4 in \( \mathcal{A}_2 \)) are utilized for AV applications. Transmit power is fixed at 10 watts (i.e., 40 dBm) for each eNB with a maximum communication range of 600 m. Since no transmit power control for both of max-utility and max-SINR schemes, transmit powers of APs are set as 1 watt with communication range of 200 m, the same as in [30]. In our simulation, the minimum inter-vehicle distance is 5 m, and the AV density over one lane, i.e., the number of AVs on one lane per meter,
The downlink channel gains for eNBs and Wi-Fi APs are described as $L_e(d) = -30 - 35 \log_{10}(d)$ and $L_w(d) = -40 - 35 \log_{10}(d)$ [30], respectively, where $d$ is the distance between an AV and a BS. We take platooning/convoying as an example to set the delay bound for delay-sensitive applications, i.e., 10 ms [8], [36], and downloading HD map is considered as an example for delay-tolerant applications [14]. Other important parameters in our simulation are listed in Table I.

We use network throughput that is, the summation of achievable transmission rate by each individual AV from BSs, to measure performances of different spectrum resource management schemes. Considering the scarcity of spectrum resources, the different AV applications, and the high network dynamic, we evaluate the performance of the proposed scheme and compare with the max-utility and the max-SINR schemes under different amounts of aggregate spectrum resource ($W_v$), probabilities of generating a delay-sensitive request by AVs ($p$), and AV densities in Fig. 3 to Fig. 5.

Fig. 3 demonstrates the network throughputs achieved by the three schemes with respect to different amounts of aggregate spectrum resources, $W_v$, where AV density is 0.05 AV/m and $p = 0.2$ and 0.8, respectively. With the increasing of $W_v$, transmission rate for each AV is increased due to the increasing of the amount of allocated spectrum resources. From Fig. 3, the minimum requirement for spectrum resources by the proposed scheme to support the downlink transmissions is 3 MHz while at least 9 MHz and 12 MHz spectrum are required by the max-utility scheme and the max-SINR scheme, respectively. Moreover, under different $W_v$, the network throughput achieved by the proposed scheme is on average over 70% and over 50% higher than that of the max-utility scheme for $p = 0.2$ and 0.8, respectively, and over 45% higher on average than that of the max-SINR scheme for $p = 0.2$. From Fig. 3(a), with the increase of $W_v$, network throughput achieved by the proposed scheme increases more rapidly than the max-utility scheme.

Network throughputs of the three schemes under different $p$ are evaluated in Fig. 4. The effect of $p$ on network throughput is mainly caused by the difference between the QoS requirements for delay-sensitive and delay-tolerant applications. According to Equation (6) and the parameter setting in Table I, the transmission rate required by a delay-tolerant request is 180.00 kbits/s, which is higher than that for a delay-sensitive request, 140.37 kbits/s. A large $p$ indicates a low total transmission rate required by all AVs to satisfy their applications' QoS requirements, therefore more remaining spectrum resources can be allocated to AVs with higher received SINRs in the proposed scheme. Thus, under the scenarios with the same AV density, 0.05 AV/m, network throughputs of the three schemes increase with $p$. For the max-SINR scheme, AVs associate the BS providing higher SINR and each BS equally allocates its available spectrum resources to AVs. To guarantee the QoS requirements for AVs, the amount of spectrum resource allocated to AVs from the same BS fluctuates with the distribution of BS-vehicle SINR and $p$, resulting in drastic impacts on the achieved network throughput. Moreover, from Fig. 4, the proposed scheme outperforms the max-SINR scheme when $p$ is small and can achieve higher network throughput than the max-utility scheme for the scenario with different $p$.

Fig. 5 shows the network throughputs of the three schemes under different AV densities with $p = 0.2$ and 0.8, respectively, and 20 MHz aggregate spectrum resources. From the figure, the proposed scheme is more robust to AV density changing than the other two. For both the max-SINR and the max-utility schemes, only scenarios with small AV densities vary within range of [0.04, 0.20] AV/m. The downlink channel gains for eNBs and Wi-Fi APs are described as $L_e(d) = -30 - 35 \log_{10}(d)$ and $L_w(d) = -40 - 35 \log_{10}(d)$ [30], respectively, where $d$ is the distance between an AV and a BS.

### Table I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum transmit power allowed by APs</td>
<td>2.5 watts</td>
</tr>
<tr>
<td>Background noise power</td>
<td>$-104$ dBm</td>
</tr>
<tr>
<td>HD map packet arrival rate</td>
<td>20 packet/s</td>
</tr>
<tr>
<td>HD map packet size</td>
<td>9000 bits</td>
</tr>
<tr>
<td>Safety-sensitive packet arrival rate</td>
<td>4 packet/s</td>
</tr>
<tr>
<td>Safety-sensitive packet size</td>
<td>1048 bits</td>
</tr>
<tr>
<td>Safety-sensitive packet delay bound</td>
<td>10 ms</td>
</tr>
<tr>
<td>Safety-sensitive request generating probability</td>
<td>0.1 - 0.9</td>
</tr>
<tr>
<td>Delay bound violation probability</td>
<td>$10^{-3}$</td>
</tr>
<tr>
<td>$\theta_1/\theta_2$</td>
<td>0.001/0.1</td>
</tr>
<tr>
<td>$\kappa_1/\kappa_2$</td>
<td>0.01/20</td>
</tr>
</tbody>
</table>
TABLE II
OPTIMAL TRANSMIT POWERS AND NUMBER OF ITERATIONS FOR THE THREE SCHEMES ($p = 0.8$)

<table>
<thead>
<tr>
<th>AV Density (AV/m)</th>
<th>Optimal Transmit Powers $P^*$ (watts)</th>
<th>Number of Iterations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$P_1^*$</td>
<td>$P_2^*$</td>
</tr>
<tr>
<td>0.05</td>
<td>0.05</td>
<td>2.500</td>
</tr>
<tr>
<td>0.10</td>
<td>0.05</td>
<td>2.500</td>
</tr>
<tr>
<td>0.15</td>
<td>0.05</td>
<td>2.500</td>
</tr>
<tr>
<td>0.20</td>
<td>0.05</td>
<td>2.500</td>
</tr>
</tbody>
</table>

Fig. 4. Average network throughput vs. $p$ (AV density is 0.05AV/m).

Fig. 5 also indicates the effect of AV density on the achieved network throughputs by the three schemes. In general, the network throughputs achieved by the three schemes overall decrease with AV density. To increase the network throughput, the proposed scheme and the max-SINR scheme prefer to slicing high spectrum ratio to the BSs providing higher SINRs to its associated AVs once enough spectrum is allocated to each AV to guarantee the QoS requirements for their applications. When the AV density is relatively lower (e.g., 0.04 AV/m), 20 MHz spectrum resource is more than enough to satisfy each request’s QoS requirement and the average probability for AVs with high SINR increases with the AV density, therefore resulting in increasing network throughput. However, the amount of spectrum resources needed to satisfy AV application’s QoS requirements increases with the AV density for the three schemes, thus less spectrum resources can be used for increasing network throughput, resulting in decreasing in network throughput.

Fig. 3 to Fig. 5 show that the proposed scheme outperforms the two comparisons in terms of network throughput. In addition to replacing the equality allocation with on-demand spectrum allocation among AVs, the performance improving is also due to the transmit power controlling in the proposed scheme. Taking scenarios with four different AV densities, i.e., 0.05 AV/m, 0.10 AV/m, 0.15 AV/m, and 0.20 AV/m, as examples, the optimal transmit powers obtained by the proposed scheme are shown in Table II. To avoid the impact of the initial APs’ transmit powers on the network throughput, APs’ transmit powers are fixed on 2.5 watts with communication range of 260 m for both comparisons. With 0.05 AV/m AV density, the network throughputs achieved by the proposed, the max-utility, and the max-SINR schemes are 0.86 Gbits/s, 0.52 Gbits/s, and 1.12 Gbits/s, respectively. However, both of the max-utility and the max-SINR schemes are ineffective to scenarios with 0.10 AV/m, 0.15 AV/m, and 0.20 AV/m, due to the high inter-cell interferences. From columns 2 to 5 in Table II, the transmit powers of AP 2 and AP 3 for the proposed scheme have been adjusted,
which helps control inter-cell interference for both eNBs and the other two APs’ transmissions. Despite the improvement in network throughput, the computational complexity of the proposed scheme is higher than the other two, resulting in more iterations, as shown in columns 6 to 8 of Table II.

In addition to adjusting the transmit powers for the APs, the spectrum slicing ratios among BSs are also adjusted by the proposed scheme, as shown in Fig. 6. With AV density increasing from 0.05 A/V/m to 0.20 A/V/m, the amount of spectrum resources sliced to Wi-Fi APs, i.e., the spectrum slicing ratio βw, is increased in the proposed scheme. This is because a large βw indicates more spectrum resources can be reused among APs and therefore improving the spectrum efficiency.

VI. CONCLUSIONS

In this paper, we have proposed a dynamic spectrum management framework to enhance spectrum resource utilization in the MEC-based AVNET with the consideration of cellular and Wi-Fi interworking. Through enabling NFV at the MEC servers, the spectrum resource utilization can be enhanced via dynamically and centrally managing a wide range of spectrum resources and adjusting the transmit power for Wi-Fi APs. To maximize the aggregate network utility and provide QoS-guaranteed downlink transmissions for delay-sensitive and delay-tolerant requests, three optimization problems have been investigated to slice spectrum among BSs fairly, to allocate spectrum among AVs associated with a BS in a QoS-guaranteed way, and to control transmit powers of Wi-Fi APs. In order to solve these three problems, we first use linear programming relaxation and first-order Taylor series approximation to transform them into tractable forms, and then design an ACS algorithm to jointly solve them. Compared with two existing spectrum management schemes, the proposed framework is more robust to AV density changing and provides higher network throughput.

APPENDIX A
DEFINITIONS AND OPERATIONS

Definition 1 (Second-Order Conditions): Suppose function \( f \) is twice differentiable, i.e., it has Hessian or second derivative, \( \nabla^2 f \), at each point in its domain, \( \text{dom} f \). Then \( f \) is concave if and only if \( \text{dom} f \) is a convex set and its second derivative is negative semidefinite for all \( y \in \text{dom} f \), i.e., \( \nabla^2 f \geq 0 \).

To express biconcave set and biconcave function, we define \( A \subseteq \mathbb{R}^n \) and \( B \subseteq \mathbb{R}^m \) as two non-empty convex sets, and let \( Y \) be the Cartesian product of \( A \) and \( B \), i.e., \( Y \subseteq A \times B \). Define \( a \)- and \( b \)-sections of \( Y \) as \( Y_a = \{ b \in B : (a, b) \in Y \} \) and \( Y_b = \{ a \in A : (a, b) \in Y \} \).

Definition 2 (Biconcave Set): Set \( Y \subseteq A \times B \) is called as a biconcave set on \( A \times B \), if \( Y_a \) is convex for every \( a \in A \) and \( Y_b \) is convex for every \( b \in B \).

Definition 3 (Biconcave Function): Define function \( f: Y \rightarrow \mathbb{R} \) on a biconcave set \( Y \subseteq A \times B \). Then function \( f: Y \rightarrow \mathbb{R} \) is called a biconcave function on \( Y \), if \( f_a(b) = f(a, b) : Y_a \rightarrow \mathbb{R} \) is a concave function on \( Y_a \) for every given \( a \in A \), and \( f_b(a) = f(a, b) : Y_b \rightarrow \mathbb{R} \) is a concave function on \( Y_b \) for every given \( b \in B \).

Definition 4 (Biconcave Optimization Problem): An optimization problem with form \( \max f(a, b) : (a, b) \in Y \) is called as a biconcave optimization problem, if the feasible set \( Y \) is biconvex on \( Y_a \) and \( Y_b \), and the objective function \( f(a, b) \) is biconcave on \( Y \).

Operation 1 (Nonnegative Weighted Sums): A nonnegative weighted sum of concave functions is concave.

Operation 2 (Composition With an Affine Mapping): Let function \( h : \mathbb{R}^n \rightarrow \mathbb{R} \), \( E \in \mathbb{R}^{n \times m} \), and \( e \in \mathbb{R}^m \). Define function \( \ell : \mathbb{R}^m \rightarrow \mathbb{R} \) by \( \ell(y) = h(Ey + e) \) with \( \text{dom} \ \ell = \{ y : Ey + e \in \text{dom} \ h \} \). Then function \( \ell \) is concave if \( h \) is concave.

APPENDIX B

PROOF OF PROPOSITION 1

Proof: For problem \( (P1') \), constraint (13a) indicates that \( \{ \beta_1, \beta_2, \beta_w \} \) is a closed set, i.e., the problem domain is a convex set, and the objective function of \( (P1') \) is the summation of AVs’ logarithmic utilities, where the logarithmic function is a concave function due to the non-positive second derivative. Moreover, for an AV associated to a BS, the utility is logarithm of the achievable transmission rate, and the corresponding achievable transmission rate is an affine function of \( \beta_1 \), \( \beta_2 \), or \( \beta_w \). Thus, based on the above two operations, we can conclude that the objective function of problem \( (P1') \) is a concave function on the three optimal variables \( \beta_1 \), \( \beta_2 \), and \( \beta_w \). Furthermore, constraint (8a) can be rewritten into inequality concave constraints, such as \( \beta_1 \in [0, 1] \) can be as \( -\beta_1 \leq 0 \) and \( \beta_1 \leq 1 \), and constraint (8b) is an equality affine function. Therefore, problem \( (P1') \) is a concave optimization problem.

APPENDIX C

PROOF OF PROPOSITION 2

Proof: Constraints (14a)-(14f) of problem \( (P2') \) indicate that \( [\mathbf{X}, \bar{\mathbf{X}}'] \) and \( [\mathbf{R}, \bar{\mathbf{R}}'] \) are convex sets, and Cartesian product is an operation that preserves convexity of convex sets [33]. Thus, the domain of \( (P2')', [\mathbf{X}, \bar{\mathbf{X}}'] \times [\mathbf{R}, \bar{\mathbf{R}}'] \), is a convex set. Moreover, as stated before, the objective function of \( (P2') \) is the summation of AVs’ achievable transmission rates from
the associated BSs, where the transmission rate achieved by an AV $k$ is an affine function on elements of $[R, R']$ for a given association pattern and is an affine function on the association pattern variable for a given resource allocation. Considering the affine function is both concave and convex, it can be proved that the objective function of problem (P2') is a biconcave function on variable set $[\vec{X}, \vec{X}] \times [R, R']$. Moreover, constraints (14g) and (14h) are equality affine on $[\vec{X}, \vec{X}]$, constraints (14a)-(14d) are equality biaffine on $[\vec{X}, \vec{X}] \times [R, R']$, constraints (14e)-(14f) are respectively inequality affine on $[\vec{X}, \vec{X}]$ and $[R, R']$, and constraints (14i)-(14p) are inequality biaffine on $[\vec{X}, \vec{X}] \times [R, R']$. Thus, we can conclude that (P2') is a biconcave optimization problem.

References

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