RSU-Aided Energy-Efficient Collaborative Perception for Connected Autonomous Vehicles

Minh David Thao Chan, Zhaojun Nan, Yukuan Jia, Sheng Zhou, and Zhisheng Niu
Beijing National Research Center for Information Science and Technology,
Department of Electronic Engineering, Tsinghua University, Beijing 100084, China
E-mails:{dwm21@mails., nzj660624@mail., jyk20@mails., sheng.zhou@, niuzhs@}tsinghua.edu.cn.

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***Abstract*—In recent years, the concept of collaborative perception (CP) in self-driving vehicles has emerged as a new paradigm for augmenting the safety and efficiency of connected autonomous vehicles (CAVs). However, CP's energy consumption remains a major concern, due to their computation- and transmission-intensive characteristics. To address this issue, this paper first presents a theoretical definition of CP coverage along with a 2-dimensional CP model, followed by a novel framework that leverages roadside units (RSU) to facilitate CP, namely the RSU-Aided Energy-Efficient Sensing, Computation, and Communication (RE2SCC). Through a mix of centralized scheduling and a decentralized data-sharing approach, RE2SCC improves perception performance and energy efficiency. The core of RE2SCC is a novel approach for reducing the overall computation load and energy-efficient CP by scheduling computation and transmission depending on CAVs topology while maintaining the perception performance. The centralized scheduling exploits CP capabilities via sensing data selection, avoiding redundant computation, and direct transmission of perception object data to CAVs, enabling extended perception while minimizing the transmission power. Simulations show the efficiency of the RE2SCC framework for energy savings along with increased perception performance by up to 51% in a given scenario.**

I. Introduction

Collaborative perception (CP) is a revolutionary concept that allows vehicles to share information to perceive the environment beyond line-of-sight and field-of-view [1]. This approach enhances individual vehicle perception performance using communication technologies, promoting safety and efficiency in connected autonomous vehicles (CAVs) [2]. The benefits of CP include improved accuracy, perception coverage, and robust capabilities, making it a revolutionary approach to achieving higher levels of autonomy in complex scenarios [3]–[6]. Despite the great potential, CP faces significant challenges, including concerns about energy consumption associated with vehicular edge computation, communication, and data processing, and the need for effective and efficient data sharing [7]–[9].

This paper addresses the energy efficiency challenge, a topic extensively explored for mobile cellular networks through strategies such as computation offloading and energy harvesting. Prior work [10]–[15] in the context of vehicular networks has shown that computation offloading improves energy efficiency. Several studies have proposed solutions to balance latency and energy consumption [10]–[14]. Furthermore, researchers have explored the potential of energy harvesting in vehicular networks, focusing primarily on road-side units (RSUs) in rural areas and along highways [15]. In addition, compression techniques have been proposed to reduce the data transmission volume and energy consumption while maintaining performance [1].

In fact, energy consumption under perception performance and communication constraints brings substantial challenges to CP system design. First, the perception based on the RSU located above the road provides a new perspective and exhibits different coverage characteristics from those of the CAVs. These models must be integrated to perform RSU-aided CP. Therefore, a joint RSU-CAV perception model should be carefully considered. Then, given that CAV and RSU now collaborate as a system as opposed to standalone to achieve sufficient perception performance and energy efficiency, it is necessary to define a new RSU-CAV CP coverage and coverage-energy efficiency metric. In addition, studies on energy efficiency focus on optimizing computation and transmission. However, very few research have explored sensor data selection to minimize energy consumption via reducing computation and transmission load.

This paper considers a RSU-Aided Energy-Efficient Sensing, Computation, and Communication (RE2SCC) framework under CP coverage performance and communication resource constraints. Coverage performance is measured by the proposed perception coverage metric defined as the area of the road, centered around the perceiving CAV within a given radius for which an obstacle can be perceived. The contributions of this paper are summarized as follows:

- We develop a 2-dimensional RSU-CAV CP model and define CP coverage and coverage-energy efficiency that combines perception coverage, and energy consumption.
- We formulate the problem as a mixed integer nonlinear programming (MINLP) to minimize energy consumption under CP coverage constraints.
- For problem-solving, we propose a sub-optimal energy minimization of computation by decision selection and transmission scheduling algorithm.
- By comparison with standalone and broadcast bench-

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marks, the numerical results demonstrate the effectiveness of the proposed algorithm in terms of energy consumption, perception coverage, and energy coverage efficiency.

II. System Model and Problem Formulation

In the system presented in Fig. 1, a road environment is equipped with two primary components: a single RSU located at height h_R covering the area of interest S on which a series of CAVs designated as set $\mathcal{N} = \{1, \ldots, N\}$ are deployed. Each CAV can process raw sensing data from its own set of sensors and share perception object data with neighboring CAVs via vehicle-to-vehicle (V2V) sidelinks. The RSU, equipped with sensing, computation, and communication functionalities, gathers data regarding the positions, speeds, and dimensions of CAVs. It leverages this information to facilitate the CP of the environment, with the aim of enhancing the perception coverage. The scheduling of all the communications is decided in a centralized manner by the RSU which broadcasts the scheduling instructions to all the CAVs. Then the transmission of perception object data consists of two parts: (i) RSU to CAVs, and (ii) CAV to CAVs. The transmitting RSU and CAVs share the same bandwidth and broadcast the perception object data to the corresponding scheduled CAVs.

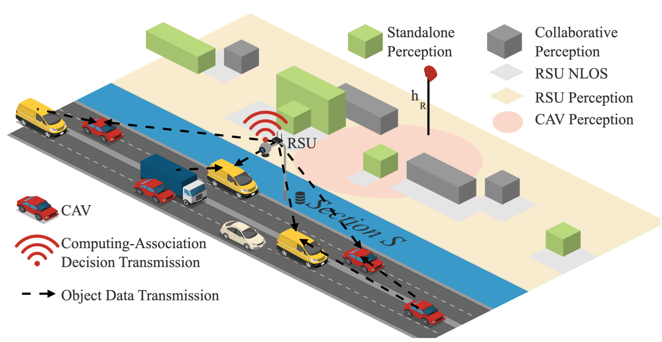

Fig. 1: Illustration of the system.

A. Collaborative Perception Model

1) CP and transmission decision: In the proposed perception model, the RSU consistently processes its perception data, maintaining a global map of the environment for the specified region S, albeit with potential visibility limitations due to obstructions. The computation decision at each CAV n is represented by a vector $\boldsymbol{o} = \{o_1, \ldots, o_N\}$, where each element o_n is defined as

$$o_n = \begin{cases} 0, & \text{if CAV } n \text{ leverages CP only,} \\ 1, & \text{if CAV } n \text{ uses standalone perception only.} \end{cases} \tag{1}$$

To facilitate CP when $o_n = 0$, RSU and other CAVs can share perception object data perception data. Following the decision of o_n, the transmission decisions are defined through an $N \times N$ transmission association matrix $A = \{a_{i,j}\}$, where

$$a_{i,j} = \begin{cases} 1, & \text{if CAV } i \text{ transmits to CAV } j \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

and $a_{i,i} = 0, \forall i \in \mathcal{N}$. This matrix outlines the transmission relationships among CAVs.

2) Standalone Perception Coverage: We define the standalone perception coverage for a CAV i in a designated area S as C_i^{s}, representing the part of the environment it can perceive, excluding its own occupied space V_i, and considering potential obstructions from other entities in the environment. The mathematical representation is as follows:

$$C_i^{\mathrm{s}} = \{x \in D_i \cap S \setminus V_i | \; l_{O_i,x} \cap V_i^- \subseteq \{x\}\}, \tag{3}$$

where D_i is the disk of diameter r centered in O_i center of CAV i, and $l_{O_i,x}$ denotes the closed line segment between $O_i, x \in \mathbb{R}^2$ and V_i^- are the space occupied by CAV j with $j \neq i$. $l_{O_i,x} \cap V_i^- \subseteq \{x\}$ verifies that the Line-Of-Sight (LOS) between the sensor at O_i and location x is not blocked by other obstacles.

3) RSU Perception Coverage: The RSU, positioned at a higher elevation, perceives the entire area S, except for the non-line-of-sight (NLOS) regions obstructed by CAVs. This coverage, denoted as C_R, is defined as

$$C_R = \{x \in S | \bigcup_{i \in \mathcal{N}} l_{O_R,x} \cap \tilde{V}_i \subseteq \{x\}\}, \tag{4}$$

where $l_{O_R,x}$ represents the closed line segment between $O_R, x \in \mathbb{R}^3$, $\tilde{V}_i$ is the 3D representation of CAV i considering its height h_i, and O_R the location of the RSU.

4) Collaborative Perception Coverage: Collaborative perception coverage, C_n^{c}, leverages both the RSU perception and the standalone coverage of those collaborating CAVs to enhance the perception capabilities of CAV n. This is defined as

$$C_n^{\mathrm{c}} = \{x \in D_n \cap S | x \in C_R \bigcup_{\substack{i \in \mathcal{N} \\ a_{i,n}=1}} C_i^{\mathrm{s}}\}. \tag{5}$$

The coverage area for each perception coverage type is denoted by $|C_i^{\mathrm{s}}|$, $|C_R|$, and $|C_n^{\mathrm{c}}|$ for standalone, RSU, and collaborative perception coverage, respectively.

B. Computation Model

In the proposed system computation model, we focus on the local computation of perception tasks which are executed either on individual CAVs or on the RSU. The computation task at hand is characterized by a tuple that encompasses the data length in bits L_n, and the necessary cycles per bit C_n.

The processing time on the CAV n is determined by the formula $T_n^{\mathrm{c}} = L_n C_n / f_n$, where f_n denotes the processor frequency of the CAV n. The power consumption of the processor follows the model $\phi_n f_n^3$ (in watts), which integrates the chip energy coefficient ϕ_n [16]. Consequently, the energy consumed for a single task in the CAV n is expressed as $E_n^{\mathrm{c}} = T_n^{\mathrm{c}} \phi_n f_n^3$.

When a CAV n does not utilize its sensing data, it relies on perception object data shared from other CAVs and RSU to compute its perception, thus avoiding the need for local computation and processing. We define the raw sensing data and perception object data in CAV n as $\mathcal{X}_n$ and $\tilde{\mathcal{X}}_n$, respectively, with $D(\cdot)$ representing the length of the data and $\tilde{\mathcal{X}}_R$ denoting the processed data at the RSU. The length of the data L_n is influenced by various parameters, including the computation decision vector o_n and the elements of the transmission association matrix $a_{i,n}$. A significant assumption here is the reduction in data size by a factor of α in the order of 10^{-2} [17]. This leads to a simplified expression for L_n as $L_n = o_n D(\mathcal{X}_n)$. Therefore, the computation energy at CAV n and the computation energy at the RSU, noted E_n^{c} and E_R^{c} respectively, is given by

$$E_n^{\mathrm{c}} = o_n D(\mathcal{X}_n) C_n f_n^2 \phi_n, \tag{6}$$

$$E_R^{\mathrm{c}} = D(\mathcal{X}_R) C_R f_R^2 \phi_R, \tag{7}$$

where C_R, f_R, and ϕ_R are the computation parameters of the RSU.

C. Wireless Communication Models

We denote $d_{i,j}$ as the Cartesian distance between the CAV i and CAV j such that $d_{i,j} = O_i O_j$. Similarly, d_n is the distance between the RSU located at $(0, 0, h_R)$ and O_n the center of CAV n. Based on Shannon's theory, given $w_R \in [0, 1]$, as the bandwidth portion allocated to the RSU, we calculate the effective data rate for the transmission to the CAV n located at the largest distance away from the RSU as follows

$$R_R = w_R W \log_2\left(1 + \mathrm{SNR}_R\right), \tag{8}$$

where the signal-to-noise ratio (SNR) from the RSU is expressed as

$$\mathrm{SNR}_R = \frac{\mu_{PA} \cdot p_R}{\sigma^2 w_R W \max\limits_{o_n=0} d_n^{\delta}}, \tag{9}$$

where μ_{PA} is the Power Amplifier (PA) efficiency, p_R is the transmitting power of the RSU, while W is the total available bandwidth, δ is distance path loss coefficient, and σ^2 is the noise variance. The longest download time to transmit the perception object data of one task is $T_R^{\mathrm{down}} = D(\tilde{\mathcal{X}}_R)/R_R$ and the energy at the RSU for transmission is given by $E_R^{\mathrm{t}} = p_R \cdot T_R^{\mathrm{down}}$, which results in

$$E_R^{\mathrm{t}} = \frac{p_R D(\tilde{\mathcal{X}}_R)}{w_R W \log_2\left(1 + \mathrm{SNR}_R\right)}. \tag{10}$$

If $o_n = 0, \forall n \in \mathcal{N}$, then there is no energy consumption for transmission at the RSU. Similarly, the transmission energy at CAV i is given by

$$E_i^{\mathrm{t}} = \frac{p_i D(\tilde{\mathcal{X}}_i)}{w_i W \log_2\left(1 + \mathrm{SNR}_i\right)}, \tag{11}$$

where p_i, w_i are the transmission power and bandwidth portion allocated for the CAV i respectively, $a_{i,j}$ is the Boolean transmission decision, and the signal-to-noise ratio from the CAV i is given by $\mathrm{SNR}_i = \mu_{PA} \cdot p_i / (\sigma^2 w_i W \max\limits_{a_{i,j}=1} d_{i,j}^{\delta})$. Here the worst case SNR is considered to satsify the correct decoding of all scheduled transmissions.

D. Problem Formulation

The objective is to minimize the total energy consumption of the RSU-CAV system from computation and communication by optimizing the computation decision of CAV n o_n, the coefficient of the association matrix $A = \{a_{i,j}\}$, the transmission power of the RSU p_R, and transmission powers of the N CAVs represented by $\boldsymbol{p} = \{p_1, \ldots, p_N\}$. We also need to satisfy coverage, signal-to-noise ratio, and bandwidth requirements. Therefore, we formulate the optimization problem as

$$\mathbb{P}: \min_{\boldsymbol{o}, A, \boldsymbol{p}, p_R} \left[E_R^{\mathrm{t}} + \sum_{n \in \mathcal{N}} \left(E_n^{\mathrm{c}} + E_n^{\mathrm{t}} \right) \right] + E_R^{\mathrm{c}} \tag{12}$$

$$\text{s.t.}\, o_n \in \{0, 1\}, \forall n \in \mathcal{N}, \tag{13}$$

$$\frac{o_n |C_n^{\mathrm{s}}| + (1 - o_n) |C_n^{\mathrm{c}}|}{|C_n^{\mathrm{s}}|} \geq 1, \forall n \in \mathcal{N}, \tag{14}$$

$$\forall i \in \mathcal{N}, \exists j \in \mathcal{N}, a_{i,j} = 1, \mathrm{SNR}_i \geq \gamma \text{ and } \mathrm{SNR}_R \geq \gamma, \tag{15}$$

$$a_{i,j} \in \{0, 1\}, \forall i \in \mathcal{N}, \forall j \in \mathcal{N}, \tag{16}$$

$$0 \leq p_i \leq p_{\max}, \forall i \in \mathcal{N}, \text{ and } 0 \leq p_R \leq p_{\max}, \tag{17}$$

where constraint (13) indicates that o_n is a binary variable and constraint (14) indicates that the perception coverage of CAV n is sufficient either it is from itself or relying on collaborative perception coverage. Constraint (15) indicates the minimum threshold for the SNR for transmitting CAVs and the RSU. Constraint (16) indicates that $a_{i,j}$ are binary. The constraint (17) indicates that the transmission power is positive and should not exceed the power limit. Note that problem $\mathbb{P}$ is a combinatorial mixed-integer non-linear programming (MINLP) problem, which is generally NP-hard.

III. RE2SCC Framework

In this section, we introduce a sub-optimal algorithm to solve $\mathbb{P}$ in the RSU-Aided Energy-Efficient Sensing Computation Communication (RE2SCC) framework, detailed in Algorithm 1 and illustrated in Fig. 2. This algorithm minimizes the total energy consumption in RSU-CAV systems while accommodating NLOS conditions.

As illustrated in Fig. 3, starting with the individual parameters of each CAV position at time $t-1$, the algorithm predicts the forthcoming positions of the CAVs and computes the NLOS conditions at time t. Subsequently, it generates all feasible combinations of CAV perception decisions o_n while retaining those that meet the coverage criteria. With each combination, an association matrix is constructed, facilitating the determination of transmission powers through a power minimization function and, consequently, the total energy consumption. Scheduling instructions and perception object data are shared via broadcast.

A. RSU NLOS Region

In the context of the proposed RE2SCC framework, we utilize a simple recursive estimator to predict the positions of

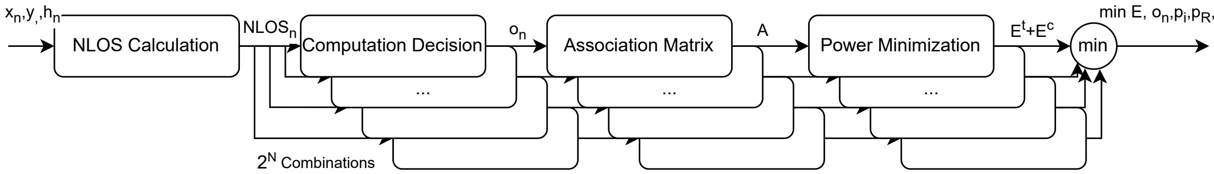

Fig. 2: An illustration of the basic idea of RE2SCC framework algorithm.

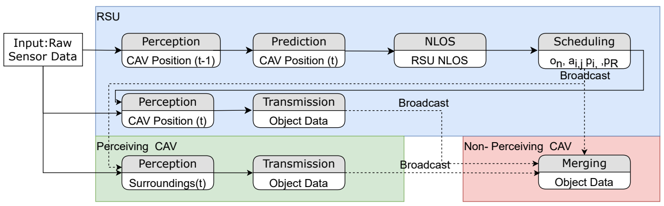

Fig. 3: Data flow of the RE2SCC framework.

Algorithm 1: RE2SCC framework

Input: $(x_n, y_n, l_n, L_n, h_n)[t-1], v_n[t-1]$
Output: $o_n, p_i, p_R, A, \min E$.
Parameters:(h_R, r)
Initialization: $\mathcal{C}' = \{\emptyset\}$, $a_{i,j} = 0$
Determining RSU NLOS Condition:
for *each CAV* $n \in \mathcal{N}$ **do**
    $(x_n, y_n)[t] \leftarrow$ Prediction $((x_n, y_n), v_n)\, [t-1]$
    $\text{NLOS}_n[t] \leftarrow$ calcNLOS $((x_n, y_n, l_n, L_n, h_n)[t])$
Generation of $\mathcal{C}'$ under coverage constraint:
Generate $\mathcal{C}$ such that $\textbf{card}(\mathcal{C}) = 2^N$
$\mathcal{C}', \mathcal{T} \leftarrow \text{CompDecision}(\mathcal{C}, (x_n, y_n)[t], \text{NLOS}_n[t])$
Generation of Association Matrix:
for *each combination in* $\mathcal{C}'$ **do**
    $A \leftarrow \text{AssociationMatrix}(\mathcal{C}', \mathcal{T}, d_{i,j})$
    Transmission Power Minimization:
    $(p_i, p_n) \leftarrow \text{PowerMinimization}(A, o_n, d_{i,j}, d_n)$
    $E \leftarrow \text{EnergyCalculation}(o_n, p_i, p_n)$
Result: $\boldsymbol{E}^* = \min_{\mathcal{C}'} E$

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the CAVs at time t based on the history positions and velocities at time $t-1$ as

$$x_n[t] = x_n[t-1] + v_{x,n}[t-1] \cdot \Delta t, \tag{18}$$

$$y_n[t] = y_n[t-1] + v_{y,n}[t-1] \cdot \Delta t, \tag{19}$$

where $x_n[t]$ and $y_n[t]$ are the predicted positions of CAV n at time t, $v_{x,n}[t-1]$ and $v_{y,n}[t-1]$ are the components of the velocity vector of the CAV at time $t-1$, and Δ is the time step between $t-1$ and t. In the context of RSU-aided vehicular networks, understanding the relationship between the NLOS region and CAV footprint is pivotal. The NLOS region and CAV footprints share the same origin, facilitating a seamless transformation process based on the central coordinates (x_n, y_n) of the CAV footprint. The length and width of NLOS region induced by the CAV n is expressed

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Algorithm 2: Computation decision

Input: $x_n, y_n, \text{NLOS}_n, \mathcal{C}$
Output: $\mathcal{C}', \mathcal{T}$.
Parameters:(h_R, r)
Initialization: $\mathcal{C}' = \{\emptyset\}$, $a_{i,j} = 0$, $t_{i,j} = 0$
Select all feasible combinations under coverage constraints:
for *each combination* c_n *of* $\mathcal{C}$ **do**
    if $\forall n \in \mathcal{N}, o_n = 0$, $\exists k \neq n$ *s.t.* $o_k = 1$ **then**
        if *CAV* k *can cover* $NLOS_n$ *;*
        $\&$ $d_{k,n} \leq r$ **then**
            $\mathcal{C}' \leftarrow \mathcal{C}' \cup c_n$
            $t_{k,n} = 1$
            $\mathcal{T} \leftarrow \mathcal{T} \cup t_{k,n}$

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as

$$\text{NLOS}_n = \frac{1}{2}\left(\frac{h_R}{h_R - h_n} + 1\right)\begin{bmatrix} l_n \\ L_n \end{bmatrix} + \left(\frac{h_R}{h_R - h_n} - 1\right)\begin{bmatrix} x_n \\ y_n \end{bmatrix}, \tag{20}$$

where h_R and h_n represent the heights of the RSU and CAV n respectively, and l_n, L_n are the length and width of CAV n facilitating a precise perspective transformation from a higher viewpoint.

B. Computation Decision

We propose a computation decision algorithm, as detailed in Algorithm 2, to identify the CAV combinations using the LOS and NLOS conditions to minimize energy consumption. The algorithm operates on CAV coordinates and NLOS data to yield a set of feasible combinations. Initially, it generates a set $\mathcal{C}$ of all possible CAV combinations of o_n, with a cardinality of 2^N, where N is the number of CAVs. It then iteratively examines each combination c_n in set $\mathcal{C}$, adhering to a defined criterion: for each CAV n with $o_n = 0$, there must be one CAV k ($k \neq n$) with $o_k = 1$ that maintains LOS to the entirety of NLOS_n and resides within radius r. Configurations that meet this condition are collected into a new set $\mathcal{C}'$. The output is set $\mathcal{C}'$, containing combinations satisfying the LOS and distance conditions, alongside a matrix representation with elements $t_{k,n}$ indicating the combinations fulfilling the criteria.

C. Association Matrix

The algorithm 3 was designed to construct an association matrix A, which delineates the relationships between different

Algorithm 3: Association matrix generation

Input: $c_n, t_{i,j}, d_{i,j}$

Output: A.

Initialization: $A = \{a_{j,k}\} = 0$

for *each CAV* k **do**

  if $o_k = 0$ **then**

    $a_{j,k} \leftarrow t_{j,k}$ where $t_{i,j}$ is the participating CAV k to the perception of CAV j

    for *all CAV* j **do**

      if $NLOS_j \cap D(O_k, r) \neq \emptyset$ **then**

        if $o_j = 1$ **then**

          $a_{j,k} \leftarrow 1$

        else

          Find i s.t. $t_{i,j} = 1$

          $a_{i,k} \leftarrow 1$

CAVs based on their perception and NLOS regions. Taking inputs such as a specific combination c_n, coefficient $t_{i,j}$ representing participation of CAV i to perception of CAV j and $d_{i,j}$ the distance CAV i to CAV j, we initialize A with zeros and iteratively update it through two nested loops that traverse all CAVs and examine their CP decision states and spatial relationships. The outer loop iterates over all the CAVs denoted as CAV k and checks each state o_k. If $o_k = 0$, it enters an inner loop that iterates over all CAV j, checking the intersection of the NLOS$_j$ region with a disk of radius r centered at O_k. Depending on CAV j's decision o_j, it updates the association matrix accordingly, setting the relevant matrix elements to one to indicate specific relationships. The final association matrix A encapsulates the relational data between CAVs based on the defined conditions.

D. Minimization of Transmission Power

Based on the SNR requirements, we can find the minimum transmission power given by

$$p_i = \gamma \sigma^2 w_i W / (\mu_{PA} \max_{a_{i,j}=1} {d_{i,j}}^{\delta}), \tag{21}$$

where $w_i = w = 1/(\bar{t} + 1)$ and $\bar{t}$ is the number of transmitting CAVs i.e. non-null rows in A. Similarly, $p_R = \gamma \sigma^2 w W / (\mu_{PA} \max_{o_n=0} {d_n}^{\delta})$, where $w_R = w$.

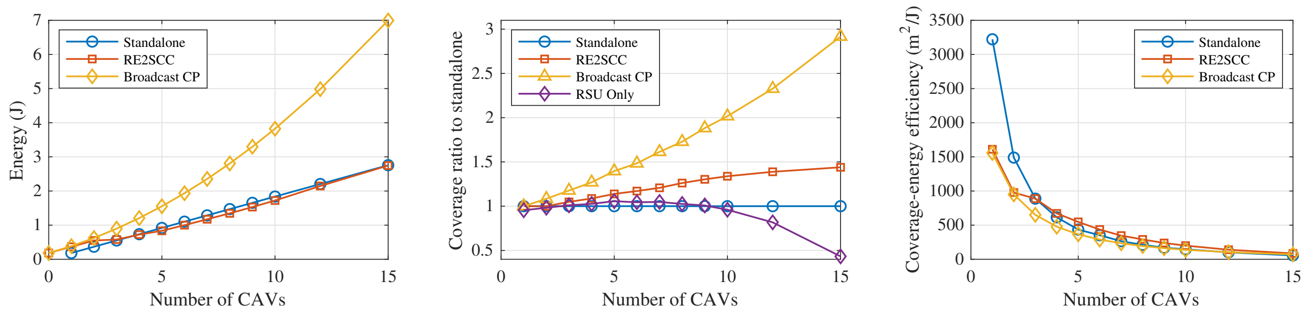
IV. Numerical Results

The simulation parameters are detailed in Table I. The simulation setup includes a three-lane roadway hosting a variable number of CAVs, the positions of which are generated in MATLAB using 300 independent Monte Carlo simulations. The RSU, a crucial element in the simulation, has specific height and coordinate attributes. The sensing model is general and can apply to multiple types or mixed types of sensor models. In the simulation, we consider a LiDAR-based sensing system. The computation parameters are set following current equipment standards [17]–[19], aiding in detailed energy consumption analysis in various contexts. The communication system, built with given bandwidth, power amplifier efficiency, and noise variance parameters, adheres to a strict energy efficiency and delay limit, ensuring a realistic representation of a collaborative autonomous driving environment. The RE2SCC framework is compared to the benchmarks of standalone perception and broadcast CP, for which RSU and CAVs are all perceiving and broadcasting perception object data. We examine three different metrics for one round of perception tasks: the energy consumption of the system, the average perception coverage, and the average coverage-energy efficiency which is defined as the average coverage per CAV when consuming 1 joule.

TABLE I: Simulation parameters: distances are expressed in meters (m), delay in milliseconds (ms), frequency and bandwidth in hertz (Hz), and SNR in decibels (dB). Parameters $D(\mathcal{X}), D(\tilde{\mathcal{X}}), C, f,$ and ϕ are identical for all CAVs and RSU. CAV length, width, and height are also all identical.

Parameter (Symbol)	Value (Unit)
Lane number	3
Lane width	4 m
Lane length	50 m
CAV Length	4 m
CAV Width	2 m
CAV Height	1.5 m
RSU Height (h_R)	10 m
RSU Location (x,y,z)	(0,0,10)
Radius	50 m
CAV count set (N)	{1,2,3,...,10,12,15}
Batch raw sensing data size ($D(\mathcal{X})$)	1.4 Mbits
Batch perception object data size ($D(\tilde{\mathcal{X}})$)	24 Kbits
Cycles-per-bit parameter (C)	297.6
Frequency (f)	2.1 GHz
Chip energy coefficient (ϕ)	10^{-28}
Bandwidth (W)	200 MHz
Power amplifier efficiency (μ_{PA})	0.5
Noise variance (σ^2)	10^{-8}
Path loss exponent (δ)	2
SNR limit (γ)	20 dB

Fig. 4 presents the simulation results obtained under various numbers of CAV varying from 1 to 15 in the area of interest 3×4 m $\times$ 50 m space corresponding to vehicle densities varying from 6.7 to 100 vehicles/lane/km, the latter considered high density. We focus on two key performances: coverage and energy consumption. We first illustrate the energy consumption by the RE2SCC framework, as shown in Fig. 4(a), the energy consumption is compared to standalone perception and broadcast CP under different values of the number of CAVs. We observe that our algorithm outperforms broadcast CP consistently, and performs better than standalone between 4 and 15 vehicles for energy consumption. This verifies that the computation decision has a significant impact on energy consumption. For a small number of CAVs, the RSU computation creates an additional energy cost, which quickly decays with more CAVs. As the number of CAVs increases, the energy reduction gained is diminished and compensated by increasing communication energy as more CAVs need to share their information within the limited bandwidth. To unveil the perception coverage performance, we define the average coverage ratio as the average perception coverage divided by the average perception coverage area of a standalone CAV. As



(a) System energy consumption.
(b) Average coverage ratio.
(c) Average coverage-energy efficiency.

Fig. 4: RE2SCC system energy and perception average coverage ratio performance per CAV compared to broadcast CP and standalone approaches for a CAV processing one task. The energy includes both computation and transmission.

shown in Fig. 4(b) the proposed design performs better than the RSU only or the standalone perception methods. However, as expected, the coverage remains significantly inferior to the coverage of broadcast CP. Note that the average coverage ratio for RSU only decreases as more CAVs on the road create more obstructions, thus less area is covered. The results validate the effectiveness of the algorithm in providing extended coverage for all numbers of CAVs. In Fig. 4(c), we finally illustrate the coverage-energy efficiency achieved by the three approaches, all decreasing with the higher number of CAVs due to more obstructions. It shows that for scenarios with more than 4 CAVs, the RE2SCC framework outperforms the coverage-energy efficiency of the standalone perception, and the broadcast CP by 18% and 36% on average respectively, and up to 51% compared to standalone for 15 CAVs.

V. Conclusion and Future Works

This paper defines a new 2-dimensional perception model with a perception coverage metric and focuses on coverage-energy efficiency. Based on this model, a novel RSU-Aided Energy-Efficient Sensing, Computation, and Communication framework for CAVs efficiently selects the computation and schedule associations among CAVs. The simulation results demonstrate that the proposed framework effectively reduces energy consumption while improving perception coverage, thus enhancing coverage-energy efficiency by up to 51% compared with standalone or broadcast CP in a given scenario. Future work should focus on optimizing these parameters to achieve higher efficiency across low- and high-density traffic, as well as to explore solutions with less complexity.

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