

Game-based computation offloading and resource allocation in stochastic geometry-modeling vehicular networks

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The underlying vertical components represented by vehicle-to-everything networks will largely accelerate the advance of the 6th generation wireless communications [1]. In this context, a plethora of Internet-of-Vehicles (IoV) applications have increasingly permeated our daily lives with the development of advocated intelligent connected vehicles [2]. In particular, the surge of these applications generates a tremendous amount of computation-intensive and delay-sensitive tasks, which have manufactured unprecedented pressure for onboard computation and cloud-based processing infrastructures. Fortunately, mobile edge computing (MEC) has been envisioned as a critical enabling paradigm to remarkably alleviate the pressure [3].

Nonetheless, due to the challenge arising from explosive task data brought by IoV applications, the traditional MEC technique gradually gets overwhelmed by energy efficiency and delay constraints. In response to the above issues, the introduction of distributed computing can be seen as a promising partial-offloading method that occupies dispersed edge nodes (ENs) equipped with computation resources, e.g. personal computers (PCs), parking vehicles (PVs), to assist task completion for enhanced experiences [4].

Inspired by the advancement of research in wireless network analysis via stochastic geometry [5], utilizing stochastic geometry approaches to model the IoV systems has become the most accurate and relevant way, which has captured the interest of researchers.

System model. With the above considerations, some idle trusted electronic devices are introduced as computing-supported ENs based on traditional vehicular networks to alleviate computation pressure as illustrated in Figure 1. It is assumed that each task vehicle (TV) contains a task to be completed. The task of TV m can be represented by $\Omega_m = \{D_m, F_m, T_m | m \in \mathcal{M}\}$, where \mathcal{M} is the TV set, D_m is task size, F_m denotes computation density and T_m is maximum tolerable delay. With the consideration of private safety, TVs cannot communicate with ENs directly. With the help of distributed computation technology, task Ω_m can be split into two parts, one of which is calculated locally and the other can be offloaded to the roadside unit (RSU). For the part offloaded onto the RSU, it can be processed by the RSU

or reallocated to an EN in cluster n for assisted computation services, where $n \in \mathcal{N}$ and \mathcal{N} is the cluster set. The splitting ratios are expressed as $\mathcal{R}_m = \{l_m, o_m\}$, respectively corresponding to the part calculated locally and offloaded to the RSU. In addition, the offloading strategy can be written as $\mathcal{S}_m = \{\vartheta_m | \vartheta_m \in \{\vartheta_m^{\text{RSU}}, \vartheta_m^n\}, \vartheta_m^{\text{RSU}}, \vartheta_m^n \in \{0, 1\}\}$. Here, $\vartheta_m^{\text{RSU}} = 1$ represents that the offloaded part is calculated by RSU, and $\vartheta_m^n = 1$ means that it is processed by an EN in cluster n , $\vartheta_m^{\text{RSU}} + \sum_{n=1}^N \vartheta_m^n \leq 1$, $\sum_{m=1}^M \vartheta_m^n \leq K_n$, where $\{N, M, K_n\}$ are the number of clusters, TVs, and ENs in cluster n , respectively. Noting the impact of traffic modeling on computation offloading, a novel stochastic geometry approach is proposed to model the traffic scenario, whose detailed description is given in Appendix A.1.

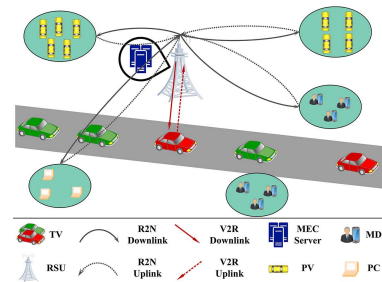


Figure 1 (Color online) The distributed computation offloading architecture of the stochastic geometry-modeling vehicular network.

Proposition 1 (The transmit rate of V2R links). Combining knowledge of stochastic geometry theory and communication theory, the communication channel model is completed. With the consideration of the mobility of vehicles due to its impact on network topology, the transmit rate of the vehicle-to-RSU (V2R) uplink and downlink can be respectively expressed as

$$C_{m, \text{V2R}}^{\text{up}}(t) = \frac{B_{\text{V2R}}}{M} \log_2 \left[1 + \frac{P_{m, \text{V2R}}^{\text{up}}(t)}{\sigma^2 + I_{\text{V2R}}} \right], \quad (1)$$

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$$C_{m,V2R}^{\text{down}} = \frac{B_{V2R}}{M} \log_2 \left[1 + \frac{P_{m,V2R}^{\text{down}}(t)}{\sigma^2} \right], \quad (2)$$

where B_{V2R} is the total bandwidth of V2R channels, $\{P_{m,V2R}^{\text{up}}(t), P_{m,V2R}^{\text{down}}(t)\}$ are the time-varying received power of V2R uplink and downlink respectively, and σ^2 is the noise power.

Proof. Please refer to Appendix A.2.

Proposition 2 (The transmit rate of R2N links). Additionally, the average transmit rate of RSU-to-node (R2N) downlink and uplink can be respectively expressed as

$$\bar{C}_{R2N_n}^{\text{down}} = \int_0^{+\infty} \mathbf{P}_{\text{SNR}_{R2N_n}^{\text{down}}}(\xi) (2^{\xi \sum_{n=1}^N K_n/B_{R2N}} - 1) d\xi, \quad (3)$$

$$\bar{C}_{R2N_n}^{\text{up}} = \int_0^{+\infty} \mathbf{P}_{\text{SINR}_{R2N_n}^{\text{up}}}(\xi) (2^{\xi \sum_{n=1}^N K_n/B_{R2N}} - 1) d\xi, \quad (4)$$

where B_{R2N} is the total bandwidth of R2N channels, $\mathbf{P}_{\text{SNR}_{R2N_n}^{\text{down}}}(\xi)$ is the SNR coverage rate of R2N downlink, $\mathbf{P}_{\text{SINR}_{R2N_n}^{\text{up}}}(\xi)$ is the SINR coverage rate of R2N uplink, and ξ is the threshold.

Proof. Please refer to Appendix A.3.

Problem Analysis and Proposed Solution. The main objective is to reduce the energy consumption of the whole system, hence the optimization problem can be formulated to minimize the total energy consumption as follows:

$$\mathbf{P1} : \min_{\mathcal{R}, \mathcal{S}, \mathcal{F}} e_{\text{total}} \quad (5a)$$

$$\text{s.t. } l_m, o_m \in [0, 1], \forall m \in \mathcal{M}, \quad (5b)$$

$$l_m + o_m = 1, \quad (5c)$$

$$\vartheta_m^{\text{RSU}}, \vartheta_m^n \in \{0, 1\}, \forall m \in \mathcal{M}, \forall n \in \mathcal{N}, \quad (5d)$$

$$\vartheta_m^{\text{RSU}} + \sum_{n=1}^N \vartheta_m^n \leq 1, \sum_{m=1}^M \vartheta_m^n \leq K_n, \quad (5e)$$

$$t_{m,\text{RSU}}, t_{m,n} \leq T_{\text{lim}}, t_{m,\text{com}}^{\text{local}} \leq T_m, \quad (5f)$$

$$\sum_{m=1}^M f_{m,\text{RSU}} \leq f_{\text{RSU}}, \quad (5g)$$

$$f_{m,\text{local}} \leq f_{\text{MD}} \leq f_{\text{PV}} \leq f_{\text{PC}} < f_{\text{RSU}}, \quad (5h)$$

where $\{t_{m,\text{com}}^{\text{local}}, t_{m,\text{RSU}}, t_{m,n}\}$ are the processing delay of partial task Ω_m locally, on RSU or an EN in cluster n , respectively, $f_{m,\text{RSU}}$ is CPU cycle frequency allocated to Ω_m from RSU, and $\{f_{m,\text{local}}, f_{\text{MD}}, f_{\text{PV}}, f_{\text{PC}}, f_{\text{RSU}}\}$ are total computation resources of each node. $\mathcal{R} = \{\mathcal{R}_m | \forall m \in \mathcal{M}\}$ describes the matrix of task-splitting ratios of all tasks, $\mathcal{S} = \{\mathcal{S}_m | \forall m \in \mathcal{M}\}$ represents the whole offloading strategies, $\mathcal{F} = \{f_{m,\text{RSU}} | \forall m \in \mathcal{M}\}$ denotes the set of computation resources allocation for the RSU, and $T_{\text{lim}} = \min\{T_m, t_{m,\text{stay}}\}$ where $t_{m,\text{stay}}$ is the staying time of TV m in RSU's coverage range. In addition, some explanations are in order. Specifically, constraint (5b) and (5c) limits the size of partial task Ω_m . (5d) and (5e) are the concrete instructions about offloading strategies. (5f) is the delay constraint for each computation node. The limitation for computation resources is clarified in constraints (5g) and (5h). The problem formulation is detailed in Appendix B.1.

It is found that the above-mentioned problem is a restricted mix-integer nonlinear non-convex problem, which is impacted by multiple vectors including \mathcal{R} , \mathcal{S} , and \mathcal{F} . Consequently, it is hard to find an ordinary method to solve such a

high-complexity problem. A computation offloading and resource allocation joint optimization algorithm (CORAJOA) is developed to derive the near-optimal solution to this optimization problem. Specifically, the problem is decoupled and solved as follows: Firstly, for determination of the offloading strategies, the TVs are seen as players in a game, and game theory is utilized to balance the conflict of interest among TVs; Next, with a matrix of determined offloading strategies \mathcal{S} , a dichotomy-based Lagrange multiplier equation with Karush-Kuhn-Tucker constraints (DLM-KKT) is proposed to derive the corresponding optimal \mathcal{R} and \mathcal{F} ; Then, with the game-based approach, the offloading strategy matrix will be adjusted, and meanwhile, \mathcal{R} and \mathcal{F} will be updated; The solution is iterating until it converges to Nash Equilibrium (NE). The problem analysis and corresponding algorithms are shown in Appendixes B.2–B.4.

Simulation Results and Discussions. The performance of CORAJOA is evaluated in MATLAB 2022a with Monte Carlo simulations. Related parameters are presented in Appendix C.1. To serve as a contrast, three baseline schemes are considered. The simulation results and elaborate discussion are demonstrated in Appendix C.2.

Conclusions and Future Work. In this paper, inspired by the idea of stochastic geometry-based wireless network analysis, a novel distributed computing model based on stochastic geometry has been designed. To minimize the system energy consumption, the corresponding sophisticated mix-integer nonlinear non-convex problem has been analyzed and then an algorithm called CORAJOA has been developed according to the game theory and the DLM-KKT. Finally, the performance evaluation has corroborated the superiority and effectiveness of the proposed CORAJOA through numerical simulations. Worthwhile future works include considering the assistance of space-air-ground integrated networks, the introduction of integrated sensing, communication, and computation technology, and the Cox process.

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Supporting information Appendixes A–C. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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