Vehicular Fog Computing Optimization through VCG Optimization in Game Theory

Dipisha Shivangi
School of Computer Engineering
KIIT
Bhubaneswar, India
dipishas21@gmail.com

Abhilipsa Sahoo
School of Computer Engineering
KIIT
Bhubaneshwar, India
riyabhilipsa@gmail.com

***Abstract*—Vehicular Fog Computing is a potentially useful concept for utilizing the computing power of cars close to the data source. In this study, we present a novel game theory-based method for the Vickrey-Clarke-Groves (VCG) mechanism in which we design a computation-based resource allocation optimization in vehicular fog networks. We develop a VCG-based mechanism to incentivize truthful reporting of computing resource preferences while guaranteeing efficient task allocation and equitable pay, by considering vehicles as strategic decision-makers with competing interests. Initially, we frame the issue of vehicular fog computation as a game in which cars must efficiently offload computational duties to maximize their value. After that, we create utility functions for cars that represent their preferences for various jobs and resource distributions while accounting for things like processing demands, latency limitations, and energy usage. We use the VCG mechanism to design a strategy-proof task allocation and payment mechanism that guarantees that honest reporting of preferences produces socially optimal results. Moreover, we assess the suggested methodology via comprehensive simulations in diverse vehicular fog computing situations, taking into account varying network densities, job allocations, and vehicle movement patterns. Our findings show how well the VCG-based optimization strategy works to increase overall system performance, shorten job completion times, and optimize resource usage. We also examine the effects of incentive compatibility and strategic behavior on the effectiveness and stability of the vehicle fog computing environment.**

To sum up, this study advances the field of vehicular fog computing by presenting a game theory-based, principled method for resource allocation optimization through VCG mechanism design. We have proposed a new algorithm, Task Allocation using VCG Mechanism (TA-VCGM) which focuses on optimized resource allocation. Our technique enables the efficient and equitable deployment of computational resources in dynamic vehicular environments by coordinating individual incentives with system-wide objectives. This sets the stage for improved services and applications in future smart transportation systems.

***Index Terms*—VCG Game Theory, Task Allocation, Resource Allocation, Equitable Pay, Game Theory, Vehicle Movement Patterns.**

I. Introduction

By utilizing the processing power of nearby automobiles, vehicular fog computing has become a game-changing paradigm for bringing cloud computing capabilities to the edge of the network. The emergence of autonomous driving technologies [1] and the spread of connected vehicles have given rise to the enormous promise of vehicular fog computing in improving the scalability, efficiency, and dependability of new smart transportation systems. However, there are many obstacles in the way of efficiently allocating computational resources and guaranteeing fair access to services due to the dynamic and varied nature of vehicular environments.

Game theory has emerged as a powerful paradigm for studying strategic interactions in distributed computing settings. It allows for the creation of incentive structures that encourage collaboration, truthful reporting, and effective resource allocation by presenting vehicles as self-interested players in a game. The Vickrey-Clarke-Groves (VCG) mechanism is particularly well-suited for solving challenges in vehicular fog computing, as it produces socially optimal outcomes while rewarding truthfulness. The TCCW algorithm is effective in real-time collision warning, outperforming conventional systems like fog-based alerts and cloud-based alerts without calibration. Vehicle fog computing is a viable way to minimize latency and maximize bandwidth use in in-vehicle networks. A taxonomy of vehicle fog computing has been proposed based on characteristics. Resource pooling in vehicular fog computing (VFC) is proposed to cooperatively provide computational services in a community. Genetic algorithms are proposed to address benefit maximization in VFC, with extensive experiments showing its effectiveness. [2], [3], [4], [5]

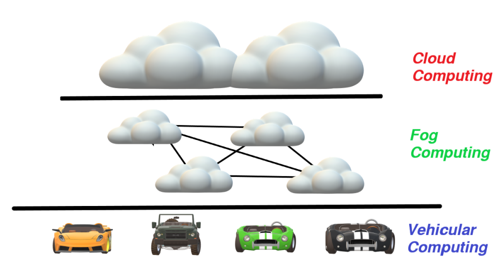

Fig. 1: Vehicular Fog Computing Service Model

The goal of this study is to better understand how to optimize vehicular fog computation by applying game theory to the design of VCG mechanisms. We specifically want to address the following major goals:

1) Efficient Resource Allocation: In a vehicular fog computing environment, we want to create a method that distributes computational jobs across vehicles in a way that maximizes overall efficiency and minimizes task completion durations.
2) Incentive Compatibility: We hope to encourage cars to accurately report their preferences for computational resources by utilizing the principles of incentive compatibility built into the design of the VCG mechanism. This will protect the integrity and dependability of the allocation process.
3) System Performance Evaluation: We seek to assess the effectiveness of the suggested VCG-based optimization approach in a range of vehicular fog computing scenarios utilizing comprehensive simulations and experimental validation, taking into account variables like network density, task distribution, and vehicle mobility patterns.

In Fig. 1, we can see the three levels of computing namely - Cloud Computing, Fog Computing, and Vehicular Computing. In the figure, we can see that fog computation is present below cloud computation which means raw data can be possessed faster using fog computation. By addressing these goals, this research aims to provide a principled approach for resource allocation optimization using game theory-based VCG mechanism design, which will further provide the field of vehicular fog computing. The results of this study should have an impact on how effective and fair vehicular fog computing systems are designed and implemented, eventually opening the door to improved services and applications in next-generation smart transportation ecosystems.

The project aims to validate network effectiveness indicators like throughput and delay by analyzing existing protocols under various scenarios and determining the best protocol for VANETs. The Greedy Perimeter Stateless Routing (GPSR) protocol is suggested for identifying network congestion and rerouting traffic, while the RSA technique is used for traffic congestion detection and rerouting safely. Apps like NS2 and SUMO can be used to imitate the VANET system. Three algorithms are suggested to enhance the performance of cluster-based routing protocol in VANETs: control overhead reduction algorithm (CORA), intersection dynamic VANET routing protocol (IDVR), and cluster-based life-time routing protocol (CBLTR). These protocols perform better on several parameters than many protocols reported in the literature. The study also offers a quantitative examination of Vehicle-Focused Communication (VFC) capabilities, considering four different scenarios involving parked and moving cars as computational and communication infrastructures. Fog computing can use data security regulations and controls in VANET contexts, facilitating globalization for analytical data and localization for crucial data. The study suggests a cooperative method for compute offloading in-vehicle networks based on cloud computing and mobile edge computing (MEC). [6], [7], [8], [9], [10]

II. Literature Review

Vehicular fog computing, or VFC, is a quickly emerging concept that uses automobiles' processing and storage capability to deliver cloud-like services at the network's edge. For latency-sensitive Intelligent Transportation Systems (ITS) applications such as cooperative collision avoidance, real-time traffic management, and autonomous driving, this presents several benefits. However, because vehicular networks are dynamic and individual vehicles behave selfishly, allocating resources in VFC efficiently is a difficult task.

The study explores the use of Vickrey-Clarke-Groves (VCG) optimization in vector field correction (VFC) to optimize resource allocation. VCG encourages sincere bidding and real-time auction modifications to ensure efficient utilization of resources. It helps in maximizing resource distribution by rewarding honest bids and effective use. VCG can also be used in vehicular fog computing (VFC) to create computationally demanding jobs and serve as computational resources for other vehicles. A recently proposed protocol, Overlapping-enabled Cooperative Vehicular Fog Computing (OCVC), improves efficiency by using under-utilized processing power of vehicles to handle tasks generated by mobile devices on the road. [11], [12], [13], [14], [15]

Vehicle fog computing (VFC) systems require several security and forensics requirements, including confidentiality, integrity, authentication, availability, and forensics. Confidentiality ensures that unauthorized parties cannot access data, while integrity detects unauthorized attempts to alter data. Authentication ensures that information is verified between parties involved in a conversation. Availability ensures cloud servers or fog nodes are always accessible to any automobile application. Forensics ensures the ability to recognize, gather, and evaluate information from fog nodes, smart cars, and supporting systems to identify malevolent actors.

A vehicular fog computing architecture for real-time collision warning in vehicular networks is presented, shifting the burden of computing and communication to dispersed fog nodes for efficient and instantaneous collision warning. The proposed trajectory calibration-based collision warning algorithm establishes real-time vehicle trajectories based on acquired vehicle status, anticipated communication delay, and packet loss detection. Opportunistic cooperative localization reduces computational complexity and communication overhead by enabling agents to choose informative links in a distributed and self-optimized manner.

To address issues like lack of specific incentives, high system complexity, and offloading collisions between vehicles during task offloading, a contract-based incentive mechanism combining resource contribution and utilization is proposed. Distributed deep reinforcement learning is suggested to simplify the system and disperse resources. A two-stage task offloading architecture is proposed for VFC, addressing information asymmetry and uncertainty. A convex-concave-procedure-based contract optimization approach maximizes the operator's expected utility using asymmetric knowledge. A pricing-based matching-based low-complexity stable task offloading system reduces overall network latency. [16], [17], [18], [19], [20]

III. System Model

Let us consider set of vehicles, $V = \{v_1, v_2, \ldots, v_m\}$ with associated resources $\{r_1, r_2, \ldots, r_m\}$ and set of tasks, $T = \{t_1, t_2, \ldots, t_n\}$ with requirements $\{q_1, q_2, \ldots, q_n\}$

Through task allocation, we aim to allocate tasks to vehicles while maximizing social welfare. We define the task allocation vector: $A = \{a_1, a_2, \ldots, a_n\}$, where a_i represents the allocated vehicle for task t_i. Each $a_i \in V$. Through vehicle payments, we determine the payments for each vehicle. We define the payment vector: $P = \{p_1, p_2, \ldots, p_m\}$. Where each p_j corresponds to the payment for vehicle v_j. We compute the marginal contributions (MC) of each vehicle v_j by using each task t_i. The marginal contribution represents how much including v_j in the allocation affects the overall social welfare.We compute $MC[v_j]$ as follows:

$$MC[v_j] = SW(T \backslash \{t_i\}, A \cup \{(t_i, v_j)\}) - SW(T, A \backslash \{(t_i, a_i)\})$$

We use optimal allocation for selecting the vehicle v_j with the highest marginal contribution for each task t_i:

$$v_j = \arg\max_{v \in V} MC[v]$$

We update the allocation A by assigning task t_i to v_j. The Payment Calculation for each vehicle is based on the difference in social welfare like:

$$p_j = SW(T, A \setminus \{(t_i, v_j)\}) - SW(T, A) + q_i$$

Then we return the task allocation vector A and the payment vector P.

IV. Proposed Mechanism

We have proposed an algorithm called Task Allocation using VCG Mechanism (TA-VCG) which is as follows:

Theorem: The VCG mechanism ensures truthfulness in reporting vehicle preferences, leading to an efficient task allocation and payment scheme in vehicular fog computing environments.

Proof: Let V be the set of vehicles and T be the set of tasks in the system. For each vehicle v_i and task t_j, let $U(v_i, t_j)$ denote the utility gained by v_i when allocated task t_j. The VCG mechanism calculates payments and task allocations based on the marginal contributions of vehicles to the social welfare of the system. Assume v_i misreports its preferences, i.e., it states incorrect utility values $U'(v_i, t_j)$ instead of the true utility values $U(v_i, t_j)$. Let A' and P' denote the task allocation and payment vectors computed based on the misreported preferences. By the VCG mechanism, the payment of v_i is calculated as:

$$P_i = \sum_j (SW(T, A) - SW(T, A \setminus \{(t_j, v_i)\})) + \sum_j U(v_i, t_j)$$

Algorithm 1 Task Allocation using VCG Mechanism (TA-VCGM)

Require: Set of vehicles: $V = \{v_1, v_2, \ldots, v_m\}$ with resources $\{r_1, r_2, \ldots, r_m\}$
Set of tasks: $T = \{t_1, t_2, \ldots, t_n\}$ with requirements $\{q_1, q_2, \ldots, q_n\}$
Ensure: Task allocation: $A = \{a_1, a_2, \ldots, a_n\}$ where $a_i \in V$ for allocated vehicle of task t_i
Vehicle payments: $P = \{p_1, p_2, \ldots, p_m\}$

```
Initialize A = ∅, P = {0}_m (all payments zero)
for each task t_i ∈ T do
    MC = {} (marginal contributions)
    for each vehicle v_j ∈ V do
        A' = A ∪ {(t_i, v_j)} (temporary allocation with t_i to v_j)
        SW_n = ComputeSocialWelfare(T \ {t_i}, A') (social welfare without t_i and v_j)
        SW_w = ComputeSocialWelfare(T, A \ {(t_i, a_i)}) (social welfare with t_i excluding current allocation)
        MC[v_j] = SW_n − SW_w (marginal contribution of v_j for t_i)
    end for
    v_j = arg max_{v∈V} MC[v] (vehicle with highest marginal contribution)
    A = A ∪ {(t_i, v_j)} (update allocation with t_i to highest marginal contribution vehicle)
end for
for each vehicle v_j ∈ V do
    SW_n = ComputeSocialWelfare(T, A \ {(t_i, v_j)}) (social welfare without v_j)
    SW_w = ComputeSocialWelfare(T, A) (social welfare with all vehicles)
    P[v_j] = SW_w − SW_n (payment of v_j)
end for
Return A, P
```

Similarly, the payment P'_i based on the misreported preferences is:

$$P'_i = \sum_j (SW(T, A') - SW(T, A' \setminus \{(t_j, v_i)\})) + \sum_j U'(v_i, t_j)$$

As per the VCG mechanism, $P_i \geq P'_i$ for all vehicles v_i, ensuring truthfulness. This property incentivizes vehicles to report their true preferences to maximize their utility and payment. Hence, through the above proof we can conclude that the VCG mechanism guarantees that vehicles will reveal their preferences truthfully, leading to an efficient task allocation and payment scheme in vehicular fog computing environments.

The time complexity of the TA-VCGM depends on the number of tasks (n) and vehicles (m). The nested loops for computing marginal contributions contribute to the overall time complexity. Overall, the time complexity is approximately O(nm). In the end, the algorithm, TA-VCGM, returns the task allocation (A) and vehicle payments (P). In summary, the

VCG mechanism optimally allocates tasks while incentivizing truthful reporting by participants. It is widely used in auction design, resource allocation, and multi-agent systems.

V. Simulation

The simulations that we've provided compare the resource allocation of vehicles based on our proposed algorithm $TA-VCGM$. The graphs show optimal resource allocation using $TA-VCGM$. $TA-VCGM$ shows better allocation according to the vehicle's valuation. In Fig. 2, the graph shows optimal allocation due to $TA-VCGM$ for 20 vehicles. In Fig. 3, the graph shows optimal allocation due to $TA-VCGM$ for 50 vehicles. In the graph, we have taken Vehicle Id in the x-axis and Optimal Allocation in the y-axis. Each vehicle having a different valuation has been allocated optimal resource. Wireless communication, [**?**], helps in faster processing of data and providing faster output.

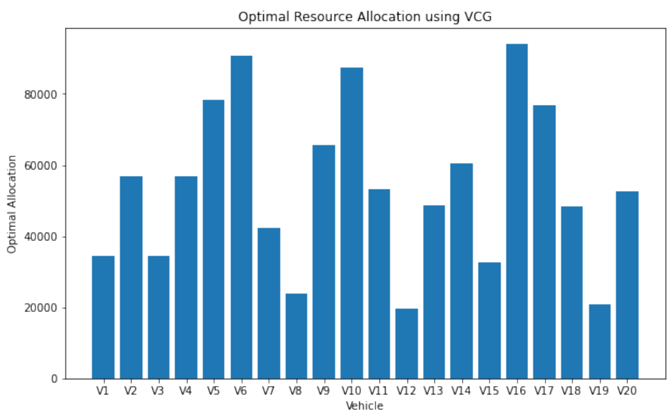

Fig. 2: VCG Task Allocation Bar Graph

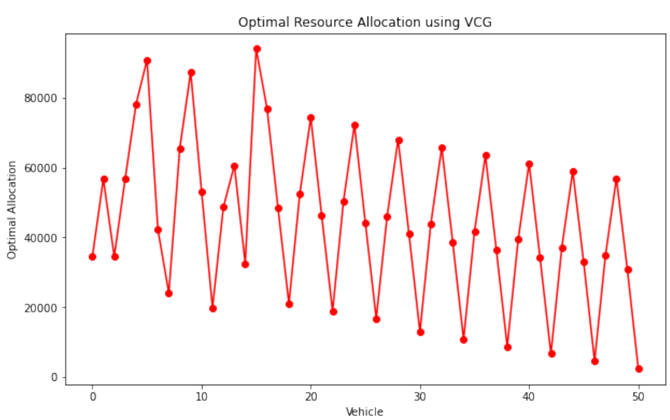

Fig. 3: VCG Task Allocation Line Graph

The graph in Fig. 2 and 3, indicates that the quantity of resources allotted to various vehicle types varies significantly. Vehicle type $V1$, for instance, seems to be allotted more resources than vehicle type $V10$. Higher allocations have been given to vehicles like the $V8$, $V11$, and $V19$, which are close to or above 80000. Less money has been allotted to vehicles like the $V5$, $V6$, and $V14$, either below or around $20,000$. The printed VCG payments list each vehicle's monetary compensation. The payments guarantee equity between the participating cars, and the graph shows how best to allocate resources using the VCG method.

VI. Conclusion

We have conducted a thorough analysis of vehicular fog computation using Vickrey-Clarke-Groves (VCG) optimization within the context of game theory in this research study. Vehicular fog computing has emerged as a promising concept for extending cloud computing capabilities to the edge of the network and enhancing the scalability, reliability, and effectiveness of intelligent transportation systems by harnessing the computational capacity of autos. We have shown how game theory may be used to improve resource allocation and encourage collaboration in dynamic vehicular environments by modeling vehicle interactions as a strategic game and creating incentive systems based on VCG principles. This idea, which is particularly relevant to intelligent transportation systems, pushes the capabilities of cloud computing out to the edge of the network. It makes use of the computing power found in automobiles, trucks, and buses to improve scalability, dependability, and efficiency.VFC seeks to offer low-latency and compute-intensive services for applications such as cooperative and autonomous driving by harnessing the processing power of automobiles.Optimization of Vickrey-Clarke-Groves (VCG): Resource allocation in multi-agent systems is optimized by the application of the mechanism design technique known as VCG. The use of VCG in our scenario is limited to vehicular fog computing scenarios, in which clients, meaning end users or automobiles, offload compute workloads to adjacent edge/fog computing nodes, such as vehicular fog nodes, or VFNs.

VII. Future Work

The goal of privacy-preserving data management in VFC is to effectively manage data while protecting user privacy. Scholars may investigate the subsequent facets: Differential Privacy: To safeguard individual data points while permitting insightful aggregate analysis, employ differential privacy strategies. Examine how computations on encrypted data can be made using homomorphic encryption to prevent the disclosure of private information. Secure Data Aggregation: Create privacy-preserving techniques to securely aggregate data from several VFNs. Game-Theoretic Privacy Models: Apply VCG game theory to users' and VFNs' privacy choices. Mechanisms of Incentive for VFNs: The aim is to motivate VFNs to engage in the VFC ecosystem by offering services and resources. Examine VCG-based auction systems in which virtual file networks (VFNs) bid on resources (such as CPU time and storage) in order to fulfill user demands. Games for Coalition Formation: Examine the ways in which VFNs can unite to strengthen their overall usefulness. Dynamic Pricing: Create price structures that reward VFNs according to system load, resource availability, and demand. The aim of this project is to improve the security and reliability of VFC systems. Examine byzantine fault-tolerant consensus techniques for virtual file networks (VFNs). Reputation Systems: Create reputation models to evaluate VFN dependability. Game-Theoretic Security: Use game theory to assess malicious VFNs' strategic conduct and create countermeasures.

References

[1] X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3860–3873, 2016.

[2] Z. Wei, B. Li, R. Zhang, X. Cheng, and L. Yang, "Ocvc: An overlapping-enabled cooperative vehicular fog computing protocol," *IEEE Transactions on Mobile Computing*, vol. 22, no. 12, pp. 7406–7419, 2023.

[3] ——, "Many-to-many task offloading in vehicular fog computing: A multi-agent deep reinforcement learning approach," *IEEE Transactions on Mobile Computing*, vol. 23, no. 03, pp. 2107–2122, 2024.

[4] Q. Li, X. Jia, C. Huang, and H. Bao, "A dynamic combinatorial double auction model for cloud resource allocation," *IEEE Transactions on Cloud Computing*, vol. 11, no. 03, pp. 2873–2884, 2023.

[5] "Vehicular fog computing: Architecture, use case, and security and forensic challenges," pp. 105–111, 2017.

[6] K. A. Darabkh and B. Z. Alkhader, "Fog computing- and software defined network-based routing protocol for vehicular ad-hoc network," in *2022 International Conference on Information Networking (ICOIN)*, 2022, pp. 502–506.

[7] "Vehicular fog computing enabled real-time collision warning via trajectory calibration," pp. 2482–2494, 2020.

[8] "Vehicular fog computing enabled real-time collision warning via trajectory calibration," pp. 2482–2494, 2020.

[9] *A Survey on Vehicular Fog Computing: Motivation, Architectures, Taxonomy, and Issues*. Springer, Cham, 2020.

[10] "Resource pooling in vehicular fog computing," pp. 1–14, 2021.

[11] Z. Zhou, P. Liu, J. Feng, Y. Zhang, S. Mumtaz, and J. Rodriguez, "Computation resource allocation and task assignment optimization in vehicular fog computing: A contract-matching approach," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3113–3125, 2019.

[12] Z. Zhou, H. Liao, X. Zhao, B. Ai, and M. Guizani, "Reliable task offloading for vehicular fog computing under information asymmetry and information uncertainty," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 8322–8335, 2019.

[13] J. Zhao, M. Kong, Q. Li, and X. Sun, "Contract-based computing resource management via deep reinforcement learning in vehicular fog computing," *IEEE Access*, vol. 8, pp. 3319–3329, 2019.

[14] "Contract-based computing resource management via deep reinforcement learning in vehicular fog computing," *IEEE Access*, vol. 8, pp. 3319–3329, 2020.

[15] R. Zhang, Z. Zhao, X. Cheng, and L. Yang, "Overlapping coalition formation game based opportunistic cooperative localization scheme for wireless networks," *IEEE Transactions on Communications*, vol. 65, no. 8, pp. 3629–3642, 2017.

[16] J. Zhao, Q. Li, Y. Gong, and K. Zhang, "Computation offloading and resource allocation for cloud assisted mobile edge computing in vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7944–7956, 2019.

[17] X. Hou, Y. Li, M. Chen, D. Wu, D. Jin, and S. Chen, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3860–3873, 2016.

[18] ——, "Vehicular fog computing: A viewpoint of vehicles as the infrastructures," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 3860–3873, 2016.

[19] A. Abuashour and M. Kadoch, "Performance improvement of cluster-based routing protocol in vanet," *Ieee access*, vol. 5, pp. 15 354–15 371, 2017.

[20] S. Arvind Narayan, R. Rajashekar Reddy, and J. Femilda Josephin, "Secured congestion control in vanet using greedy perimeter stateless routing (gpsr)," in *Artificial Intelligence and Evolutionary Computations in Engineering Systems*. Springer, 2020, pp. 683–700.