A Framework on Intelligent Transportation System for Smart Cities

Mohammad Husain[1], Arshad Ali[2]
[1]*Faculty of Computer and Information Systems, Islamic University of Madinah, KSA*
[2]*Faculty of Computer and Information Systems, Islamic University of Madinah, KSA*
Corresponding author's email: dr.husain@iu.edu.sa

***Abstract* - One essential element of smart cities is Next Generation Intelligent Transportation Systems (ITS). Smart transportation can be achieved by strategically controlling vehicle traffic and enhancing vehicle safety. Applications like entertainment and driverless driving will also result from this. We will look into future 6G technology in this paper for smart city applications including vehicles. Our goal is to provide effective algorithms that facilitate data sharing between infrastructure Road Side Units (RSUs) and 6G-capable automobiles. In this we consider two main objectives: The first is creating an effective algorithm for distributing application data in smart cities with an ITS foundation. The creation of effective computing algorithms for ITS-based smart cities is the second objective. The suggested approach will significantly contribute to the advancement of ongoing research in the domains of intelligent transportation systems, 6G communications, and ITS.**

***Keywords* – Internet of Things, Communication Networks, Fog Computing, Mobility, Cloud Server.**

1. Introduction

Recently, the primary goal of research has been to develop fully autonomous systems that are managed by artificial intelligence (AI) and learning approaches. The domains of wireless communications, data communications, Internet of Things (IoT) technology, and learning methodologies have all seen tremendous breakthroughs as a result. The integration of contemporary safety features in cars, which help drivers with navigation, path planning, lane discipline, blind spot monitoring, and most importantly the emergency brake system, is a clear example of how human and machine interaction has completely changed [1-6]. The use of fully autonomous, self-driving vehicles is quickly approaching.

Fifth Generation (5G) communication systems have emerged as a result of these requirements, and although 5G is still in the deployment stage, academics have already begun to anticipate the next generation of communication networks, known as 6G [7]. In addition to meeting these needs, 6G will offer a plethora of other characteristics to facilitate ubiquitous connectivity, namely the utilization of Tera Hz spectrum with sub-1 ms latency and 99.99999\% reliability [8–10]. AI, drones and driverless cars, augmented and virtual reality, smart gadgets, smart technologies, and intelligent machines will all undergo revolutionary changes on the way to 6G. The communication focus will evolve from ubiquitous connectivity to automated and intelligent connectivity [11-12].

Billions of devices will be connected at once under 6G, enabling near real-time user experiences and an explosive increase in the number of connected devices [13–14]. The existing Internet of things will become huge IoT due to the massive amount of data that will be generated [15–17]. Massive IoT will have a very high network density—up to around $1 million devices per square kilometer—generating enormous amounts of data that need to be processed, stored, shared, and analyzed [18]. On the other hand, there will be a significant rise in network complexity due to this growth in capacity and connectivity. In order to overcome obstacles like heterogeneity, interoperability, network capacity, network congestion, and battery lifespan, 6G massive IoT will combine decentralized processing techniques like fog and edge computing with intelligent learning techniques. Fog and edge computing will not only take the load off from cloud computing but will also improve energy efficiency by performing computation close to the end devices [19-20].

The transportation system is changing in tandem with the expansion of communication resources. There have already been a lot of advancements, and there will be a lot more in the near future. The current transportation system is evolving into an Intelligent Transport System (ITS) due to the increasing intelligence of vehicles. Future cars that are safe and don't require autonomous driving will need to be simultaneously connected to the web and to other vehicles. To that end, the development of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication concepts is necessary [21–22]. 6G huge IoT will improve vehicle communication by advancing data management and sharing methods. It will make it possible for cars to work together and coordinate in order to serve a variety of sophisticated applications and enhance user comfort, efficiency, sustainability, and safety [23–24]. In addition to being extremely intelligent, future cars will also be extremely cooperative, transforming ITS into C-ITS—a necessary step toward the realization of fully autonomous vehicles.

The future road traffic management system is greatly aided by C-ITS. When completely investigated, C-ITS applications will yield advantages such as autonomous and linked cars, traffic prediction and control, road safety, and accident prediction. High levels of coordination and collaboration amongst all network components would be necessary for C-ITS applications, which would put extreme strain on the V2V and V2I communication infrastructures. Massive amounts of data would be produced by transportation sensors, posing a number of scientific and engineering problems, including those related to computational complexity, hardware and software development, data multi-source heterogeneity, and privacy protection.

High processing power is needed to meet the ultra-low latency requirements of C-ITS applications. However, due to their low computational capacity, vehicles are unable to meet the stringent latency requirements of these applications. This restricts the practical implementation of C-ITS applications. Numerous applications are still in the conceptual stage and cannot be used in day-to-day life without strong computational assistance. By delegating some or all of their processing functions to other vehicular network parts, vehicles can overcome this restriction. In order to decrease task latency, these network components compute for that vehicle. Using V2V and V2I communication ideas, a vehicle can make use of the extra computational resources of other cars as well as infrastructural resources that are within its communication range.

Devices enhance task latency and save energy that would have been used for task computation when they offload their jobs. Offloading tactics are used to coordinate this energy-saving method and increase network energy efficiency. To prevent them from running out of power entirely, extra care is paid to network resources that are battery-operated or have restricted power supplies. In the majority of cases, these network pieces with low power resources are transport sensors and road side units (RSUs).

In vehicular networks, one of the main issues is also high-speed connectivity. Communication connections are brittle and challenging to create and sustain. As a result, the communication links' range and duration are decreased. In vehicular communication, while establishing a communication link with the cloud can be challenging, automobiles occasionally find it impossible to create a direct communication link with RSU, instead relaying their message to RSU through other vehicles in the vicinity. Because of this unpredictability, unique tools must be developed in order to identify communication links that are available and to forecast how long such links will be available for task offloading. For this, a variety of learning algorithms that are capable of accurately predicting and assessing the benefits of accessible communication channels can be used.

To enhance data exchange between cars and RSUs, intelligent data transfer strategies can be used. Furthermore, the utilization of heuristic and learning approaches can be applied to forecast the computational availability of neighboring vehicles as well as the probable duration of those vehicles' availability. These forecasts would aid in making better use of the network resources at hand in order to reduce latency. Therefore, using information about the fog node's energy, computational load, mobility, and wireless link capability is essential for creating effective job offloading algorithms.

2. Literature Review

In [25], authors shown the importance of fog computing through effective task offloading for mobile devices. Two steps of an online learning-based offloading approach are being used to address the delay-sensitive applications. During the initial phase, resources are divided across the fog nodes while minimizing the cost of computation. At a later stage, task allocation and spectrum scheduling are optimized to reduce the offloading delay. The proposed technique outperforms the Upper Confidence Bound (UCB) technique, according to simulation data.

In [26], work is done on the effective use of servers for computation and task offloading in the face of asymmetric and uncertain information transmission. It is suggested that a two-phase design be used to accomplish this. A convex-concave optimization strategy is defined for the effective assignment of servers while optimizing the operator's predicted usages under the assumption of symmetric information. Additionally, a pricing matching solution is also suggested in order to minimize the network's overall latency. This price matching is expanded to include scenarios with information ambiguity, and a matching-based offloading architecture is created with the goal of minimizing the overall latency. The suggested approach ensures bounded divergence and facilitates effective resource sharing without requiring global information.

In [27], vehicular fog computing (VFC) is used, offloading compute tasks from Base Station (BS) to nearby automobiles' underutilized computational capacity. The main issues facing VFC are discussed, including the lack of effective incentives and a task assignment system. To optimize the expected utility of BS, a method for an efficient incentive is first provided. This mechanism is based on contract theoretical modeling, in which each vehicle type's unique characteristics are examined to create the contract. Task assignment is transformed into a dual-sided matching problem between vehicles and user equipment, which is solved by pricing-based stable matching algorithm. Numerical findings demonstrate that the suggested technique significantly improves performance.

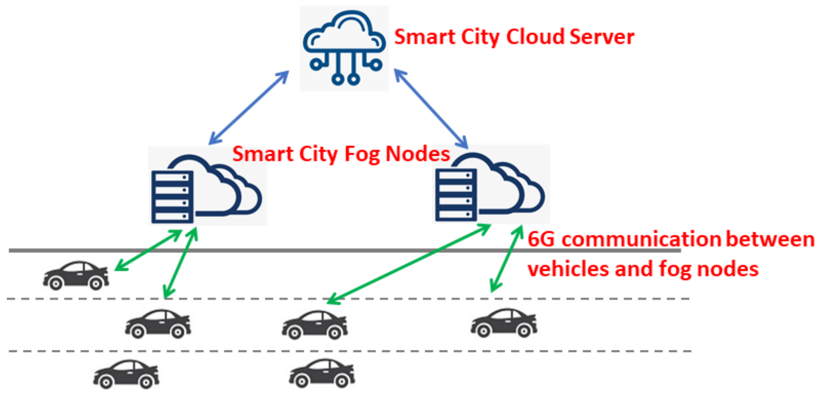
One interesting paradigm for enabling C-ITS is autonomous driving. To handle autonomous driving, a large amount of computing and a delay-intensive response are required. Consequently, in [28], VFC is used to move the computational resources from the busy base station to the vicinity of the vehicle end. Assuming information asymmetry and uncertainty, a two-stage-based VFC architecture is proposed to handle the issues of server assignment and task processing strategies. Contract theory governs the management of the vehicular computing resources, whereas learning-based matching governs the effective offloading of workloads. Additionally, simulation findings show that resource management and offloading delay performance have improved.

At peak hours, VFC may potentially be a factor in the load problem in a very crowded region. As a result, a car can be thought of as a fog node that helps with the offloaded job computation. Concerns with the introduction of VFC include the lack of incentives for resource allocation, the system's increased complexity, and collisions between unloading vehicles. The authors of [29] provide a novel contract-based process that uses deep reinforcement learning to accomplish cooperative resource contribution and utilization. Distributing resources while lowering system complexity is the goal. Moreover, a queuing approach is also suggested to address the collision issue for simultaneous offloading in many vehicle scenarios. The outcomes demonstrate a notable improvement in work offloading and resource allocation performance.

Comparable to the model mentioned above, authors in [30] proposed the concept of cars equipped with computing power, which guarantees reduced latency and improves system efficiency overall. How and which vehicle is to be chosen for job offloading while taking the delay cost and resource allocation for the multi-vehicle model into account is a significant problem in this situation. The consumption function of the offloading model is written as a convex optimization problem and then subjected to inequality constraints. Additionally, the Lagrange dual approach is used to tackle this problem, and a low-complexity algorithm is created in the end to determine the ideal values for the offloading ratio, computing vehicle selection, and system consumption.

3. Methodology

Fig. 1 depicts the architecture of the suggested approach. Here, 6G communications connects cars to smart city fog nodes and to one other. Moreover, a cloud server for smart cities across the city is connected to the fog nodes. A significant obstacle in putting this architecture into practice is figuring out how to share data between cars and fog nodes through effective 6G connection methods. Efficiently offloading ITS activities, like traffic management, infotainment, and cooperative awareness, to the fog nodes in a fair manner while reducing latency is the second main difficulty.



Challenges in 6G communications in ITS for Smart City	
Communication between vehicles & smart city fog nodes	• Efficient 6G transmission techniques • Efficient 6G transmission parameters • Performance metrics such as packet delivery ratio, throughput and end-to-end delay
Resource allocation in smart city fog nodes & cloud server	• Fair and efficient task offloading from vehicles to fog nodes and cloud server • Performance metrics such as load on fog nodes and task computation delay

Fig. 1 Architecture of proposed 6G communications in ITS for Smart City

Fig. 2 displays a flow chart of the research approach. In this instance, the vehicles generate ITS tasks related to safety, traffic management, and infotainment. These jobs are to be transported by vehicles to the appropriate fog nodes. To do this, we need to design an efficient 6G communication infrastructure that can convey these tasks to the fog nodes. Next, we will develop a task offloading strategy to make the most of the computational power of fog nodes.

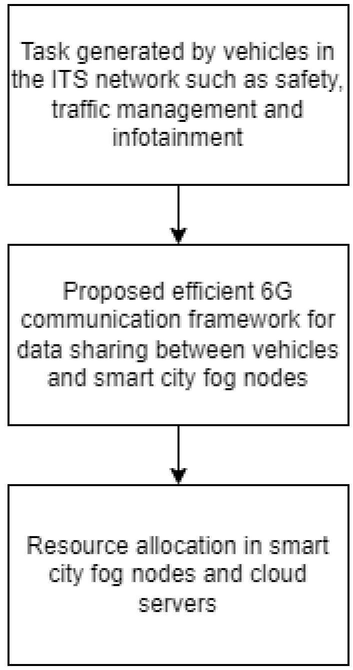


Fig. 2 Flow Chart of Research Methodology

4. Conclusion

Intelligent Transportation System is one of the major parts of smart cities. There is a dire need to design efficient communication and computation algorithms for ITS based smart cities. Vehicular fog and cloud computing system may consume large computing power for processing numerous computation-intensive and delay sensitive tasks. To solve this problem, an optimal offloading scheme is proposed that takes in to account the departure of occupied vehicles. The task offloading is formulated as a Semi-Markov Decision Process and a value iteration algorithm is used to maximize the utility of the system. As compared to the greedy scheme, the proposed algorithm achieves higher utility.

References

1. M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, “Toward 6g networks: Use cases and technologies,” IEEE Communications Magazine, vol. 58, no. 3, pp. 55–61, 2020.
2. Z. Na, Y. Liu, J. Shi, C. Liu, and Z. Gao, “Uav-supported clustered noma for 6g-enabled internet of things: Trajectory planning and resource allocation,” IEEE Internet of Things Journal, pp. 1–1, 2020.
3. F. Tang, Y. Kawamoto, N. Kato, and J. Liu, “Future intelligent and secure vehicular network toward 6g: Machine-learning approaches,” Proceedings of the IEEE, vol. 108, no. 2, pp. 292–307, 2020.
4. V. Ziegler, H. Viswanathan, H. Flinck, M. Hoffmann, V. R¨ ais¨ anen, and K. H¨ at ¨ onen, “6g architecture to connect the worlds,” IEEE Access, pp. 1–1, 2020.
5. I. F. Akyildiz, A. Kak, and S. Nie, “6g and beyond: The future of wireless communications systems,” IEEE Access, vol. 8, pp. 133995– 134030, 2020.
6. S. Chen, Y. Liang, S. Sun, S. Kang, W. Cheng, and M. Peng, “Vision, requirements, and technology trend of 6g: How to tackle the challenges of system coverage, capacity, user data-rate and movement speed,” IEEE Wireless Communications, vol. 27, no. 2, pp. 218–228, 2020.

7. J. Kim, T. Ha, W. Yoo, and J. Chung, "Task popularity-based energy minimized computation offloading for fog computing wireless networks," IEEE Wireless Communications Letters, vol. 8, no. 4, pp. 1200–1203, 2019.
8. Y. Jiang, Y. Chen, S. Yang, and C. Wu, "Energy-efficient task offloading for time-sensitive applications in fog computing," IEEE Systems Journal, vol. 13, no. 3, pp. 2930–2941, 2019.
9. F. S. Abkenar and A. Jamalipour, "Eba: Energy balancing algorithm for fog-iot networks," IEEE Internet of Things Journal, vol. 6, no. 4, pp. 6843–6849, 2019.
10. K. Wang, Y. Tan, Z. Shao, S. Ci, and Y. Yang, "Learning-based taskoffloading for delay-sensitive applications in dynamic fog networks,"IEEE Transactions on Vehicular Technology, vol. 68, no. 11, pp. 11 399–11 403, 2019.
11. Z. Zhou, H. Liao, X. Zhao, B. Ai, and M. Guizani, "Reliable task offloadingfor vehicular fog computing under information asymmetry andinformation uncertainty," IEEE Transactions on Vehicular Technology,vol. 68, no. 9, pp. 8322–8335, 2019.
12. J. Zhao, M. Kong, Q. Li, and X. Sun, "Contract-based computingresource management via deep reinforcement learning in vehicular fogcomputing," IEEE Access, vol. 8, pp. 3319–3329, 2020.
13. H. Li, X. Li, and W. Wang, "Joint optimization of computation cost anddelay for task offloading in vehicular fog networks," Transactions onEmerging Telecommunications Technologies, vol. 31, no. 2, p. e3818,2020.
14. Q. Wu, H. Ge, H. Liu, Q. Fan, Z. Li, and Z. Wang, "A task offloadingscheme in vehicular fog and cloud computing system," IEEE Access,vol. 8, pp. 1173–1184, 2020.