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Dedication

"

To my beloved parents, Malek and Louisa. I am really grateful to them for the sacrifices they have made, their unconditional love, patience, encouragement, and their prayers every day to make this dream a reality.

To my beloved husband Maamar. I am very thankful for all what he has done for me to reach this goal.

To my adorable sons, Abd El Mouiz and Ilyes. I am pleased by your arrival in my life; your presence has made me stronger and better than I could have ever imagined.

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To all my beloved family and my husband's family.

To my friends and colleagues, who never left my side.

This work is a sign of my love and gratitude to you all.

"

- Somia

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ملخص

في حياتنا اليومية، يتزايد عدد المركبات على كوكب الأرض بشكل سريع، ومن المتوقع أن تستمر المدن في النمو بشكل مستمر. ويؤدي ذلك إلى زيادة عدد السيارات على الطرقات بالإضافة إلى الازدحام المروري وتلوث الهواء والحوادث الحتمية، مما قد يؤثر على الجانب الاجتماعي والاقتصادي والبيئي. من المؤكد أن تحسين شبكات النقل من خلال تحسين تدفق حركة المرور على الطرق كان محور تركيز بحثي رئيسي منذ دمج أنظمة النقل الذكية في هذا المجال. ومع ذلك، فإن إيجاد المسارات المثلى في السيناريوهات الحضرية يمثل تحديًا كبيرًا نظرًا لأنه يجب أن يأخذ في الاعتبار عدة عوامل، مثل تقليل الاختناقات المرورية ووقت السفر والمسافة وتقليل استهلاك الوقود ومستويات التلوث وفقًا لذلك. لذلك، نقترح في هذه الأطروحة نهجًا محسّنًا يستند إلى منهجية المحاكاة الفوقية لتحسين مستعمرة النمل (ACO) التي تسمح لسائقي المركبات بالبحث عن الطرق المثلى في المناطق الحضرية من وجهات نظر مختلفة، مثل قصر المسافة والوقت.

علاوة على ذلك، تم إدخال الشبكات المخصصة للمركبات (VANETs) لتمكين الاتصال المباشر بين المركبات والبنية التحتية. ومع ذلك، واجهت التطبيقات العملية لشبكات VANETs تحديات مثل خدمات الشبكة غير المستقرة، وبنى الشبكة غير المتوافقة، والقيود في قدرة الحوسبة ومساحة التخزين. ونتيجة لذلك، ولمعالجة أوجه القصور هذه، تتحول شبكات المركبات إلى إنترنت المركبات .(IoV) ومع ذلك، يواجه إنترنت المركبات (IoV) تحديات كبيرة، كما أن مناهج الحوسبة السحابية التقليدية غير كافية للمعالجة في الوقت الحقيقي واتخاذ القرارات المطلوبة في بيئات المركبات. ولذلك، تضمن الحوسبة الضبابية/حافة الحوسبة تقليل زمن الاستجابة وتحسين إدارة النطاق الترددي من خلال معالجة بيانات حركة المرور المحلية. وفي هذا الصدد، نقترح بنية قائمة على الحوسبة الضبابية/الحواسيب الطرفية من أجل إدارة ومراقبة أنظمة المرور الحضرية بكفاءة.

وبالفعل، تتضمن التحسينات المقترحة على ACO للبحث عن المسارات المثلى في المناطق الحضرية دمج عوامل متعددة، مثل طول السفر والوقت ومستوى الازدحام، في عملية اختيار المسار. علاوةً على ذلك، تم اقتراح البحث العشوائي واستراتيجية النخبوية وقواعد تحديث الفرمون المرنة لمراعاة التغييرات الديناميكية في ظروف شبكة الطرق وجعل النهج المقترح أكثر ملاءمة وفعالية. علاوةً على ذلك، تهدف البنية المقترحة القائمة على IoV إلى تحسين التنسيق والتواصل بين كيانات شبكة الطرق، مما يؤدي إلى تحسين أنظمة النقل. بشكل عام، تساهم هذه التحسينات في أصالة هذه الأطروحة، ولديها القدرة على تطوير مجال توجيه حركة المرور في أنظمة النقل.

كلمات مفتاحية : أنظمة النقل الذكية، إنترنت المركبات ، الحوسبة الضبابية/الحافة ، شبكات النقل ، تحسين المسارات ، وقضايا المرور في المناطق الحضرية

Abstract

In our daily lives, the number of vehicles on the planet is growing rapidly, and cities are expected to continue growing. This leads to an increase in the number of road automobiles as well as traffic congestion, air pollution, and inevitable accidents, which can affect the societal side, the economy, and the environment. Certainly, optimizing transportation networks by improving road traffic flow has been a major research focus since the integration of Intelligent Transportation Systems in this field. However, finding the optimal routes in urban scenarios is very challenging since it should consider several factors, such as reducing traffic jams, travel time, and travel distance, and decreasing fuel consumption and pollution levels accordingly. For that, in this thesis, we propose an enhanced approach based on the Ant Colony Optimization (ACO) meta-heuristic that allows vehicle drivers to search for optimal routes in urban areas from different perspectives, such as shortness and rapidness. Furthermore, Vehicular Ad hoc Networks (VANETs) were introduced to enable direct communication between vehicles and infrastructure. However, practical applications of VANETs have faced challenges such as unstable network services, incompatible network architectures, and limitations in computing ability and storage space. Consequently, to address these shortcomings, vehicle networks are transforming into the Internet of Vehicles (IoV). However, IoV faces significant challenges, and traditional cloud computing approaches are insufficient for the real-time processing and decision-making required in vehicular environments. Therefore, fog/edge computing ensures reduced latency and improved bandwidth management through localized traffic data processing. In this regard, we propose an IoV-based architecture, using the fog/edge computing concept, in order to efficiently manage and monitor urban traffic systems. Indeed, the proposed improvements to the ACO to search for optimal paths in urban areas include incorporating multiple factors, such as travel length, time, and congestion level, into the route selection process. Furthermore, random search, elitism strategy, and flexible pheromone updating rules are proposed to consider the dynamic changes in road network conditions and make the proposed approach more relevant and effective. Moreover, the proposed architecture-based IoV aims to improve coordination and communication among the road network entities, leading to improved transportation systems. Overall, these enhancements contribute to the originality of this thesis, and they have the potential to advance the field of traffic routing in transportation systems.

Keywords : Intelligent Transportation Systems, Internet of Vehicles, Transportation Networks, Route Optimization, and Urban Traffic Issues, Fog/Edge Computing

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Résumé

Dans notre vie quotidienne, le nombre de véhicules sur la planète augmente rapidement, et l'on s'attend à ce que les villes continuent de s'étendre. Cela entraîne une augmentation du nombre d'automobiles sur les routes ainsi que des embouteillages, de la pollution de l'air et des accidents inévitables, qui peuvent avoir des répercussions sur la société, l'économie et l'environnement. Certes, l'optimisation des réseaux de transport par l'amélioration de la fluidité du trafic routier a été un axe de recherche majeur depuis l'intégration des systèmes de transport intelligents dans ce domaine. Cependant, trouver les itinéraires optimaux dans les scénarios urbains est très difficile car il faut prendre en compte plusieurs facteurs, tels que la réduction des embouteillages, du temps et de la distance de déplacement, ainsi que la diminution de la consommation de carburant et des niveaux de pollution en conséquence. Pour cette raison, dans cette thèse, nous proposons une approche améliorée basée sur la méta-heuristique ACO (Ant Colony Optimization) qui permet aux conducteurs de véhicules de rechercher des itinéraires optimaux dans les zones urbaines sous différents angles, tels que la brièveté et la rapidité. En outre, les réseaux ad hoc véhiculaires (VANET) ont été introduits pour permettre une communication directe entre les véhicules et l'infrastructure. Cependant, les applications pratiques des VANET ont été confrontées à des défis tels que l'instabilité des services de réseau, l'incompatibilité des architectures de réseau et les limitations de la capacité de calcul et de l'espace de stockage. Par conséquent, pour remédier à ces problèmes, les réseaux véhiculaires se transforment en Internet des véhicules (IoV). Cependant, l'IoV est confronté à des défis importants, et les approches traditionnelles du cloud sont insuffisantes pour le traitement en temps réel et la prise de décision nécessaires dans les environnements de véhicules. Par conséquent, le Fog/Edge computing permet de réduire les temps de latence et d'améliorer la gestion de la bande passante grâce au traitement localisé des données de trafic. À cet égard, nous proposons une architecture basée sur l'IoV, qui utilise le concept du Fog/Edge computing, afin de gérer et de surveiller efficacement les systèmes de trafic urbain. En effet, les améliorations proposées à l'ACO pour la recherche de chemins optimaux dans les zones urbaines comprennent l'incorporation de multiples facteurs, tels que la longueur du trajet, la durée et le niveau d'encombrement, dans le processus de sélection de l'itinéraire. En outre, la recherche aléatoire, la stratégie d'élitisme et les règles flexibles de mise à jour des phéromones sont proposées pour prendre en compte les changements dynamiques dans les conditions du réseau routier et rendre l'approche proposée plus pertinente et plus efficace. En outre, l'architecture proposée pour l'IoV vise à améliorer la coordination et la communication entre les entités du réseau routier, ce qui permet d'améliorer les systèmes de transport. Dans l'ensemble, ces améliorations contribuent à l'originalité de cette thèse et ont le potentiel de faire progresser le domaine du routage du trafic dans les systèmes de transport.

Mots clés : Systèmes de Transport Intelligents, Internet des Véhicules, Réseaux de Transport, Informatique du Fog/Edge , Optimisation des Itinéraires et Problèmes de Trafic Urbain

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Glossary

ABC	*Artificial Bee Colony*
ACO	*Ant Colony Optimization*
AI	*Artificial Intelligence*
BLE	*Bluetooth Low Energy*
C-ITS	*Cooperative Intelligent Transportation Systems*
CPU	*Central Processing Unit*
DSRC	*Dedicated Short-Range Communication*
ESTI	*European Telecommunications Standards Institute*
I2I	*Infrastructure to Infrastructure*
ICT	*Information and Communication Technologies*
IEEE	*Institute of Electrical and Electronics Engineers*
IoV	*Internet of Vehicles*
IoT	*Internet of Things*
ITS	*Intelligent Transportation Systems*
MAC	*Media Access Control*
MANET	*Mobile Ad Hoc Networks*
OBU	*On-Board Unit*
OSM	*OpenStreetMap*

PHY *Physical layer*

PSO *Particle Swarm Optimization*

RFID *Radio Frequency Identification*

RSU *Roadside unit*

SDN *Software-Defined Networking*

TRP *Traffic Routing Problem*

VANET *Vehicular Ad Hoc Networks*

VEC *Vehicular Edge Computing*

VFC *Vehicular Fog Computing*

V2V *Vehicle to Vehicle*

V2I *Vehicle to Infrastructure*

V2S *Vehicle to Sensor*

V2R *Vehicle to Roadside unit*

V2P *Vehicle to Person*

WPAN *Wireless Personal Area Network*

WAVE *Wireless Access in Vehicle Environment*

Chapter 1

General Introduction

Do the difficult things while they are easy, and do the great things while they are small. A journey of a thousand miles must begin with a single step.

– Laozi

1.1 Context

The global automobile population is increasing at an explosive rate in our daily lives, and urban areas are expected to experience continued growth. This leads to traffic congestion, air pollution, and unavoidable accidents. Therefore, these issues can have an impact on several aspects of society, the economy, and the environment. The challenges highlighted underscore the critical need for research initiatives worldwide to enhance transportation systems. However, this task is generally difficult due to the decentralized , dynamic, and partially controllable aspects of transport networks, making it a complicated domain. Furthermore, transportation networks have a significant influence on the development of our society. Efficient transportation of goods and individuals promotes prosperity and affects our areas by enhancing accessibility. Hence, the advancement of transportation serves as a crucial indicator of a country's well-being (Vongsingthong and Smanchat, 2014). Additionally, leveraging innovative Information and Communications Technologies (ICT) to enhance transportation systems has become a pivotal solution in the field. Advancements in processing power, together with significant progress in embedded systems and the quality of modern sensors, have enabled the development of more efficient control methods, and the result is what is commonly referred to as Intelligent Transportation Systems (ITS) (Figure 1.1).

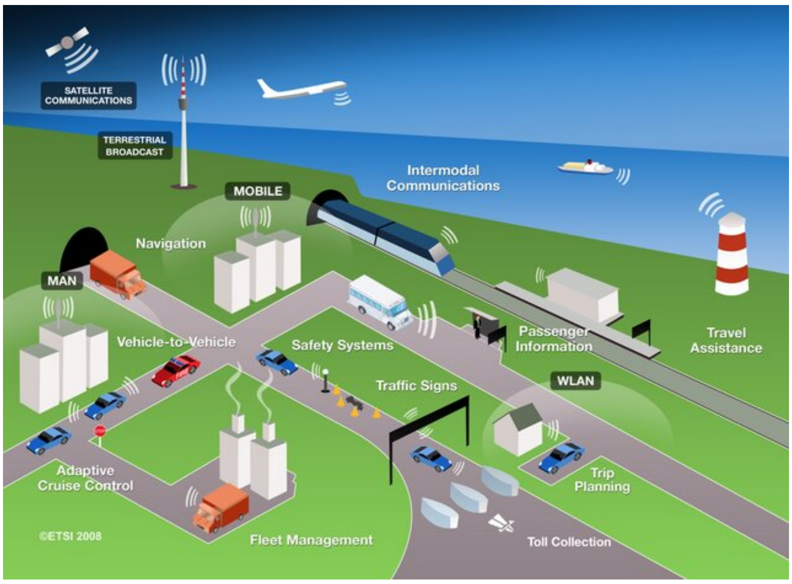

Figure 1.1: Intelligent Transportation System Model (Hess et al., 2009).

Moreover, Information and Communication Technologies (ICT) have emerged as an essential aspect since they hold significant influence in every field and provide substantial advantages to individuals and society. This involves the rapid expansion of the Internet of Things (IoT), which refers to the connection of numerous devices and sensors, known as ”smart objects”, that collaborate to fulfill our requirements despite their limited capabilities in terms of energy, memory, and processing power (Subramaniam et al., 2017). With the considerable progress made in sensing technologies, IoT has been a hot research topic in the last decade due to its wide range of applications. Indeed, it has been the basis for the implementation of many transport applications (Safety, Traffic efficiency, and comfort-related applications).

Furthermore, Urban traffic system researchers have prioritized the utilization of Internet of Things technology. This has led to the emergence of an innovative concept called the Internet of Vehicles (IoV). IoV is constructed using the Internet, wireless sensor networks, and various sensing technologies. It is employed for the intelligent recognition of road users, which are considered as objects. It enables the monitoring and real-time management of road traffic.

Similarly, with the demographic expansion worldwide, exploiting information technologies dedicated to transportation systems is primordial for users of the road (both drivers and pedestrians). This plays a vital role in improving the quality of people’s daily lives. especially in big and crowded cities. Indeed, optimizing transportation networks by improving road networks in terms of travel time, path length, congestion level, and pollution has been a major research focus in the last decade (Harrou et al., 2020; Afrin and Yodo, 2021). Roughly speaking, to overcome different issues in road traffic systems, several techniques in artificial intelligence (AI), heuristics, meta-heuristics in the swarm, and evolutionary intelligence are introduced in the literature (Celtek et al., 2020; Shang Tong, 2019).

Furthermore, one main aim of vehicle drivers while driving is to find ”optimal Origin-Destination routes”. By ’optimal’, not only the path length or the arrival time of the destination is considered, but also many other factors such as fuel consumption, traffic jams, the number of turns, traffic signals, and stop signs in a route, as well as safety, which is a major concern. The importance of factors such as work, emergencies, personal business, shopping, and leisure varies for each driver, influencing their travel decisions. Furthermore, the complexity of determining the ”optimum” route for a driver’s trip poses a challenge for the path planner (Pang et al., 2002). Hence, empowering the driver to choose the optimal route based on their preferred criteria is the most effective approach, considering various satisfactory factors.

1.2 Background and motivations

The traffic congestion in urban areas persists, and the incidence of fatalities and accidents on roads stays considerable. Human error is frequently considered to be the main factor leading to traffic problems. Hence, it is imperative to minimize human intervention in the driving procedure. Therefore, car makers are working to develop automobile technologies that aid drivers in ensuring safety and improving driving performance.

Figure 1.2: Traffic congestion in big cities.

Indeed, Ward’s study indicates that in 2010, the number of cars in use globally exceeded 1 billion. Based on the total sales of new vehicles, it is projected that there might be as many as 2 billion vehicles by 2035. The traffic continues to be chaotic, and the frequency of fatalities and injuries on roads remains elevated (Alam et al., 2016).

Furthermore, the population residing in urban regions exceeds those living in rural areas, and cities will continue growing. According to the United Nations, around 66% of the global population is expected to reside in urban areas by 2050. This progress has a big impact on the overall quality of human life (Silva, 2020).

Traffic problems are a major concern in cities, particularly during peak hours (Zamri and Hamzah, 2022). As stated in (Contreras-Castillo et al., 2017), the United States allocates more than 836$ billion towards expenses linked to crashes, insurance premiums, and traffic law enforcement.

Hence, the presence of heavy traffic in cities can have a negative impact on the overall travel experience of road users, as well as on society and the economy (Zamri and Hamzah, 2022).

- **Road users:** Urban traffic congestion can induce anxiety and tension among motorists. Furthermore, other than causing a loss of time for drivers and passengers and limiting their productivity, it can also diminish the accuracy of estimating trips for road users.
- **Society:** High levels of traffic jam can contribute to elevated fuel use, thereby increasing air pollution levels. However, in certain instances, the traffic congestion in cities might be regarded as a direct cause of road accidents. Additionally, it might result in delayed delivery of goods.
- **Economy:** Based on historical consequences, bottlenecks in urban highways can lead to a decrease in employees' productivity. This might lead to a decline in economic growth and need spending on improving Traffic Management Systems.

Governments worldwide have implemented various countermeasures, including traffic regulations and advanced automotive systems, to mitigate road traffic accidents. Despite the numerous countermeasures implemented globally, the transportation system continues to require enhancements for optimal efficiency and safety (Silva, 2020).

The concept of the Internet of Vehicles, involving connected vehicles, intelligent transportation systems, and IoT technologies, offers the potential to revolutionize transportation systems, providing efficient and sustainable solutions that are integral to daily life (Datta et al., 2016).

The combination of ITSs and the IoV has transformed traditional transportation systems into more efficient and interconnected networks, empowered the development of smart cities, and therefore fundamentally transformed the way we perceive and operate transportation systems. However, this integration also introduces several challenges (Aldegheishem et al., 2018; Alam et al., 2016). One of the primary concerns raised against IoV is the issue of the standardization and interoperability of communication protocols within IoV. With the rapid development of wireless communication technologies, ensuring that all vehicles and roadside infrastructure can communicate effectively and seamlessly becomes crucial (Sadiku et al., 2021). It is essential to establish uniform communication protocols and standards to enable interoperability and smooth operation of the Internet of Vehicles within intelligent transportation systems. Moreover, the sheer volume of data generated by the Internet of Vehicles poses challenges in terms of data management and analysis. Therefore, efficient data storage, processing, and analysis capabilities need to be implemented to effectively utilize the vast amount of data generated by IoV for improved transportation planning (Sadiku et al., 2021; Aldegheishem et al., 2018; Yakusheva et al., 2019; Alam et al., 2016). In addition to these concerns, the development and integration of IoV raises questions about the ethical implications of autonomous vehicles and intelligent transportation systems. As vehicles become more automated and interconnected, there are ethical considerations surrounding issues such as liability in the event of accidents, decision-making algorithms in potential collision scenarios, and the overall impact on human control and responsibility in driving (Sadiku et al., 2021; Aldegheishem et al., 2018; Yakusheva et al., 2019)

The problem considered in the second part of our thesis is selecting optimal paths for vehicle drivers in urban road networks, which is a fundamental task to gain time, reduce fuel consumption (which represents money, energy, and pollution), decrease traffic jams, damages, and accidents in urban road systems, and more generally deal with road traffic issues.

In the following, we report some questions in order to find the suitable responses in this thesis:

- ☞ What type of useful data we need to select optimal paths to drivers. In reality, we have lot of factors like: travel distance, travel time, route speed, route safety, traffic jam, number of turns, traffic signal, stop signs, and fuel consumption.

- ☞ What is the kind of computation methods is suitable to select optimal paths to drivers in urban areas? Approximate or exact methods? In the case of choosing approximate methods, which meta-heuristic is more efficient in solving our problematic?

- ☞ How to detect a congestion, an obstacle or an accident in a road segment? (from data transferred from vehicles, road sensors, roadside units to the sink nodes (master nodes))

To respond to these questions, several contributions are presented in this thesis, as we can explain it in brief in the next section.

In this regard, we mainly focus on decreasing time and distance to select short and fast paths. Furthermore, we boost the quality of the selected paths by adding the congestion level to the search criteria. This helps to avoid congested roads, leading to a readjusted traffic flow all over the city. The three mentioned factors are time, distance, and congestion level. The three mentioned factors — time, distance, and congestion level — are the principal factors considered in our contribution.

The problem discussed in this thesis is an NP-hard combinatorial optimization problem, a problem that cannot be solved in a short time using exact methods but requires the use of meta-heuristic algorithms (Yu and Yang, 1998; Handler and Zang, 1980). Therefore, we propose to use an adapted Ant Colony Optimization (ACO) algorithm for the problem of finding optimal paths in traffic networks.

1.3 Objectives of the thesis

In this section, we explain the principal aims of this thesis:

- ☞ **Aim 1**: Conducting an overview on the impact of integrating Intelligent Transportation Systems (ITSs) in the field of transport.
- ☞ **Aim 2**: Presenting an overview about vehicle networks, especially VANETS, and the Internet of Vehicles and their integration in Intelligent Transportation Systems.
- ☞ **Aim 3**: Reporting an overview of the fog/edge computing paradigms.
- ☞ **Aim 4**: Proposition of an IoV-based model to efficiently manage urban traffic systems. Indeed, the proposed architecture based on Fog-Edge concept, aims to improve coordination and communication among the road network entities, leading to improved transportation systems.
- ☞ **Aim 5**: Development of an efficient framework based on the Ant Colony Optimization (ACO) algorithm to calculate the optimal routes in an urban road network by adopting an elitism strategy, a random search approach, and a Flexible Pheromone Deposit-Evaporate Mechanism, in order to make a trade-off between route length, travel time, and congestion level, and regulate the urban traffic flow.
- ☞ **Aim 6**: Validation of the proposed approach, by simulation, and testing different scenarios to demonstrate the effectiveness of the proposed algorithm, and the comparison with other meta-heuristic algorithms.

1.4 Contributions of the thesis

In this thesis, several contributions can be reported:

First, we propose a layered architecture-based IoV and Fog/Edge computing concepts to efficiently manage urban traffic systems. Overall, the proposed architecture aims to improve coordination and communication among the road network entities, leading to significantly ameliorating urban transportation networks. In the second part of this thesis, we make some improvements to the original Ant Colony Optimization (ACO) algorithm in order to find the optimal route in urban areas. The improved algorithm includes elitism strategies to orient the next ant colonies to select the best paths.

1. The elitism of the queen of each colony
2. The elitism of the best queen ever, or the queen of all queens
3. The elitism of the best ants in each colony depends on a certain threshold thr.

However, the elitism strategy can cause premature convergence in the first iterations and fall into a local optimum early. To fix this problem, we added a random search strategy to ensure more exploration of other unexplored roads in the network. In addition, we propose a flexible deposit-evaporate mechanism to further enhance the performance of the found solution.

- ☞ The elitism strategy ensures that the best solution found so far is preserved throughout the iterations, preventing the algorithm from falling back to suboptimal solutions.
- ☞ The random search method is used to avoid falling into a local optimum and expedite the exploration of the solution space.
- ☞ Finally, flexible pheromone updating rules are proposed to take into account the dynamic changes in road network conditions and make the proposed approach more relevant and effective.

These improvements allow our algorithm to adapt and optimize the selected routes in real time, making it more robust and flexible compared to other state-of-the-art methods. In addition, to make a trade-off between short routes, fast routes, and less congested routes, we give the same value to the metrics' weights (time, distance, and congestion level). However, the vehicle driver can select which metric is more important to him and assign different weights to these metrics. While existing ant colony algorithms typically consider only one factor, such as distance, in traffic routing, our approach extends the algorithm to consider additional factors, thereby making it more relevant and effective for real-world scenarios where multiple factors may affect route selection.

Furthermore, we have conducted extensive experimental tests and demonstrated that our proposed algorithm outperforms existing state-of-the-art works that use the basic Ant Colony Algorithm itself. In addition to the experimental results of the comparison of our proposed approach against well-known and reliable meta-heuristics such as the genetic algorithm (GA) and the Swarm Optimization algorithm (PSO), in terms of minimizing the overall cost and improving the average and best fitness values of the found solutions. These improvements and their novelty are detailed in the chapter 5 and 6 of this thesis.

In addition, our research has expanded into Information Technologies (IT) in the transportation field to address the need for efficient and effective traffic management solutions. The proposed algorithm, which integrates these additional elements into the ACO algorithm, is a novel approach that advances the state of the art in solving Traffic Routing Problems (TRP) in road networks. We believe that our proposed improvements to the ACO have the potential to advance the field of traffic route planning and contribute to practical applications in real-world scenarios.

Next, we calculate the road graph from OpenStreetMap (OSM) using the Python library OSMnx (Boeing, 2017), which facilitates the manipulation of street networks. For that, we tested our proposal on the road network of Valencia, Spain. Our results demonstrate the effectiveness and soundness of our proposal based on the assessed fitness values.

Summary of related publications

In this subsection, the list of publications related to this thesis is presented.

Journal Papers

- Boubedra, S., Tolba, C., Manzoni, P., Beddiar, D. and Zennir, Y. (2023), ”Urban traffic flow management on large scale using an improved ACO for a road transportation system”, International Journal of Intelligent Computing and Cybernetics, Vol. 16 No. 4, pp. 766-799. https://doi.org/10.1108/IJICC-02-2023-0020 (Boubedra et al., 2023)

Conference Papers

- Boubedra, S., Tolba, C. (2019), ”A vehicular network architecture based on Internet of Vehicles for improving the urban traffic management”, 2nd Conference on Informatics and Applied Mathematics (IAM’19), 12th – 13th June, 2019, Guelma, Algeria. (Boubedra and Tolba, 2019)

- Boubedra, S., Tolba, C. (2023), ”Enhancing Urban Traffic Management using Internet of Vehicles: A Layered Architecture-based System”, 2023 International Conference on Decision Aid Sciences and Applications (DASA’23), 16th – 17th September, 2023, Annaba, Algeria. (Boubedra and Tolba, 2023)

1.5 Organization of the thesis

To discuss the details of our thesis, we have organized it as follows:

- **Chapter II: Intelligent Transportation Systems for Safer and Smarter Mobility** In this chapter, we provide an overview on the impact of integrating Intelligent Transportation Systems (ITSs) in the field of transport.

- **Chapter III: Towards VANETS and the Internet of Vehicles** In this chapter, we present an overview about vehicle networks, especially VANETS, and the Internet of Vehicles and their integration in Intelligent Transportation Systems. Additionally, we explore how VANETS are transformed into the Internet of Vehicle networks.

- **Chapter IV: Enhancing Urban Traffic Management using Internet of Vehicles** In this chapter, we present an efficient IoV architecture based on Fog/Edge computing concept, and we explain in detail its layers and its functioning.

- **Chapter V: Urban Traffic Flow Management on Large Scale using an Improved ACO for a Road Transportation System** In this chapter, we provide a summary of relevant works related to our contribution, and we present the ”Traffic Routing Problem” statement. Then, we explain the proposed approach in detail.

- **Chapter VI: Evaluation and Results** In this chapter, we describe different scenarios, and report the obtained results that demonstrate the effectiveness of the proposed algorithm, the comparison with other meta-heuristic algorithms.

- **Chapter VII: Conclusions and perspectives** In this chapter, we present the general conclusion of this thesis, including the limitations and perspectives of our work.

Chapter 2

Intelligent Transportation Systems for Safer and Smarter Mobility

Public transportation is like a magnifying glass that shows you civilization up close.

– Chris Gethard

2.1 Introduction

The number of vehicles on the planet is growing rapidly, and cities are expected to continue growing. This leads to an increase in the number of road automobiles as well as traffic congestion, air pollution, and inevitable accidents, which can affect the societal side, the economy, and the environment. These issues explain why many research programs around the world aim to improve transportation systems; this is indeed a difficult task because the distributed, open, dynamic, and partially controllable nature of transport networks makes it a complex area. In this chapter, we provide an overview on the impact of integrating Intelligent Transportation Systems (ITSs) in the field of transport.

2.2 ITS: Definition, historical data and the main components

2.2.1 Definition

Intelligent transportation systems (ITSs) encompass transportation management systems that use advanced information and communication technologies for transportation and logistics. They seek to enhance road safety, mitigate accidents caused by human error, alleviate traffic congestion and pollution in urban areas, and improve the overall driving experience. Furthermore, they can be perceived as cognitive systems that assimilate knowledge from historical data gathered from the surrounding environment to effectively address the needs of various users, including drivers, pedestrians, cyclists, public safety, and security officers. This enables more efficient and sustainable transport systems (Rabah, 2021; Bouquillon, 2022; Chtourou, 2021). In the specific context of ITS applications, wireless communication is employed to facilitate the dissemination of automatic emergency warnings in the event of accidents, collisions, or other hazardous incidents. This exchange of information using wireless communications, involving road users, vehicles, and other entities, forms what is commonly referred to as Cooperative Intelligent Transport Systems (C-ITS) (Chtourou, 2021).

2.2.2 Historical data

With the increase in the number of vehicles in the past decades (75 million vehicles in the 1960s), traffic congestion and accidents have emerged as major transportation concerns in various parts of the world, posing serious challenges to the efficient movement of people and goods. Every year, an average of 1.3 million people die from road accidents worldwide, and 20–50 million people suffer non-fatal injuries. For these reasons, transport management technologies using road infrastructure, such as traffic lights in the United States in 1914 and parking meters in 1935, have emerged as (Rabah, 2021; Chen, 2019). Significant advancements in the transportation field have made considerable progress since the 1930s in Japan, Europe, and the United States in three distinct steps: the preparation phase, feasibility study, and product development (Nassar, 2021). During the preparation phase, the technologies have not yet reached a level of maturity, thus prompting a strong emphasis on enhancing transportation infrastructure through the construction of novel roadways and bridges. For example, the first ITS was the implementation of electric traffic signals in 1928. Subsequently, in the 1960s, the United States introduced the first computer-controlled traffic signals. Towards the end of the 60s and the beginning of the 70s, ITSs emerged with the advent of the Comprehensive Automobile Traffic Control System (CACS) in Japan and the Autofahrer Leit und Information System (ALI) in Germany.

These systems represent dynamic path control mechanisms based on real-time traffic conditions. In addition, the Electronic Route Guidance System (ERGS) was established in Germany and the United States, where the first route guidance programs were launched, including the installation of the first sensors. This has led to the widespread introduction of the first localization algorithms represented on digital maps, the appearance of microprocessors, and GPS. All of these technological advancements have played a crucial role in the development of ITS. Therefore, they were effectively utilized in the establishment of the first traffic management centers (TMS), which successfully integrated various data related to meteorology, vehicle speed, congestion, and accidents (Rabah, 2021; Chen, 2019;

Nassar, 2021). The feasibility study phase (1980-1995), saw an increase in technological industry-funded projects across Europe, Japan, and the US, which played a pivotal role in the advancement of ITSs. The subsequent product development phase, starting from 1995 until the present, marked a shift in focus towards the creation of tangible products within the realm of ITS. This shift in focus led to the initiation of several important projects, such as the Chauffeur project in Europe and concentrated efforts in the United States to integrate and install large-scale ITSs by the late 90s. (Nassar, 2021)

2.2.3 ITS Roles and Objectives

ITSs have the capacity to revolutionize both public transportation and personal vehicle usage. It is widely acknowledged that information systems hold immense potential in terms of minimizing travel delays and reducing unnecessary mileage. Numerous studies have documented the advantageous effects of ITS, such as a notable decrease in total travel duration (Joachim, 2002).

We cite the principal objectives of ITSs as follows:

- Increase the level of traffic safety for road users (drivers, pedestrians, operational agents, etc.).
- Improving the awareness of road users about the traffic state to prevent and reduce crashes and road accidents is an essential function of ITSs. This enhanced perception is achieved through data transmission between the ITS components.
- Optimization of the vehicle distribution across the network more efficiently. This process begins by collecting data on current traffic conditions throughout the entire network.
- Minimizing traffic jams in congested areas to reduce the time and fuel consumed while driving.

- Effective management of traffic data, dissemination of pertinent information in real time, and reduction of network latency.
- Contributing to autonomous and collaborative vehicles in the future.

2.2.4 Main components of ITS

ITSs must ensure road safety by accurately transmitting information to drivers and transport authorities using a mobile wireless network known as a vehicular ad hoc network (VANET). To facilitate this communication, various components have been specifically designed (Rabah, 2021; Thomas, 2020).

- **The On-board unit (OBU)** This car-embedded equipment ensures communication between the vehicle and surrounding network entities. V2X communication is used to process the data collected from vehicle sensors. The OBU comprises sensors such as GPS and LIDAR, a network interface (antenna), a central control module, and an application unit (AU). The AU is an integrated element within vehicles that allows users to access supported applications.
- **The Roadside unit (RSU)** is a stationary wireless access point strategically positioned along roads, such as intersections and parking areas, to facilitate vehicular communication. The RSU has two crucial roles. First, it propagates information locally to vehicles and can act as an intermediary for data exchange between vehicles and central entities. In addition, it can act as an internet gateway for vehicles.
- **The Central Station** The Central Station infrastructure provides a comprehensive overview of the network and is used to manage the cellular communication of events. (Mendiboure, 2020; Leblanc, 2020; Chtourou, 2021)

Moreover, ITSs encompass a wide variety of technologies, ranging from fundamental management systems, such as traffic light management, radar, and video surveillance, to advanced applications integrating real-time data and feedback from multiple sources, including on-board navigation systems (Rabah, 2021).

In the current context, the ITS plays a crucial role in addressing the deficiencies of the existing transportation infrastructure. ITSs aim to address traffic congestion issues and enhance overall transportation efficiency by utilizing technologies such as the Global Positioning System (GPS), communication technologies between vehicles and networks, and Advanced Driver Assistance Systems (ADAS) embedded in modern vehicles to enhance driving experience (Bouquillon, 2022).

2.2.5 Vehicle components

In order to gather, process, and broadcast data in the transportation network, modern vehicles are equipped with numerous components, including the **computing platform** , which is a module that serves as the central processing unit of the vehicle and supervises protocols, especially safety-related protocols. Another essential component is the **On-Board Unit (OBU)**, which has been previously discussed in the "Main Components of ITS" subsection. In addition to the **mobile wireless** gateway, which is a cellular gateway used to ensure reliable and high-bandwidth communication between the vehicle and the road infrastructure.

Moreover, car manufacturers have implemented a comprehensive safety system that encompasses both passive and active features. Passive features focus on enhancing safety within the car's body structures, such as seatbelts, airbags, and head restraints. In contrast, active features include Electronic Stability Control (ESC), Anti-Lock Braking Systems (ABS), Adaptive Light Control, legal speed limit assistance, Forward Collision Avoidance, and Autonomous Emergency Braking. Also, the powertrain system, which constitutes the engine and provides the necessary driving power, Lastly, the body control system is responsible for various tasks, including the management of interior and exterior lighting, door locking, and the control of windows and mirrors. (Rabah, 2021; Silva, 2020). In vehicular networks, the vehicle node supports embedded applications and in-board services, like navigation systems, in addition to mobile apps such as **Android Auto** developed by Google (Silva, 2020).

Therefore, smartphone apps and in-board services are connected to the network as the same node. These modern technologies can be categorized into two main groups: critical functionalities, which aim to prevent crashes and accidents, and functionalities for comfort purposes, designed to enhance the driver's overall comfort. (Bouquillon, 2022)

- Critical functionalities encompass essential features, such as Cooperative Adaptive Cruise Control (CACC) and collision avoidance systems (CAS) utilizing active sensors. In the latter case, the driver is assisted by an automatic obstacle detection feature, which notifies the driver of any obstacles in the vehicle's path, thereby preventing accidents resulting from a lack of attention or fatigue. In addition to Antilock Braking Systems (ABS) and Autonomous Emergency Braking (AEB), these features demand strict adherence to time constraints to avoid severe consequences (Bouquillon, 2022).

- Functionalities for comfort purposes aim to automate noncritical tasks and provide additional information to the driver. Examples include Automatic Climate Control, Automatic High Beam Control, Biometric Seat functionality that monitors the driver's distraction and fatigue levels, GPS for real-time position tracking, and other convenient features (Bouquillon, 2022).

2.3 ITS: Functional Areas and Applications

ITSs have revolutionized the way we manage and optimize transportation systems. Hence, by using information and communication technologies (ICT), ITS has significantly improved the efficiency and safety of transportation networks (Wu et al., 2020). In this section, we present some functional areas, applications and services offered by ITSs.

2.3.1 ITS functional areas

ITS functional areas aim to improve road safety and traffic efficiency by influencing road users' behavior and regulating traffic through real-time traffic data. Therefore, we can categorize them as follows: Advanced Traveler Management Systems (ATMS) play a crucial role in ITS by gathering and analyzing real-time traffic data to forecast traffic congestion. Advanced Traveler Information Systems (ATIS) play a vital role in ITS by providing travelers with real-time in-vehicle data on road conditions, incident locations, and optimal routes to reduce traffic congestion, save time and fuel, and improve traffic flow. These systems also include features such as dynamic route guidance and traffic signal priority. ATIS receives raw data from several detection tools, encompassing recent as well as historical information. This data is then preserved in a database, evaluated by simulations, and exploited in order to generate dynamic knowledge about the present condition of traffic. The process results are up-to-date data about the traffic state. ATISs offer knowledge and guidance to travelers. However, road users have the autonomy to make their own decisions based on this information. (Joachim, 2002) Advanced Vehicle Control Systems (AVCS) warn drivers of collisions and assist in vehicle control, especially in emergencies, such as Automatic Cruise Control (ACC) systems, by automatically applying emergency braking to enhance road user safety. Advanced Rural Transportation Systems (ARTS) utilize ICTs to address challenges in rural areas, such as blind corners, limited passing lanes, long travel distances, and insufficient infrastructure support. These systems aim to increase transportation efficiency and safety, ultimately improving the quality of life for rural residents. Advanced Public Transportation Systems (APTS) improve the accessibility of traffic information in public transport by combining data from ATMS and ATIS. (Joachim, 2002; Chen, 2019)

2.3.2 ITS applications

A wide range of ITS applications are considered, which can be classified into three principal categories: road safety, traffic flow efficiency, comfort and convenience for drivers, and all road users, as it is illustrated in the figure 2.1:

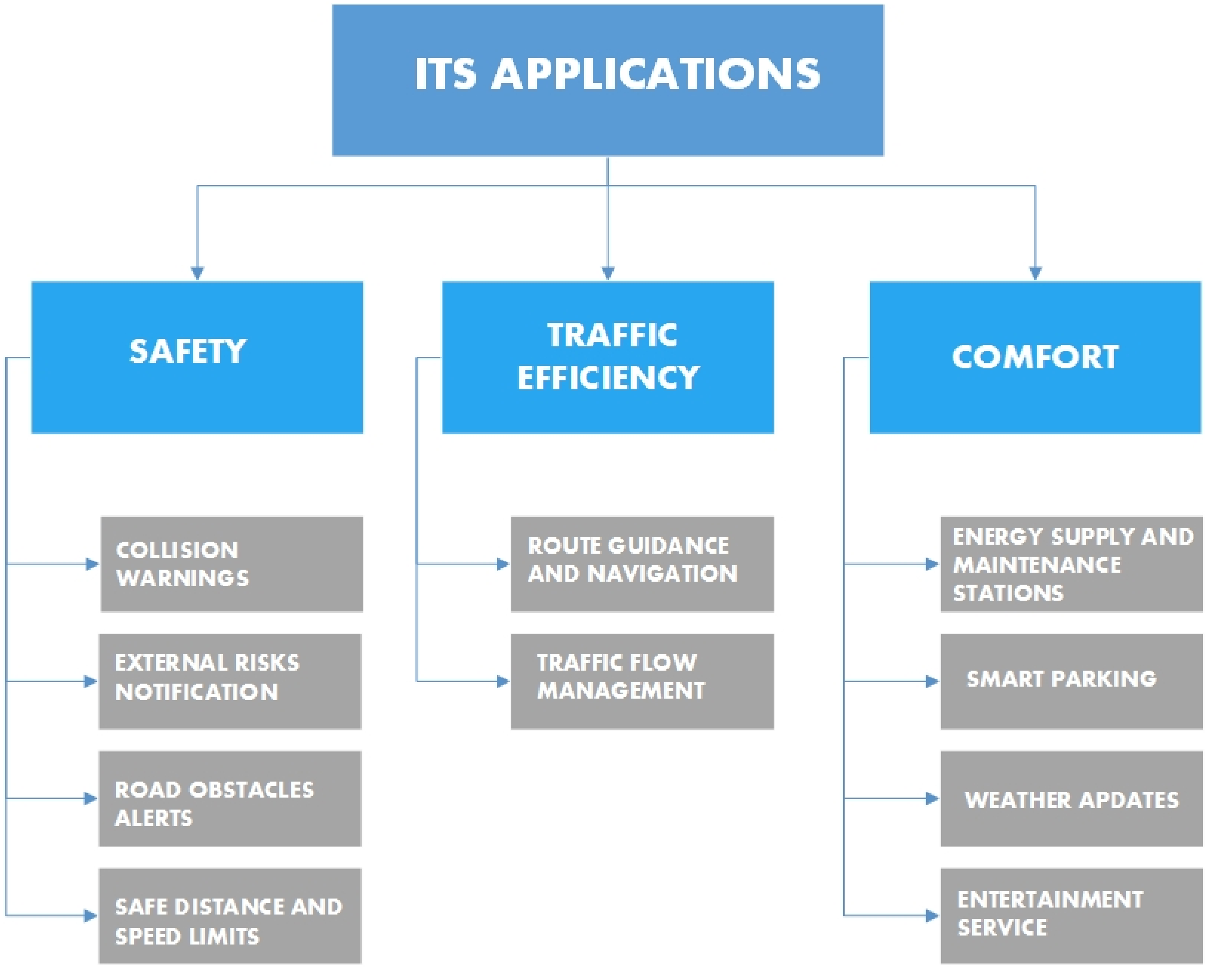

Figure 2.1: ITS applications classification.

- **Road safety applications** aim to reduce accidents and protect lives, emphasizing the importance of safety for all road users. The road network and its constituents (roads, vehicles, drivers, pedestrians, cyclists, etc.) can be actively monitored through the use of safety-oriented applications; drivers can be early notified of external risks through V2X communications; for example, these applications may provide alerts for road obstacles (such as those encountered in construction zones and hazardous turns), intersection collisions, speed limits, and safe distances, demonstrating how ITS applications enhance road safety (Mendiboure, 2020). In addition, an additional category of road safety applications is capable of autonomously implementing suitable actions (e.g., automated braking) (Rabah, 2021). However, this kind of ITS application requires short latency and robust communication links because they concern individuals' health. (Van Phu, 2022)

- **Traffic efficiency applications** in ITS attempt to improve traffic flow, decrease congestion, and optimize travel plans by taking into account factors like travel time, distance, cost, environmental impact, and traffic density, and therefore, advance the field of traffic routing, like in a previous research work (Boubedra et al., 2023).. Furthermore, traffic data can be disseminated among road network components (roads, vehicle drivers, bicycles, pedestrians, etc.), roadside infrastructure, and central servers through the use of this type of ITS application. Thus, the reduction in traffic congestion has a direct advantage over society in terms of decreasing fuel consumption, in addition to the time lost during a traffic jam. For instance, the ”Congested Road Notification” application (Rabah, 2021), alerts nearby vehicles of traffic jams, prompting them to switch lanes, or modify their travel plans. In the interim, the roadside infrastructure can gather real-time traffic data from vehicles and other infrastructure, and traffic planners can use this data to perform traffic analysis to make more precise and reliable traffic predictions. (Chen, 2019)

- **Infotainment and comfort applications** enhance the convenience of road users (including cyclists, passengers, and drivers), by providing drivers with current information regarding energy supply and maintenance stations, weather conditions, available parking spaces, and weather updates, and guarantee entertainment services (e.g., video streaming exchange with adjacent nodes, which may be vehicles or road infrastructures).

2.4 Standardization Initiatives in Vehicular Networks

The significant benefits of vehicular networks for governments and people have led academic research centers and automakers around the world to initiate numerous projects in this field. Furthermore, following the allocation of dedicated spectrum at 5.9 GHz for ITS in Europe and the United States, several standardization organizations have focused on defining vehicular communication standards. Among these organizations, we can consider the Institute of Electrical and Electronics Engineers (IEEE), in addition to the European

Telecommunications Standards Institute (ETSI), as some of the most prominent ones (Alam et al., 2016).

2.4.1 Vehicular communications standards

Specific sets of standards are intentionally created to support V2X operations and achieve the main goals of ITSs (Karoui, 2021). We note the most commonly used in the following paragraphs:

Dedicated Short-Range Communication (DSRC): The car manufacturing sector has established the Dedicated Short-Range Communication standard to improve V2X communications. It provides a dedicated communication channel specifically designed for transmitting high-priority messages, which is crucial for enhancing road safety applications. Both vehicles and infrastructure sites can use it, with a maximum estimated range of one thousand meters (Yakusheva et al., 2019).

Wireless Access in Vehicle Environments (WAVE): The Institute of Electrical and Electronics Engineers (IEEE) improved the 802.11 standards (Wi-Fi) to incorporate Wireless Access in Vehicular Environments (WAVE), to enhance safety, convenience, and traffic flow efficiency, and to ensure seamless interoperability between vehicles and infrastructure (Yakusheva et al., 2019). The IEEE 802.11p standard is the result of this amendment, which specifies the physical and MAC layers that operate in the 5.9 GHz band in order to enable DSRC for ITS (Silva, 2020). Therefore, the WAVE standard enables data exchange between high-speed vehicles and between vehicles and infrastructure (Hayes, 2019).

Millimeter Waves for V2X (mmWAVE): an essential component of the 5G networks of the future. (Yakusheva et al., 2019).

Cellular networks: These technologies aim toward achieving better quality of service (QoS) with increased throughput, decreased latency, and a high degree of trustworthiness. Also, transportation research centers and manufacturing communities are becoming more and more interested in how cellular networks (4G–5G) might be able to meet the needs of vehicles for reliable, low-latency, trusted, and multi-hop communications. However, the 5G network capability is anticipated to outperform 4G in terms of data rate (> 1 Gbps per user; ten times faster than LTE), exceptionally low latency (one millisecond versus ten milliseconds in LTE), and improved energy efficiency. In addition, Mobile Edge Computing (MEC) and other emerging 5G features enable additional benefits in the field of vehicular communications. (Chtourou, 2021).

C-V2X: Cellular V2X The 3GPP established the C-V2X standard in 2017 using LTE as its primary technology to ensure alignment with the quick advancement of vehicular communication and emerging applications of this technology. To differentiate it from 802.11p-based V2X technology, it is commonly referred to as ”cellular V2X” (C-V2X) or LTE-V2X. C-V2X enables wide area communication (V2N) via cellular networks in addition to direct communication (V2V, V2I). Employing two different types of communication on a single technological foundation is the core concept of C-V2X. (1) A direct short-range type, which functions within the 5.9 GHz spectrum and does not necessitate a subscription or network coverage. It enables direct communication via V2R (vehicle-to-roadside). (2) A long-range type that employs conventional cellular network resources and spectrum licensed by a mobile network operator (Chtourou, 2021; Mendiboure, 2020)

2.5 ITS Protocol Stack

There are two principal protocol stacks of ITS: the European stack (ESTI ITS-G5) and the American stack (DSRC/WAVE).

- In the USA, DSRC standard SAE J2735 has been a key technology in ITS since 2006, enabling communication between vehicles and various systems, using a Wireless Personal Area Network (WPAN) that operates via radio waves. Vehicles and other ITS components can utilize DSRC to transmit both private and public data, with a higher priority assigned to public data. Similarly, WAVE is considered Wi-Fi for vehicles and operates based on IEEE 1609 for the application and network layers, along with IEEE 802.11p for the physical and MAC layers. (Kenney, 2011;

Yakusheva et al., 2019; Alam et al., 2016)

- In Europe, the ETSI ITS-G5 standard is the most commonly used in ITS projects. Therefore, this standard acts as a technology that enables direct communication between vehicles (V2V) and road infrastructure (V2R) by utilizing the 5.9 GHz frequency band. Also, it relies on IEEE 802.11p, a member of the IEEE 802.11 family of WiFi standards, to function effectively. Consequently, it facilitates direct V2V and V2R communication in dynamically mobile environments.(Thomas, 2020; Alam et al., 2016; Chtourou, 2021)

2.6 ITS Network architectures

A multitude of standardization projects have been dedicated to the development of an extensive and adaptable ITS network architecture. Accordingly, these initiatives are designed to establish the foundations for interoperability in vehicular communication. Likewise, collaboration among academic institutions, road administrators, automobile manufacturers, and telecommunications providers is essential for the implementation of these standards. (Leblanc, 2020)

- Firstly, the Institute of Electrical and Electronics Engineers (IEEE) proposed the Wireless Access in Vehicular Environment (WAVE) architecture, which relies on IEEE 1609 for the application and network layers and IEEE 802.11p for the physical and MAC layers. (Kenney, 2011; Alam et al., 2016).

- Likewise, the Car-to-Car Communication Consortium/GeoNet (C2C-CC) architecture was established by prominent vehicle manufacturers and partners such as BMW, Renault, Volkswagen, and Fiat as an extension of the WAVE architecture. Indeed, the primary objective of this architectural design is to improve traffic safety. Accordingly, it defines standardized protocols and interfaces for wireless communication between vehicles and their surroundings (Silva, 2020). Moreover, the use of urban Wi-Fi networks (e.g., IEEE 802.11 a/b/g) for IPv6-based Internet communication is enabled. similarly, a geographical routing-based addressing scheme is implemented by C2C-CC. (Karoui, 2021).

- Finally, ISO has recognized the ITS reference architecture consisting of independent layers as a component of the ISO 21217 standardization framework (Silva, 2020).

In the rest of this subsection, we will provide details on the layers of the ISO ITS architecture. Indeed, we have decided to provide a thorough explanation of this proposed ITS design due to its advantageous attributes in road traffic systems. Therefore, it represents the most sophisticated conceptual design:

- It has the ability to simultaneously manage different access networks allows for the retrieval of important information via the administration of diverse applications.
- Furthermore, it produces operational modules that function as ”black boxes” that are not implemented. While standards present directives and recommendations, developers have the ability to code their own methods within the ITS architecture. (Silva, 2020).
- The system is compatible with several technologies, such as LTE, WiFi,..etc. Additionally, it supports various communication modes, including broadcast and multicast. It also utilizes different addressing schemes, such as IP-addressing and Georouting. Additionally, it aims to enhance all ITS applications, encompassing safety, traffic efficiency, and comfort services. All of these features distinguish the ISO ITS architecture from the WAVE and C2C-CC architectures. (Karoui, 2021)

Thus, ETSI and ISO have launched the ITS standard architecture for vehicle communications to enhance safety and mobility for all road users. Indeed, the framework has two vertical sections, namely Management and Security, and four horizontal levels, namely Access, Networking and Transport, Facilities, and Application, (Chtourou, 2021) as seen in the figure 2.2:

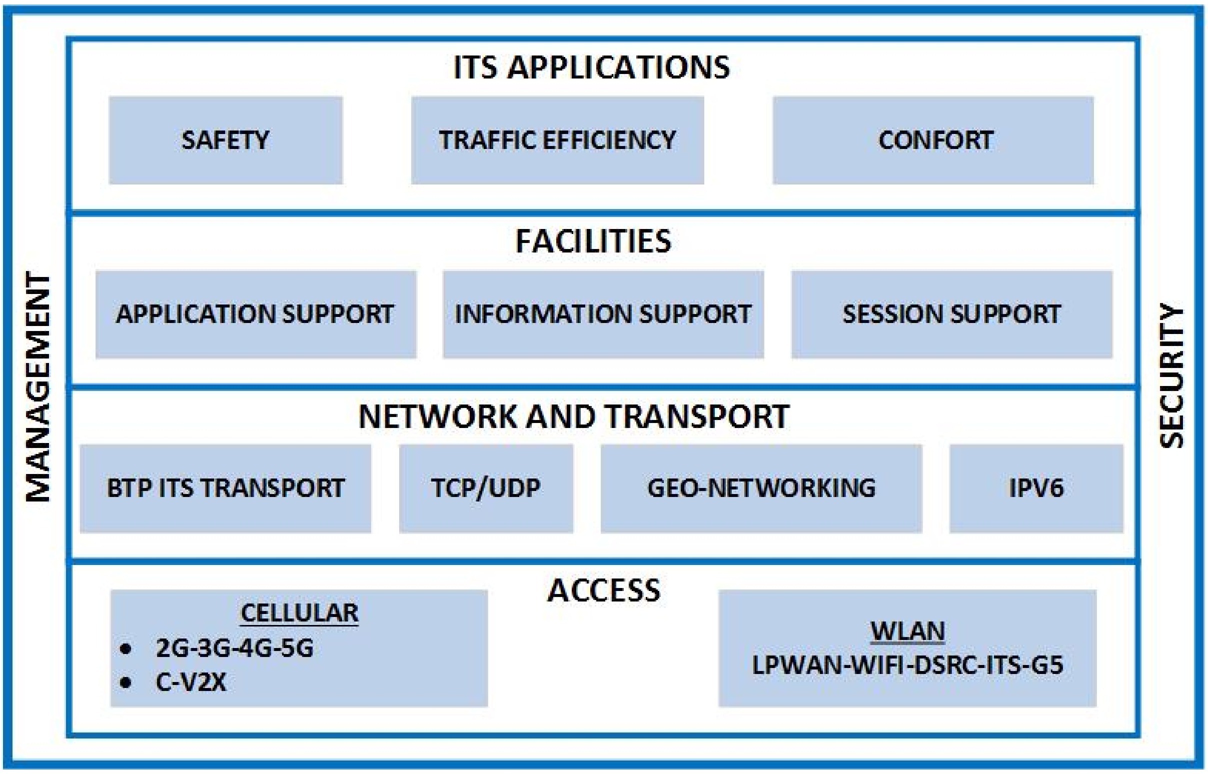

Figure 2.2: ISO ITS reference architecture.

- **Access layer:** this layer is analogous to the PHY and MAC layers in the OSI network architecture. Moreover, it is designed to work seamlessly with various interfaces, such as vehicular Ad Hoc technologies like ITS-G5 in Europe and DSRC in the USA, urban Wi-Fi standards such as 802.11 g/n/ac, and cellular technologies including 3G, 4G, and the upcoming 5G networks.

- **Networking and transport layer:** integrates the network and transport levels of the OSI network architecture. The system is accountable for carrying out operations such as packet routing, IP and Geo addressing, and other duties associated with data transmission and network administration.

- **Facilities** are aligned with the Session and Presentation levels of the OSI stack. This layer offers assistance to ITS applications by carrying out duties such as message encoding/decoding, ensuring message distribution, verifying information, facilitating repeated message transmission, and other associated services.

- **Application layer** is a component that may host several kinds of ITS applications and services such as navigation systems, collision avoidance systems, emergency response applications, and others. The primary function of this layer is to provide a Human-Machine Interface (HMI) that simplifies user interactions and control.

- **Management (vertical entity):** is an organizational unit that supervises and enhances operations at all levels of the ITS system. Therefore, it enables the transfer of information across the multiple layers of the ISO ITS reference architecture, in addition to several duties involving the selection of communication profiles, management of applications, and communication interfaces.

- **Security (vertical entity):** The ITS architecture must provide a strong cyber security foundation to safeguard cars from cyber-attacks. This entity is in charge of guaranteeing the critical security functions, such as authenticity, integrity, and confidentiality of the communications and data network.

2.7 V2X communications

To enhance ITS systems, it is necessary to boost the awareness of automobiles regarding their environment and build efficient and secure exchanges. Hence, it is essential for automobiles to establish communication with their surroundings, including infrastructure, other vehicles, and pedestrians. Nevertheless, ITSs are complex and heterogeneous systems due to several elements such as road state, climate conditions, different types of applications, and the variety of communication modes. (Chtourou, 2021) Hence, C-ITSs involve the collaboration of cars, roadside infrastructure, urban infrastructure, and control centers to collectively make decisions that improve traffic efficiency. The automobile sector is making significant investments to incorporate V2X communication technology into automobiles in order to enhance vehicle communications. Thus, Vehicle-to-Infrastructure (V2I) and Vehicle-to-Vehicle (V2V) communications constitute vital modes of communication that are essential for transferring data among vehicular network.

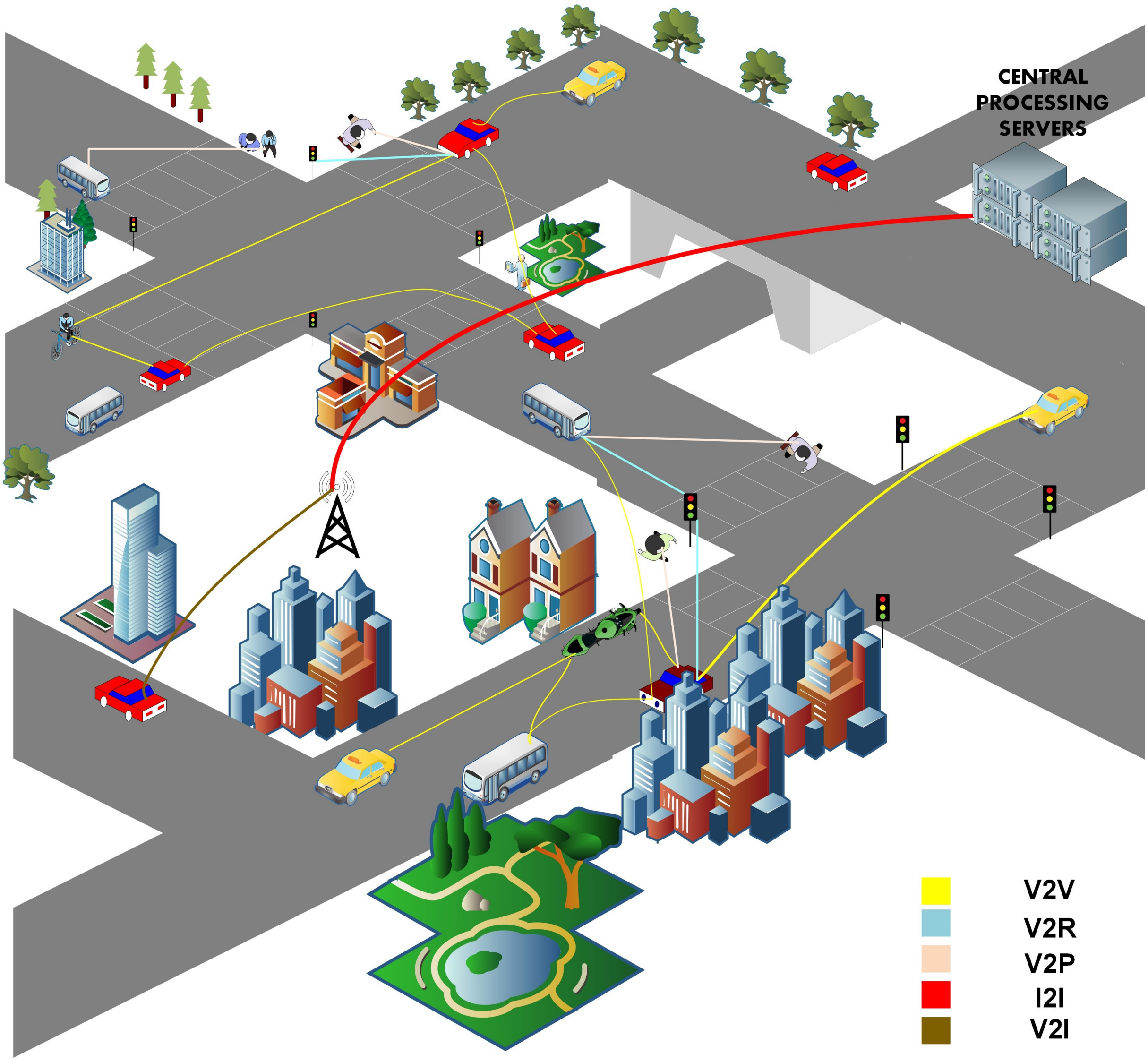

Figure 2.3: V2X Communication modes.

Vehicle-to-Vehicle (V2V) communications provide wireless communication between vehicles without the need for a permanent infrastructure. Indeed, this may be achieved using direct or multi-hop, multicast, or broadcast methods. First, these communications allow the vehicle to identify its position by collecting data from adjacent vehicles, such as their location, velocity, and distance. Furthermore, these interactions also facilitate the fast distribution of preventative messages among neighboring vehicles. Indeed, these communications have the purpose of decreasing the number of traffic accidents. Hence, V2V communications may use short-range communication technologies that are especially designed for effective vehicular communications. Additionally, they can rely on cellular communications tailored to meet the requirements of vehicular networks. (Mendiboure, 2020)

Vehicle-to-Infrastructure (V2I) communications refer to the exchange of information between a vehicle and specific elements of the road system, such as roadside units responsible for road lighting, road signs, radar, and bus stops, along with cellular base stations, access points, and similar equipment. Indeed, when the infrastructure is a roadside unit, it is called vehicle-to-roadside (V2R) communication (Chtourou, 2021). Hence, roadside equipment broadcasts several forms of information into its surroundings, including details about road works, traffic jams, and speed limits. In addition, they collect and combine the data provided by vehicles, including traffic congestion levels, collisions, and obstacle detection. (Mendiboure, 2020; Van Phu, 2022) Moreover, communication can occur in the opposite direction, known as I2V (Infrastructure to Vehicle). Accordingly, the infrastructure can generate and broadcast events to cars under the supervision of the ITS centers. Additionally, they can transmit events over a larger distance compared to vehicles, thanks to their powerful antenna capabilities (Leblanc, 2020). Similarly, in order to help road users anticipate and make informed decisions using accurate data, I2V and V2I communication modes are used to share traffic data and environmental information with them. Consequently, the aforementioned modes have the potential to augment road safety, diminish fuel consumption, lessen road congestion, and enhance the entire driving experience.

Infrastructure-to-Infrastructure (I2I) refers to the wired or wireless communication that takes place between two pieces of network equipment, namely roadside units, base stations, and fog/edge servers. Thus, this mode of communication allows geographic data distribution, enabling nearby BSs and RSUs to share traffic data, which is subsequently sent to the cars. Additionally, these communications may provide Internet connections to RSUs that are located in remote areas or have limited network access. Hence, this enables the transmission of data to the cloud and facilitates global data processing. (Mendiboure, 2020)

Vehicle-to-Everything (V2X) communication encompasses all forms of vehicular communication under a unified framework. Therefore, V2X networks should facilitate communication between the vehicle and all nodes present in its surroundings. As a result, the effective functioning of traffic flow services and road safety could be ensured. (Mendiboure, 2020)

Vehicle-to-Person (V2P) communication facilitates data exchange between moving vehicles and various vulnerable road users, including police officers, pedestrians, cyclists, and more. (Van Phu, 2022)

2.8 ITS traffic data

The effectiveness of an ITS relies on its precise analysis and modeling of transportation data. Therefore, real-time data processing is significant for increasing the efficiency of the system and improving the services provided to users. Hence, in this section, we provide an overview of ITS traffic data. We define some traffic collector and estimator devices, types of traffic data, and finally, the most common challenges in traffic data processing.

2.8.1 Data collection devices in road traffic

In road management systems, the observation process provides input data to the control process, enabling the attainment of optimal road traffic conditions and effects. Among the three processes, which are observing, modeling, and controlling, we see that observing road traffic can not be neglected. A good observation of the road traffic will allow a better understanding of it ; hence, better control decisions towards the desired road traffic states could be taken. Simultaneously, reducing errors in observing road traffic can alleviate undesirable road traffic conditions and consequences. Thus, the quality and efficiency of transportation models heavily rely on the type and accuracy of the input data they receive. Likewise, input data is needed for the estimation and control of road traffic. Furthermore, by fusing and analyzing the collected automotive data, drivers can be offered a faster, safer, and more fuel-efficient mobility experience (Nassar, 2021). Accordingly, to gather the required traffic data, several detection devices are used.

Sensors are created to supply data to systems that monitor and manage traffic. Over time, various types of sensors have been practical and useful. However, we distinguish between fixed sensors and mobile sensors. Therefore, an example of a fixed sensor is a magnetic loop placed on the road or a video camera placed next to the road. Similarly, an example of mobile sensors are modern vehicles used to travel: connected and automated vehicles (CAVs). Connected vehicles can send their trajectory data to another vehicle or to the infrastructure (Van Phu, 2022). However, the limitations of these devices are, firstly, limited range detection in road segments. In addition to the high cost of installation and maintenance in terms of money and human resources, another issue with sensors is that they can handle only one type of data. However, sensor data is not sufficient, as it usually needs to collaborate with data from other sources that could affect the traffic condition, such as events and weather. (Alajali, 2020)

Inductive Loops These are the most common devices since their structure is simple and they have high reliability. Hence, their concept involves detecting the presence of metal passing through a specific area. The disadvantage of this type of device is its high cost of installation and maintenance and limited range of detection (Alajali, 2020).

Infrared Beacons The idea behind these devices is to detect cars using the infrared spectrum. Most of the detectors are event-driven, i.e., there is a classification of traffic patterns and whether a significant change between the classes is reported. (Joachim, 2002)

Camera which has better range and precision than GPS; however, processing videos and images to count vehicles, estimate queue lengths, and identify vehicle types in real-time can be time-consuming. Some researchers rely on videos recorded by cameras installed on roads to detect congestion. They analyze the key points or moving area, where the congestion level is evaluated based on the number of critical points and the moving object's speed. (Alajali, 2020; Van Phu, 2022)

GPS in mobile devices and vehicles: Most vehicles and mobile devices are equipped with GPS trackers, providing several benefits such as improved accuracy in tracking vehicle movements and supporting real-time traffic analysis. In addition, the range of the monitored area is more extensive than the range covered by fixed sensors. Also, the cost of installation and maintenance is lower. (Alajali, 2020)

Social media Currently, social media is a rich source of data in different fields. For example, Twitter is commonly used by both users and transportation departments. The advantage of using social media is that the range of data is wide since tweets are from drivers, passengers, and so on (Alajali, 2020).

2.8.2 Nature of automotive data

Since the main idea of ITS is to provide reliable information to road users, the temporal nature of data as well as its use in traffic scenarios should be discussed. Conceptually, information may fall into three distinct temporal classes:

Historical Data Historical information reflects the previous states of the network. It can be either objective, i.e., measured by road detection devices, or subjective, i.e., based on the user's experience. Hence, objective historical data is utilized to categorize daily traffic demands and extract heuristics that aid in traffic prediction.

Current Data Current information is provided in real-time and should be the most up-to-date information. Additionally, road detection devices measure this type of data.

Predictive Data This kind of data reflects the expected traffic conditions. The predictive information can be short-term, up to one hour, or long-term, up to one day. (Joachim, 2002)

2.8.3 Challenges in traffic data processing

Processing and analyzing traffic data is very challenging because traffic flow in road networks is very dynamic, and certain events can affect the accuracy of the forecast if the system is not updated in real-time to ensure appropriate decisions are made. We present in the following some challenges that traffic data analysts face in maintaining accurate forecasts.

Multiple Sources of Data Due to urban development and population expansion, traffic flow and traffic congestion have increased dramatically. It is difficult to use traditional models that employ data from one source to evaluate traffic conditions in real-time. The effectiveness of integrating multiple sources of data in the process of analysis and developing solutions has been indicated. In large cities, real-time congestion estimation requires that multi-source data be incorporated.

Real-Time Processing Data stream processing plays an important role in the real-time collection, integration, and analysis of scalable and continuous data produced by IoT devices. Indeed, modern information technology systems are often evaluated by their real-time and scalability factors. Actually, stream processing is the solution for real-time processing of continuous, scalable data. The other advantage of stream processing is that it is suitable for a dynamic environment because it updates the query result incrementally. Due to the features listed above, stream processing is essential for IoT applications.

Big Data Processing The big data era represents an opportunity to improve transportation systems (Van Phu, 2022). Moreover, because sensors continuously produce data, a substantial amount of data is generated, increasing the load on the network (Alajali, 2020). Most ITSs currently depend on central data processing, using cloud computing to deliver enhanced services to smarter vehicles. However, the increasing number of cars on road networks and the increasing amount of data transmission between vehicles and between vehicles and the cloud can cause communication delays and affect real-time response. This approach is usually used in roadside equipment-based ITS, where the system is used to collect data related to traffic conditions on the road network using different installed sensors (such as inductive loop sensors, cameras, and magnetic sensors).

2.9 Conclusion

Intelligent Transportation Systems have been a prominent solution for road safety in recent decades. However, currently they enable the development of new applications for road users, including guidance and navigation systems, traffic flow management, and other comfort services. Therefore, by using advanced sensing, computing, and communication technologies, ITS can significantly overcome road traffic challenges and provide real-time data for better decision-making.

In this chapter, we present an overview of Intelligent Transportation Systems, their functional areas, and their applications. We also present vehicular standards, protocol stacks, network architectures, and V2X communication modes. Then, we highlight ITS traffic data and, therefore, discuss the challenges faced in data processing.

Chapter 3

Towards VANETs and the Internet of Vehicles

This is the beginning and the dawn of a new era of transportation.

– Shervin Pishevar

3.1 Introduction

By leveraging real-time data collection and analysis, ITS enables enhanced traffic management, reduced congestion, accidents, and infrastructure damage caused by overloaded vehicles, and therefore, improved overall road safety. Additionally, ITS and VANETS play a crucial role in modernizing transport systems and maximizing the capacity of existing transportation infrastructure. Meanwhile, the integration of the Internet of Things (IoT) has allowed for smarter, interconnected vehicles and has paved the way for the development of smart cities. Consequently, as an application of the IoT, the Internet of Vehicles (IoV) has seen rapid development and integration into the field of Intelligent Transportation Systems. IoV, with its technical characteristics resembling those of IoT, has revolutionized connectivity among smart vehicles, paving the way for a more efficient and interconnected transport network (Sadiku et al., 2021; Yakusheva et al., 2019). Furthermore, IoV has attracted widespread attention in the market and has applications in different fields of transportation. (Sharma and Kaushik, 2020, 2019) The prime goal of IoV is to ensure interconnectivity among smart vehicles, enabling them to connect to one another using a wireless network. This interconnectedness has led to significant advancements in road safety, improved traffic efficiency, and the provision of entertainment services through real-time sharing of vehicular messages. This has resulted in numerous benefits, such as efficient transportation, increased road safety, fuel efficiency, and enhanced travel experiences for drivers. (Sadiku et al., 2021) In this chapter, we present an overview about vehicle networks, especially VANETS, and the Internet of Vehicles and their integration in Intelligent Transportation Systems. Finally, we explore how VANETS are transformed into the Internet of Vehicle networks.

3.2 VANETS

The applications of electronic and communications technology and the possible opportunity to work with vehicles that could be managed as nodes are two of the key reasons that VANET research is an appropriate research topic for technologists at present and in the future (Hayes, 2019). The deployment of VANETs is an important challenge to improve road safety, enhance passenger flow to avoid road congestion, etc.(Leblanc, 2020). However, traditional solutions like expanding the present transportation systems by increasing the number of roads are recognized to be expensive, disruptive and involve protracted effort. (Chen, 2019)

3.2.1 Definitions

Several academic definitions of VANETs have been proposed in the literature:

- VANETs is a category of Mobile Ad Hoc Networks (MANET) composed of communicating vehicles which use wireless radio transceivers to provide ubiquitous connectivity between vehicles and the road infrastructure. (Van Phu, 2022).
- VANET is a set of mobile nodes composed of vehicles, as well as fixed nodes called RSUs deployed at critical locations such as slippery roads, service stations, administrative buildings, intersections…(Rabah, 2021)
- A VANET is a network consisting of nodes representing vehicles travelling along a road network. Communication between vehicles is achieved by transmitting messages called beacons. Beacons include relevant information on each vehicle, such as position, speed, and destination (Alajali, 2020).
- VANETs are a specification of Mobile Ad-hoc Network (MANET) adapted to vehicles. It is a hot research field, especially since governments initiated the deployment of ITS (Leblanc, 2020).

3.2.2 Properties of VANETs

A significant part of ITS research focuses on vehicular networks, namely VANETs, where automobiles serve as the primary network nodes. VANET is a flexible network with a changeable density that may be deployed in cities, rural zones, roads, and other locations. These ad hoc, decentralized vehicular networks are mainly based on direct communications between vehicles. These communications ensure low transmission times and therefore allow for the rapid distribution of information regarding obstacle detection, road conditions or emergency braking. In addition, the use of RSUs, positioned at strategic locations (intersections, parking) could allow the dissemination of information in larger geographical areas and more efficient supervision of road traffic. Thus, ad hoc vehicle networks improve road safety and traffic flow. (Mendiboure, 2020). Although it is seen as an application of MANET, and unlike other types of wireless networks, VANETs are characterized by a some particular characteristics that make them very distinct:

- **High mobility:** The main difference of vehicular networks from other mobile networks lies in the high mobility and dynamic topology due to the high-speed movement of vehicles, with speeds reaching 130Km/h on highways and not exceeding 60Km/h in urban areas. While vehicle movements may be predictable, the impact of mobility on network connectivity poses significant challenges for vehicular networks. Thus, despite the highly dynamic network topology, vehicles typically adhere to the speed limits. It is also possible to define mobility models to reliably determine the future position of vehicles;

- **Frequent disconnection:** It occurs when vehicular nodes regularly lose connection due to the highly dynamic topology, changes in their connectivity state, and the existence of obstacles and limits imposed by road topology. This means that vehicles are in constant motion while communicating with each other. Moreover, given the high volume of vehicles on the road, vehicular networks need to support substantial scalability. As a result of the rapid movement of vehicles, communication links between vehicles or between vehicles and infrastructure frequently experience interruptions.

- **Unknown network size:** A vehicular network can be deployed in a specific region such as a highway, a city, or even a whole country, resulting in an extensive geographical network coverage.(Chtourou, 2021). Therefore, the number of vehicles in a given area depends on different factors such as the time of day (peak time or not), the geographical position (city center, near suburbs, countryside) or the type of road (departmental road, motorway) ;

- **Heterogeneous Actors:** In VANETS, various stakeholders, including application managers, users, and network administrators need to express their requirements, preferences, constraints, and policies. There is a wide variety of applications, each one with one or more data flows that have specific communication requirements. Flows may request a specific Data Rate (e.g., 1 Mbps), latency (e.g., 30 ms), security level (e.g., encryption), and more. For instance, a safety-based service such as emergency breaking information is highly sensitive to packet loss and latency due to the critical nature of the data, whereas a video streaming service is less affected by latency and bandwidth changes.

- **Diverse Network Technologies:** To ensure widespread connectivity and meet the needs for various applications, it is essential to utilize multiple types of wireless technologies. These include vehicular WiFi (ITS-G5 in Europe or DSRC in USA), urban WiFi (e.g., 802.11 g/n/ac/), and cellular technologies (LTE-V2X, 3G, 4G, and 5G).

- **Variety of Connected Devices:** In a vehicular network like a VANET, cars should possess the capacity to interact not just with other vehicles (V2V) and infrastructure (V2I), but also with a diverse range of interconnected devices. The connection can either be local, occurring between equipment belonging to neighbors (such as a link with a sensor located on the roadside), or global, which refers to a connection made via the Internet. In addition, embedded systems possess distinct attributes in regards to memory, CPU, and communication capabilities. Certain devices may not have the capacity to support numerous communication interfaces and, in certain cases, they might not have communication management capabilities. (Silva, 2020)

- **Energy Potential:** Unlike traditional wireless networks, where energy constraint is an important factor, vehicle network entities have large energy capacities that they derive from the vehicle's power system. Vehicles provide more energy, computational capacity and storage space than current mobile objects. Also, although the development of low-energy solutions is a hot topic, vehicles support a greater number of local operations and processing;

- **The existence of zones of interest:** for many vehicular applications, the information generated is relevant only in a given geographical area. This includes information about road conditions, sudden braking or cooperative data downloading. The existence of zones of interest is therefore an important feature of vehicular applications (Mendiboure, 2020).

3.2.3 Limitations and Challenges of VANETs

VANET is subject to many problems due to its volatility: network nodes appear and vanish all the time. In addition, dynamic network topology is another reason that makes VANETs more vulnerable to attack. Therefore, the routing of messages to ensure the dissemination of information in the network is then a difficult task (Leblanc, 2020). VANet networks have certain limitations that could hinder the development of comprehensive and effective C-ITS services.

- **Lack of interoperability:** VANET architecture relies solely on short-range communications between vehicles and RSUs. It therefore does not allow the use and interconnection of different communication networks: ITS-G5, LTE-V2X, Li-Fi, etc. This complicates the deployment of global and reliable intelligent transport services;

- **The limited number of communication types supported:** VANet networks, rely solely on V2V and V2I communications. They therefore do not allow the integration of new types of connected objects: cameras, phones, etc. This could limit the effectiveness of different applications such as pedestrian detection or cooperative map creation;

- **Limited Internet connectivity:** VANet architecture does not guarantee Internet connectivity to road users. Indeed, due to the low number of RSUs deployed, few vehicles could benefit from Internet connectivity.

- **Complex data processing:** Poor Internet connectivity and limited computing and storage capacity make it impossible to process large volumes of data with the VANet approach. Thus, making global and ”smart” decisions is complex.

- **Vehicular networks** are only effective when every vehicle has equipped an OBU and the road side infrastructure is also deployed concurrently. However, due to the cost and budget constraints, it is expected to be a long journey for all car manufacturers to install OBUs on each vehicle, and for the government to upgrade the vehicular network infrastructure.

- There are still some urgent technical issues remaining to be solved. Due to the high-mobility nature of vehicular network, randomness in wireless channel dynamics and link interferences, vehicular communications may become intermittent and unreliable.

- Meanwhile, the vulnerability of wireless communications makes message dissemination in vehicular networks susceptible to malicious attacks, and these attacks could potentially result in catastrophic consequences like traffic congestion, traffic crashes, and even loss of lives. Extensive research needs to be conducted to protect secure message dissemination in vehicular networks (Chen, 2019; Mendiboure, 2020). Therefore, while ITS is a goal for many cities worldwide, there are challenges related to privacy and security in the real implementation of applications. Ensuring the confidentiality and integrity of data transmission, as well as addressing privacy concerns, is crucial for the successful development and deployment of ITS(Sadiku et al., 2021).

3.2.4 Future Prospects

The use of communication technology and smart devices in vehicles has revolutionized the automotive industry. As a result, intelligent transportation systems have emerged with vehicles equipped with sensors and computers that may collect and process data for information exchange (Ji et al., 2020). Vehicular ad hoc networks (VANETs) were introduced to enable direct communication between vehicles and infrastructure, but they face challenges such as unstable network services and limited handling of big data. Moreover, the initial goals of VANET research technology were to ensure traffic safety (Bektache et al., 2014), improve travel efficiency, and reduce pollutant emissions (Brahmia and Tolba, 2020). However, practical applications of VANET have faced challenges in commercialization. These challenges include the loss of network services when disconnected from other networks, incompatible network architectures, limitations in computing ability and storage space, and low accuracy of application services due to localized traffic data processing. To address these shortcomings, and in the era of 5G and the Internet of Things (IoT), VANETs are transforming into the Internet of Vehicles (IoV). Therefore, IoV aims to enhance safety, reduce congestion, and provide services through information exchange between vehicles and relevant entities. Moreover, IoV encompasses various communication models and relies on vehicle networking and intelligence technologies. These advancements expand the communication scope and potential of the IoV system (Ji et al., 2020). Therefore, the emergence of the Internet of Vehicles offers promising prospects for the development of smart transportation systems. IoV overcomes the limitations of VANET through its heterogeneous network architecture, enabling cooperation with other communication networks. IoV is also compatible with most communication devices in daily life. The mutual cooperation of different networks and the availability of multiple communication models in IoV facilitate the sharing of big data, enhance the reliability of communication services, and expand the application scope of automotive communication. These advantages position IoV as a crucial development in the field (Ji et al., 2020).

3.3 Internet of Vehicles

3.3.1 Definitions

In this subsection, we introduce some definitions of the main concepts related to the use of the Internet of Things in Intelligent Transportation Systems. These definitions may help give a global idea of the field studied

Internet of Things

The concept of the internet was to connect computers to a global network using a set of protocols and provide significant benefits for millions of users in different fields. Recently, this concept has evolved, connecting different things to the network rather than computers alone. There are multiple definitions of the Internet of Things (IoT). It is defined as a network of connected objects, in addition to servers, that provides services to users around the world.

IoT refers to how intelligent and self-adaptive objects are connected to the internet to communicate and interact with each other. The term IoT emerged in 1990, when it was initially coined by Kevin Ashton in supply chain management. However, rapid technological developments and the decreasing costs of radio frequency identification (RFID) devices and sensors expanded IoT into other fields such as health care, transport, environment, emergency situation awareness and smart manufacturing. (Alajali, 2020)

In (Li et al., 2015), IoT was defined as a "dynamic global network infrastructure with self-configuring capabilities based on standards and interoperable communication protocols; physical and virtual 'things' in an IoT have identities and attributes and are capable of using intelligent interfaces and being integrated as an information network".

From the viewpoint of a network, the IoT is a very complicated heterogeneous network, which includes the connection between various types of networks through various communication technologies (Da Xu et al., 2014).

In addition, the Oxford Dictionaries offer a concise definition of the IoT: Internet of

Things (noun): The interconnection via the Internet of computing devices embedded in everyday objects enables them to send and receive data (Rose et al., 2015).

Furthermore, the capabilities offered by the IoT can save people and organizations time and money, as well as help improve decision-making and outcomes in a wide range of application areas (Whitmore et al., 2015).

As well, IoT plays an important role in the transportation field, as vehicles have increasingly powerful sensing, networking, and data processing capabilities For instance, IoT technologies make it possible to track each vehicle's existing location, monitor its movement, and predict its future location (Da Xu et al., 2014).

Internet of Vehicles

The Internet of Vehicles network refers to a highly dynamic mobile communication system that enables information exchange between vehicles and between vehicles and their surroundings (possibly mobile or stationary) using V2X communications. Therefore, it promises huge commercial interest and research value, thereby attracting significant industrial and academic attention. (Atallah, 2017).

Moreover, IoV leverages road objects (e.g. traffic lights, cameras, speed sensors, etc.) with the ability to sense, process, and exchange information related to the safety and comfort of road users. When conventional vehicles are supplemented with the IoV concept, the feasibility of vehicle dynamics monitoring, intelligent navigation, fleet management, and value-added services becomes endless. (Atallah, 2017)

By using other words, it is a dynamic network that consists of IoT-enabled cars using modern embedded and electronic devices like sensors and GPS and the integration of information and communication systems to improve traffic flow and offer more effective road management and accident avoidance.

The urban traffic system has benefited from a lot of IoT applications like the 'Internet of Vehicle' concept, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) communications and has been transformed to a new level of interoperability, stability, and efficiency because, if vehicles communicate with each other, the risks of accidents and mishaps would be very low. In addition, by using IoT technologies in road traffic, we can monitor urban transportation systems, determine the state of traffic and pedestrian densities, identify damages and accidents, avoid collisions as needed, and optimize travel routes (Suresh et al., 2014).

3.3.2 Characteristics of IoV

The Internet of Vehicles environments illustrate a multitude of significant characteristics that contribute to their unique nature and functionality. In particular, we highlight the following key aspects (Sharma and Kaushik, 2020):

- **Dynamic topology and non-uniform node distribution:** The IoV network is composed of various entities. One prominent characteristic of this network is the mobility of vehicles, pedestrians, cyclists, drones, and mobile radars, which are constantly changing their locations, speed, and direction. Furthermore, the distribution of these entities in an IoV network depends on several factors, such as road conditions and driving habits. (Sharma and Kaushik, 2020; Alajali, 2020). This mobility aspect requires efficient communication and coordination mechanisms to ensure seamless connectivity and accurate data exchange, even in high-speed scenarios.

- **Heterogeneity:** IoV encompasses diverse vehicles with different types of communication technologies, such as DSRC, 4G/LTE, WiFi, and Zigbee. The heterogeneous nature of IoV enables compatibility and interoperability between different vehicles and infrastructures (Sharma and Kaushik, 2020; Alajali, 2020).

- **Granularity:** In the IoV, vehicles on the road can be categorized into subsets called Sub-IoVs, which operate at a more localized level and have lower granularities. By using different granularities, the IoV enables flexible and scalable data collection and analysis for intelligent transportation systems (Sharma and Kaushik, 2020).

- **Scalability:** The IoV network is massive, with a large number of vehicles and infrastructure; as a consequence, IoV should be scalable rapidly to handle the growing volume of data, the number of connected devices, and the complexity of IoV applications (Sharma and Kaushik, 2020; Alajali, 2020).

- **Big data and high processing capability:** In IoV networks, vehicles, sensors, road infrastructure, drivers, pedestrians, and all other entities continuously generate huge amounts of data at a high speed (Alajali, 2020). Therefore, it should be collected, aggregated, processed, and analyzed in real time to make decisions and extract valuable insights for improving transportation efficiency (Sharma and Kaushik, 2019). Furthermore, data processing and decision-making are assured by the fog/edge servers for rapid responses and by the cloud servers for general and large-scale decisions.

3.3.3 IoV Benefits in transportation systems

The Internet of Vehicles has attracted extensive attention from both academia and industry. It includes research areas such as intelligent transportation and telematics. The research focus of intelligent transportation is to improve travel efficiency and safety through projects such as the intelligent vehicle road system in the United States, the Eureka plan in Europe, and the advanced dynamic traffic information system in Japan. The Internet of Vehicles combines mobile Internet, intelligent transportation systems, cloud computing, automotive electronics, and geographic information systems to become a mixture of Internet of Things (IoT) and mobile Internet applications in the field of transportation (Yang et al., 2017). In (Contreras-Castillo et al., 2017; Atallah, 2017; Ji et al., 2020), authors have cited several advantages of the IoV, in particular, we highlight the following ones:

- IoV an heterogeneous network architecture which realizes the cooperation between the vehiclar communication network and the other communication networks. Consequently, all communication devices in daily life are compatible with IoV.

- IoV has transformed the road network entities into "new mobile devices". ex: Vehicles, pedestrians, drones, etc.
- IoV creates networks that support functions such as intelligent traffic management.
- IoV consists of inter-vehicular, intra-vehicular, and vehicular mobile Internet components, enabling continuous connectivity and information exchange in vehicles.
- IoV facilitates the exchange of information between vehicles, road infrastructures, passengers, drivers, sensors, roadside units, and the Internet. Furthermore, it guarantees the sharing of big data and the reliability of various communication services. Therefore, it expands the application range of vehicular communications.
- IoV uses several protocols and standards like IEEE 802.11p, DMAC, VC-MAC, AODV (Brahmia and Tolba, 2018; Djemili and Tolba, 2013), DSR, and GPRS, among others, in order to ensure communication between road entities and the internet gateways.
- IoV differs from Intelligent Transportation Systems by emphasizing information exchange among vehicles, humans, road infrastructures, central servers, edge/fog servers, and cloud servers.
- Estimated benefits per vehicle per year include savings on insurance rates, operation costs, and time spent in traffic for vehicle users.
- Society benefits from decreased accidents, traffic jam control, and reduced CO2 emissions.
- IoV has the potential to create around 400,000 new jobs in the United States.
- The global market size for IoV components is estimated to reach 115.26 billion Euros by 2020, according to the European Union.
- IoV enables various services such as traffic management, road safety, healthcare apps, comfort, and entertainment.

- IoV can ensure greater efficiency achieved through the reduction of fuel consumption using fuel-saving assistance that accounts for the driving distance, road conditions and driving patterns.

- IoV guarantee increased safety using remote vehicle diagnostics that promote the responsiveness of service centers to driver drowsiness, vehicle theft, accidents as well as maintenance requests.

- IoV provides enhanced quality of experience achieved through the support of infotainment services for the purpose of recuperating road information like weather and roads conditions, or identifying hot spots like rest stops, restaurants, parking.

3.3.4 Communication modes in IoV

The Internet of Vehicles (IoV) is a considerable shift in vehicle networking, leading to the development of intelligent transportation systems. IoV is a heterogeneous network consisting of various communication modes illustrated in Figure 3.1:

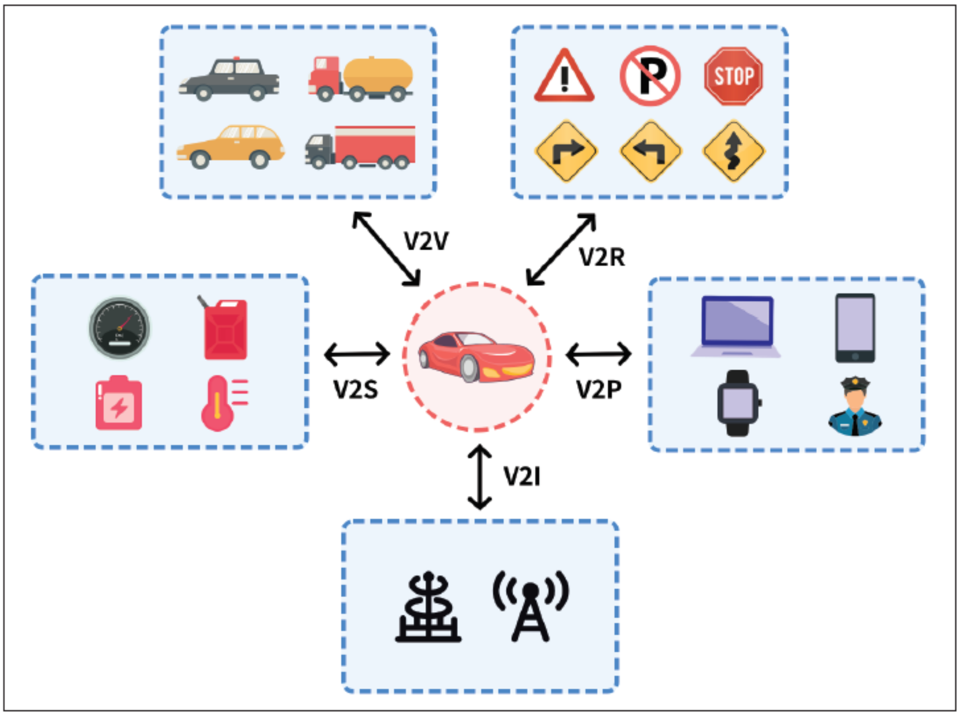

Figure 3.1: The communication modes in IoV (Ji et al., 2020).

- Vehicle-to-Vehicle (V2V): inter-vehicle communication allows vehicles on the road to exchange information, messages, and even sensor data. Such communication not only ensures road safety but also enables cooperative driving by sharing details like location, speed, acceleration, and destination of each vehicle.
- Vehicle-to-Person (V2P): it enables vehicles to communicate with drivers, pedestrians, cyclists, and traffic police personnel, providing them with important information to enhance safety and improve overall traffic management.
- Vehicle-to-Roadside (V2R): the exchange of information or messages between vehicles and roadside units, like traffic lights, road signs, toll booths, parking systems, cameras, and radars.
- Vehicle-to-Infrastructure (V2I): it represents the communication between vehicles and the infrastructure responsible for high processing capabilities via WiFi or cellular networks like LTE/4G/5G (Ji et al., 2020).
- Vehicle-to-Sensors (V2S): This communication enables vehicles to interact with various types of sensors located on both sides of the road, such as radar sensors, Inductive Loop Detectors, Ultrasonic sensors, microwave sensors, infrared sensors, and acoustic sensors (Boubedra et al., 2023).

3.3.5 IoV Protocols

As an important component of ITS, IoV networks use a multitude of protocols to facilitate seamless communication between the ITS components. Among these protocols, we identify the most significant ones as follows:

- **6LoWPAN** It is one of the IoT technologies used in smart city design. (Qasem et al., 2020)
- **MQTT** MQTT is a lightweight, publish/subscribe messaging protocol that can be used on top of TCP/IP and it is designed for unreliable networks with low-bandwidth, high-latency characteristics. Thus, (Bonomi et al., 2012) discuss the

potential benefits of using edge devices, such as routers and switches, to act as MQTT brokers in a fog computing scenario.

- **HTTP/2** It is an updated version of the HTTP protocol that improves performance by multiplexing multiple requests between the client and the server over a single connection (Mao et al., 2017; Yakusheva et al., 2019).

- **ZigBee** is the only open, global wireless standard to provide the foundation for the Internet of Things by enabling simple and smart objects to work together, improving comfort and efficiency in everyday life. (Hayes, 2019; Yakusheva et al., 2019)

- **Bluetooth Low Energy (BLE)** This technology, with 20 years of experience, is therefore massively deployed on many devices on the market and for many applications, ranging from smartphones to the IoT network. Consequently, many documentation and APIs are available on different media, accelerating the understanding of this type of communication and greatly facilitating the development and maintenance of applications. Also, this massive deployment of Bluetooth gives us access to many media already equipped by inexpensive Bluetooth chips. This adds freedom of action to our equipment choices and, therefore, increased modularity on our work. (Thomas, 2020; Yakusheva et al., 2019)

3.4 Internet of Vehicles and Vanets

The use of communication technology and smart devices in vehicles has revolutionized the automotive industry. As a result, intelligent transportation systems have emerged with vehicles equipped with sensors and computers that may collect and process data for information exchange (Ji et al., 2020). Vehicular ad hoc networks (VANETs) were introduced to enable direct communication between vehicles and infrastructure, but they face challenges such as unstable network services and limited handling of big data. In the era of 5G/B5G and the Internet of Things (IoT), VANETs are transforming into the Internet of Vehicles. Therefore, IoV aims to enhance safety, reduce congestion, and provide services through information exchange between vehicles and relevant entities. Moreover, IoV encompasses various communication models and relies on vehicle networking and intelligence technologies. These advancements expand the communication scope and potential of the IoV system (Ji et al., 2020).

Firstly, according to (Ji et al., 2020), IoV network makes up for the shortcomings of VANET and will bring bright prospects for the development of smart transportation systems in the future. Also, authors present some issues and challenges faced in VANET that IoV overcomes:

- The failure to work with other networks causes the vehicles in the ad hoc network to lose network services once they are disconnected. Therefore, VANET cannot guarantee continuous and stable communication. Luckily, IoV makes up for this shortcoming through its heterogeneous network architecture, which realizes cooperation between the vehicle communication network and other communication networks.

- Incompatible network architectures have prevented many current communication devices from communicating with VANET. IoV solves this issue because most communication devices in daily life are compatible with IoV.

- Lack in computing capacity and storage space have made many intelligent applications impossible to implement using VANET. fortunately, IoV overcomes this issue through the improvement of information processing capabilities and the development of cloud computing and AI technology, enabling vehicles to autonomously choose to access better-performing networks to ensure stable network connectivity.

- The accuracy of each application service is low because VANET calculates and processes only localized traffic data information. Also, IoV overcomes this through the mutual cooperation of different types of networks and the emergence of multiple communication models (V2S, V2V, V2P, V2R, and V2I), which have realized the sharing of big data and the reliability of various communication services and at the same time expanded the application range of automotive communication.

In addition, in (Al-Turjman and Lemayian, 2020), authors state that IoV is more scalable, flexible, and supports various applications compared to VANETs. They also highlight the challenges associated with VANETs, such as limited performance capabilities, constrained medium access controls, high latency, and limited multi-hop routing. Hence, IoV replaces VANETs by integrating vehicular networks into the IoT infrastructure, which provides a more efficient and reliable communication system through better hardware and software capabilities. This helps to reduce network congestion and improve network performance for vehicular communication.

In another paper, (Contreras-Castillo et al., 2017), it is mentioned that as the number of vehicles connected to the IoT increases, new requirements for vehicular networks, such as seamless, secure, robust, and scalable information exchange among vehicles, humans, and roadside infrastructure, are emerging. To address these evolving requirements, VANETs are transforming into a new concept called the Internet of Vehicles. Thus, IoV enables the exchange of information among vehicles, road infrastructure, passengers, drivers, sensors, electric actuators, and the Internet using communication protocols and standards such as IEEE 802.11p, Directional Medium Access Control (DMAC), Vehicular Cooperative Media Access Control (VC-MAC), Ad hoc On Demand Distance Vector (AODV), and Dynamic Source Routing (DSR). Therefore, IoV differs from ITS as it puts more emphasis on information interaction among vehicles, humans, the surrounding road infrastructures, the central processing servers, forg/edge servers, and the cloud servers. While VANETs are well-suited for short-term applications or for small-scale services such as collision prevention or road hazard control notification services, they have limited capacity for handling global data and struggle to analyze, process, and evaluate the global information that they collect within the network. By contrast, IoV allows vehicles to be permanently connected to the Internet, forming an interconnected set of vehicles that can provide information for different services such as traffic management, road safety, and entertainment. Furthermore, IoV also includes vehicles, humans, components of the transportation infrastructure, and a set of devices allocated in the environment that exchange information directly or indirectly to contribute towards a more efficient, safer, and greener world of transportation (Contreras-Castillo et al., 2017).

However, in (Yang et al., 2017), authors state that IoV and VANETs are complementary rather than competing with each other. VANETs focus primarily on data communication between vehicles, and they have limitations in large-scale deployments and signal coverage. On the other hand, IoV provides a broad scope of integrated services, including vehicular information services, intelligent transportation, and modern information and communication technologies, which can help overcome limitations in VANETs. IoV involves not only vehicle-to-vehicle communication but also the communication of the vehicle with surrounding environments, such as roadside units and cloud servers, which makes it more scalable and comprehensive than VANETs. Therefore, in the future, the two technologies can provide complementary solutions for each other in the field of intelligent transportation.

Therefore, authors (Yang et al., 2017), suggests that VANETs can be integrated into the IoV architecture to provide a reliable and efficient communication network among vehicles, overcome connectivity issues, and improve data transmission rates. In return, the IoV can provide VANETs with a wider scope of information and communication services. For example, IoV can use cloud servers to provide real-time traffic updates to vehicles, which can be shared with other vehicles in the network through VANETs. Thus, combining IoV and VANETs can create a more comprehensive and effective transportation system by enabling vehicles and other transportation infrastructure to communicate seamlessly. They can work together to solve complex transportation problems and improve traffic safety, energy efficiency, and environmental sustainability. (Yang et al., 2017)

Another paper, survey (Sharma and Kaushik, 2020), where authors describes IoV as an integration of VANETs and IoT to enhance the proficiency of VANETs by incorporating smartness. Likewise, IoT connects everything with the internet, including vehicles, drivers, and roadside units, making it easy to access and share information. IoV ensures the safety of passengers and handles various traffic-related issues efficiently, such as dynamic routing, accidents, and traffic jams, by incorporating intelligent technologies such as Edge computing, artificial intelligence, and Big Data Analysis.

Furthermore, and according (Maglaras et al., 2016), communication in VANETs rely on roadside units (RSU) and on-board units (OBU) to facilitate connectivity and the intelligence of smart vehicles. However, in IoV, vehicles themselves become active members of a smart city. Therefore, they report that IoV has many more applications and methods that enable the intelligent communication between vehicles and connection to the internet than VANETs.

In Addition, (Cheng et al., 2015) state "...IoV can be seen as a superset of VANET. It extends VANET's scale, structure and applications... Different from traditional Intelligent Transportation System (ITS), it puts more emphasis on information interaction among vehicles, humans and roadside units (RSU). Its goal is to make people gain real-time road traffic information easily, to protect the travel convenience, and to improve the travel comfort." In addition, they (Cheng et al., 2015) mention some advantages of IoV over VANETs that can better address the challenges brought by vehicular environments. For instance: IoV extends VANET's scale, structure and applications. In addition, and unlike traditional transportation systems, IoV puts more emphasis on information interaction among vehicles, humans, and RSU. Furthermore, current well-known ad hoc routing protocols fail to fully address the specific needs of IoV. Thus, IoV has a wider scope and can potentially address more challenges than VANETs (Cheng et al., 2015).

Similarly, (Yang et al., 2014) indicate that VANET is evolving into IoV, and they explain that IoV is a more comprehensive and sustainable network system, while VANET is limited and temporary due to its dependence on the mobility of participating vehicles. Likewise, VANET has some limitations, such as mobility constraints and a relatively small number of connected vehicles. In contrast, IoV promises a higher degree of network resource utilization, manageability, control, operation, and credibility. IoV also includes vehicle telematics and mobile internet, and it is an open and integrated network system that provides services for large cities or even a whole country. The ideal goal for IoV is to realize the in-depth integration of human-vehicle-thing- environments, reduce social costs, promote transportation efficiency, improve the service level of cities, and ensure that users are satisfied with their vehicles. Therefore, IoV has overcome some issues with VANET by providing a more holistic, comprehensive, and sustainable network system.

From the comparatif table 3.1, we conclude that the IoV is a more advanced, scalable, and flexible system compared to VANETs, integrating IoT, edge/fog computing, and cloud technologies. Furthermore, VANETs are suitable for localized, short-term applications, while IoV supports global, long-term, and diverse applications. Therefore, IoV and VANETs are complementary: IoV enhances VANETs' capabilities and addresses their limitations, also, they work together to solve complex transportation problems, improving safety, efficiency, and sustainability.

Aspect	VANETs	IoV	Complementarity
Scalability	Limited scalability due to reliance on vehicle mobility and small-scale connectivity	Highly scalable, integrating vehicles, infrastructure, IoT devices and Cloud data centers for large-scale applications	IoV extends VANETs' scale and structure, enabling broader applications
Flexibility	Rigid architecture, primarily focused on vehicle-to-vehicle (V2V) communication	Flexible, supporting diverse interactions (V2X) and integration with IoT ecosystems	IoV enhances VANETs by incorporating IoT, enabling seamless communication across diverse entities
Applications	Suited for short-term, small-scale services (e.g., collision prevention, hazard notifications)	Supports a wide range of applications (e.g., traffic management, road safety, entertainment, smart cities)	IoV provides a broader scope of services, while VANETs handle localized, immediate communication needs
Communication Protocols	Relies on protocols like IEEE 802.11p, AODV, DSR for V2V communication	Uses advanced protocols (e.g., DMAC, VC-MAC) and integrates with IoT standards for comprehensive communication	IoV leverages VANETs' protocols while extending them for IoT integration
Latency and Performance	High latency and limited performance due to constrained medium access and multi-hop routing	Low latency, high performance, and efficient resource utilization through edge/fog computing and cloud integration	IoV addresses VANETs' latency issues by leveraging cloud-edge collaboration and advanced computing
Global Data Handling	Struggles to process and analyze global data due to limited capacity	Capable of handling and analyzing global data through cloud servers and big data analytics	IoV complements VANETs by providing global data insights while VANETs handle localized data exchange
Connectivity	Dependent on road-side units (RSUs) and on-board units (OBUs) for connectivity	Vehicles act as active members of a smart city, connected to the internet and surrounding environments	IoV enhances VANETs' connectivity by integrating vehicles into a broader IoT ecosystem
Sustainability and Scope	Temporary and limited due to mobility constraints and small-scale deployments	Comprehensive, sustainable, and scalable, supporting large cities or even nationwide networks	IoV provides a holistic and sustainable network system, overcoming VANETs' limitations

Table 3.1: Comparative Table: IoV vs VANETs

3.5 Conclusion

In order to better understand vehicle networks, especially VANETs, we emphasized in this chapter their main characteristics, their limitations and issues, and their future prospects, which is the Internet of Vehicles concept.

After that, we presented an overview of the IoV and its related paradigms. Firstly, we defined Internet of Things and the Internet of Vehicles. Then, we presented the main characteristics of IoV, the benefits of its integration in ITS. In addition, we explained the communication modes in IoV, and some IoV protocols. Finally, we highlighted the main reasons of integrating IoV in ITS and complementing VANETS.

Chapter 4

Enhancing Urban Traffic Management using Internet of Vehicles

Transportation is the center of the world! It is the glue of our daily lives. When it goes well, we don't see it. When it goes wrong, it negatively colors our day, makes us feel angry and impotent, curtails our possibilities.

– Robin Chase

4.1 Introduction

In this chapter, we present an overview of the fog/edge computing paradigms, in addition to some related works that helped us propose a layered architecture-based IoV and Fog/Edge computing concept to efficiently manage urban traffic systems. Therefore, in the second part of this chapter, we explain in detail its layers and its functioning. Overall, the proposed architecture aims to improve coordination and communication among the road network entities, leading to improved transportation systems.

4.2 Fog-Edge Computing paradigms

In this section, we explore the fog/edge computing paradigms, their characteristics, benefits, and distinguishing features. Then, we review related works to provide a comprehensive understanding of the current state of research on using fog/edge computing in order to improve the Internet of Vehicles networks and transportation systems in general.

4.2.1 definitions

Fog computing

Firstly, (Feng et al., 2018) defined it as follows: "Fog computing is an extension of cloud computing that enables services to be provided near the network edge, depending on the characteristics of services. It leverages the resources of the devices at the network edge for the delivery of timely and context-aware services"

Likewise, (Mao et al., 2017) said: "Fog computing is a new horizontal architecture that distributes computing, storage, and communication services closer to end users and devices along the cloud-to-things continuum of classic cloud computing paradigms to support applications that demand ultra-low latencies, real-time analytics, context-awareness, mobility, and dynamic adaptation"

Otherwise, (Zhang et al., 2017) reported that "Fog computing extends the cloud computing paradigm to the network edge and promotes geographical distribution and low-latency computing by sharing the proximity, computational, and network resources of smart IoT devices and fog nodes deployed at the edge"

meanwhile, (Bonomi et al., 2012) noted that "Fog computing is an emerging computing paradigm that aims to bring the cloud computing concept down to the ground or closer to the end users. Its primary objective is to provide a middleware between the cloud and the end devices, complementing the cloud-centric computing paradigm and enabling novel and real-time applications, especially for IoT services that require low latency and location awareness"

Similarly, (Zhou et al., 2020) declared that "Fog computing has emerged as a complement to cloud computing that leverages the benefits of distributed computing in the edge and fog devices such as reduced latency, energy efficiency, context-awareness, location-awareness, and mobility to support a wide range of applications and services that involve massive amount of real-time data processing and analytics"

Recently, fog computing has been proposed as a distributed solution for ITS applications. fog computing entails the integration of both cloud centres and network edge devices in a seamless manner and is an effective solution for surmounting the limitations faced by VANET highlighted in the previous section.

Fog computing is a geographically distributed computing architecture using, at a network edge, several heterogeneous devices that are connected ubiquitously to deliver elastic storage and computation services. Importantly, the most noticeable facet of fog computing remains the extension of cloud services to the network edge. This, in turn, makes computation, communication, storage, and control closer to users by enabling the pooling of local resources.

The fog paradigm is capable of adequately addressing the real-time demands of applications that are latency-sensitive and removing bandwidth bottlenecks. The architecture adds a layer between end devices and the cloud to tackle the underlying problems affecting high security and reliability, low latency, high performance, interoperability, and mobility. This platform consists of several fog nodes that are inclusive of the number of devices and management systems, even encompassing some virtualized data centres that are edge-centric. Fog nodes can store data created by edge devices as well as sensors.

Edge computing

It is defined as a distributed computing paradigm that brings computation closer to where the data is being generated and/or consumed, either on local devices or in a nearby edge location such as a base station, gateway or router. The main idea behind edge computing is to address the limitations of cloud computing in terms of latency, bandwidth, and network congestion, by processing data locally and reducing round-trip time to the cloud. Edge computing is seen as an enabler for low-latency and high-performance applications, such as real-time analytics, machine learning, and control. Furthermore, Edge computing, can support the high mobility of road networks, ensures low latency, and real-time processing, it also can guarantee scalable deployments, in addition it assure a good level of security and privacy. (Bonomi et al., 2012; Geng et al., 2022; Mao et al., 2017; Feng et al., 2018; Tang et al., 2020)

Vehicular Fog computing

Fog computing has been applied in different fields. One of its potential applications in ITSs is integrating it with VANETs to produce the Internet of Vehicles, or the Vehicular Fog Computing (VFC). The aim is to share the computational resources among vehicles, reduce energy use, eliminate latency, and provide real-time local services. Therefore, VFC could accelerate safety and emergency applications such as accident warnings and route recommendations.

(Zhou et al., 2020) defined the VFC as a technology that enables vehicles to participate in the computing and networking process by forming a vehicle-to-everything (V2X) network. Vehicular fog computing can be integrated into various applications, such as autonomous driving and intelligent transportation systems, to provide low-latency and high-reliability services. Likewise, (Tang et al., 2020) defined vehicular fog computing as a new distributed computing paradigm that leverages the computational resources of vehicles, road-side units, and mobile edge computing servers to enable low-latency and high-bandwidth data processing at the edge of the network.

Recently, several studies have used fog computing as a distributed architecture in VANETs—vehicular fog computing (VFC). Fog computing features make it possible to locally deal with large amounts of data and reduce the load on the communication network. However, there is limited work in this research area. (Alajali, 2020)

Extending fog computing to encompass support for vehicular networks, has many advantages: for example, it enhances communication efficiency, elevates the range of the vehicular networks covered, and resolves vehicular network limitations such as latency, location awareness, and real-time response. These benefits also significantly improve the performance of several functions, such as monitoring traffic and ensuring safe driving. collected and processed data locally using intelligent vehicles equipped with sensors to collect data about cars and the environment. It is an early research field and still requires more research on unsolved problems. (Alajali, 2020)

Various ITS devices (such as GPSs, sensors, cameras, and smartphones) continually provide extensive data from which extracting useful information is essential for ITS efficiency. The data accumulated through central processing can be stored in the cloud for a long period of time until it is needed for further investigation. The problem that arises in this respect is the need for a large storage space. In contrast, distributed processing eliminates the need for data storage because data collection, processing, and analysis are carried out close to the data sources, and real-time communication enables data to be processed as a data stream. This approach also prevents the latency problem that is commonly encountered in central processing.

The second challenge identified in the study is the dynamic nature of traffic, for which data processing should be implemented in real-time for managers to respond to changes and make decisions at the right time without delay. In the central processing approach, data needs to be transferred to the cloud before being processed and analysed. This feature can lead to delayed responses, thereby posing a serious impediment to issues that require rapid response time. The distributed processing approach can reduce response time by processing data locally and reducing data throughput. Central processing provides suitable applications for storing voluminous data in the cloud, but such innovations increase load on a communication network (e.g., a VANET). Each vehicle has to transfer information to the cloud at frequent intervals. Distributed processing can minimise the load imposed on a network by processing data locally. Recently, a new direction is using VFC in ITSs to increase performance and accuracy. (Alajali, 2020)

4.2.2 Characteristics and benefits of fog computing

By collaborating with the conventional models of cloud computing, fog computing plays a more effective role in its utilisation as a green computing platform, something it also helps cloud computing accomplish. Therefore, fog computing facilitates computation and storage on network edge devices. In the following points, we present some characteristics and benefits provided by this concept to the IoV:

- **Low latency and real-time interactions:** Fog nodes locally acquire data produced by devices and sensors. In addition, they process data generated by devices within the confines of a local area network. Furthermore, Fog computing addresses the demands of interactions in real-time, particularly for applications that are sensitive to both time and latency.
- **Bandwidth conservation:** Fog computing expands the implementation of storage and computation to the edge, thereby enabling fast data processing and storage between the traditional cloud and end nodes. Also, it locally performs specific computational tasks, including the removal of redundancy, the preprocessing, cleaning, and filtering of data, and the extraction of invaluable information. Only a portion of the data is transmitted into the cloud. There is no need to transfer a considerable proportion of the data online.

- **Geographical distribution and decentralised data analytics:** The implementation of fog computing makes a strong case for geographical location-based distribution and deployment. As opposed to storing and processing data within a specific data centre that is situated far from end users, fog computing guarantees the proximity of data analytics to end users. This feature can facilitate speedy big data analysis, enhancing the utility and reach of location-based services. A ubiquitous computing environment, such as the IoT, aims to decentralise data analytics and geographical distribution to improve the interconnections among numerous and widely distributed networks. This characteristic enables fog computing to effectively address the demands and road users' queries.

- **Interoperability:** Due to the heterogeneity of fog nodes and end devices, these components are sourced from a variety of service providers and typically deployed across a variety of environments. An essential requirement for fog computing is to enable interoperation with a plethora of service providers to seamlessly accommodate several offerings. As a case in point, a streaming service based on fog computing necessitates interactivity among different types of providers, wherein services are federated over different domains.

- **Data security and privacy protection:** Given that cloud computing providers host services that are close to customers, it presents distinct advantages concerning privacy protection and data security. In addition, fog nodes allow for encryption schemes, access control policies, integrity checks, and isolation measures, thereby improving privacy procedures for sensitive data.

- **Low energy consumption:** The geographical dispersal of fog devices occurs in accordance with the architectural framework of fog computing. Optimal policies of energy management within a short scope affect communication and energy consumption, which reduces power consumption, provides energy savings, and incurs low costs.

4.2.3 Fog vs Edge computing paradigms

According to (Charaf et al., 2021), both fog and edge computing are parts of the cloud computing paradigm, but they differ in where computing power is placed:

- ☞ First, edge computing pushes the intelligence directly into devices, while fog computing pushes intelligence down to the local area network level.
- ☞ Second, fog computing is a highly virtualized model of computation, storage, and networking resources between end devices and classical cloud servers.
- ☞ Additionally, in fog computing, and due to bandwidth and energy consumption concerns, there is no need to process the massive data generated by different IoT devices in the centralized cloud infrastructure. Fog computing is more organized as a distributed architecture and provides faster response and greater quality compared to cloud computing.
- ☞ On the other hand, edge computing is an open, distributed computing architecture with decentralized processing power enabling the deployment of mobile computing and IoT technologies. Data in edge computing is processed by the device itself or by a local computer or server, instead of being transmitted to a datacenter.

4.2.4 Related works

The design of fog/edge computing architecture for Internet of Vehicles is a complex task, requiring consideration of real-time constraints, low latency, and device integration. In this subsection, we present some research studies that collectively underscore the importance of fog/edge computing in IoV systems and provide valuable insights into its design and implementation.

- ☞ **(Charaf et al., 2021)**

  Problem Statement: What are the challenges in IoT access control and how can they be addressed using Fog Computing?

Authors have conducted a comparative study of fog computing architectures. Therefore, they proposed a distributed model to address IoT access control problems using the (eXtensible Access Control Markup Language) XACML language in a Fog Cloud. Indeed, they have attached to each fog node a specific module in order to manage users' access requests.

☞ **(Martinez et al., 2020)**

Problem Statement: What are the implementation aspects required to build a practical large-scale fog computing infrastructure to support the general IoT landscape?

In this study, authors aim to design, dimension and evaluate a fog infrastructure through simulation and emulation. Additionally, they focus on allocating fog resources for IoT applications, and installing fog frameworks for resource management.

☞ **(Cao et al., 2021)**

Problem Statement: What are the challenges in resource allocation for 5G IoV architecture based on SDN and fog-cloud computing?

First, authors introduce the challenges in meeting low latency requirements in the current intelligent transportation system. Additionally, they present the potential of fog computing to improve quality of service in IoV, and the need for an efficient architecture and resource allocation algorithm. Furthermore, authors propose a 5G IoV architecture based on software-defined networking (SDN) and fog-cloud computing, and a many-objective optimization algorithm to address service requirements, addressing the need for efficient resource allocation.

☞ **(Tufail et al., 2021)**

Problem Statement: How can moisture computing optimize network delays, enhance response time, and reduce infrastructure costs in Internet of Vehicles (IoV) architecture?

Therefore, the study objectives are to propose moisture computing (MC) for IoV architecture, demonstrate its assistance in smart vehicle operations, reduce infrastructure costs, and analyze its efficiency compared to edge and cloud infrastructure.

The main findings of this study include the efficiency of moisture computing in reducing communication delays and providing instant services in IoV architecture, its assistance in addressing traffic and safety issues for smart vehicles, and its optimization of network delays and response time compared to traditional computing approaches.

authors discusses the proposal of moisture computing (MC) as a solution between edge and cloud computing to reduce delays, enhance response time, assist in traffic monitoring and road safety, be cost-efficient, and optimize processing time through mathematical analyses and simulations.

☞ **(Zhao, 2021)**

Problem Statement: What are the applications and benefits of fog computing in the Internet of Vehicles?

Authors discuss the importance of Internet of Vehicles within the Internet of Things, the emergence of fog computing as a suitable technology, and the benefits of fog computing in addressing traffic issues and enhancing security in the Internet of Vehicles.

The methodology in this survey involves a review of recent works, the analysis of architectures and scenarios of fog computing in the Internet of Vehicles, proposing applications in VANETs, big data processing, and security.

☞ **(Muneeb et al., 2021)**

Problem Statement: How can we enhance data analysis systems based on IoT devices in real-time through a multi-layer fog computing platform?

The main objectives of this research include providing automation in managing and configuring data analysis tasks over cloud and edge environments, researching Edge-Artificial Intelligence (Edge-AI), enhancing real-time data analysis systems based on IoT devices, developing collaboration methods between fog computing nodes, and conducting experiments in real-world scenarios.

Authors discuss the challenges and opportunities in IoT applications, emphasizes the importance of big data analysis, and motivates the enhancement of real-time data analysis systems based on IoT devices. In addition, they explain the role of cloud computing, and the utilization of iFogSim for modeling Fog computing environments.

Therefore, their methodology involved the implementation of a monitoring system through cameras with real-time analytics and minimum latency. After that, they simulate the surveillance application in order to evaluate efficiencies, latency, network usage, and energy consumption to highlight the significance of the fog computing-based architecture.

The authors proved over simulations that the proposed prototype architecture outperformed the cloud-only environment in terms of delay-time, network usage, and energy consumption. Furthermore, the study is based on the policy of the OpenFog Consortium, offering good outcomes in terms of surveillance and data analysis functionalities. However, like every research work, this research suffer from certain limitations such as the lack of sufficient storage and computing resources in fog computing nodes for handling huge IoT data. Also, the cloud layer may not be applicable due to the random nature of the internet.Moreover, the research on Edge-Artificial Intelligence (Edge-AI) is still in its initial stage. Finally, the study was based on laboratory-level simulations, and future experiments in real-world settings are needed to address unpredictable situations.

☞ **(Wang et al., 2022)**

Traditional cloud servers and single-point edge servers are unable to fulfill the demand for a large number of application services in a short period of time in vehicular edge computing networks.

Problem Statement: How to optimize computation offloading in vehicular edge computing networks to minimize the total long-term cost of the system under communication and resource constraints, considering the delay and energy consumption requirements of the computation tasks?

In this paper, authors discuss the challenges of computation-intensive and latency-sensitive tasks in vehicular edge computing (VEC) due to the rapid development of the Internet of Vehicles and propose a cloud-edge collaboration network architecture as a solution. Therefore, they propose an efficient computation offloading strategy based on cloud-edge collaboration to enhance VEC performance. Their methodology involved formulating the computation offloading strategy as an optimization problem, transforming it into a Markov decision process, and proposing an efficient computation offloading strategy.

☞ **(Abbasi et al., 2021)**

Problem Statement: How can workload distribution be optimized between cloud data centers and edge systems in vehicular networks to reduce processing delays and energy consumption?

The principal objective of this paper is to reduce processing delay, optimize power consumption of edge systems, and achieve fair distribution of workloads. For that, authors discuss the growth of IoV, the challenges in workload distribution in ITS, and propose a Genetic Algorithm (GA) to optimize power consumption at edge systems, leading to significant reductions in processing delays and improvements in energy efficiency compared to existing methods. As results, processing workloads at the edge-systems reduces processing delay and energy restrictions. The proposed method distributes workloads evenly between cloud and fog servers, and decrease processing delay significantly. In addition, and according the authors of this paper (Abbasi et al., 2021) the proposed algorithm outperforms existing methods in using green energy for recharging fog server batteries and reducing data processing delay.

☞ **(Liu et al., 2021)**

Problem Statement: How can resource management in the IoV be optimized to improve energy efficiency and meet the communication requirements of modern intelligent transportation?

In this paper, authors discuss resource management in the Internet of Vehicles to optimize energy efficiency, and introduces a non-orthogonal multiple access NOMA-based fog computing vehicular network architecture. Therefore, the methodology involved implementing the chemical reaction optimization (CRO) and real-coded chemical reaction optimization (RCCRO) algorithms for sub-channel and power allocation problems, along with introducing fog computing technology to enhance local capabilities. As results, simulations prove the effectiveness of the proposed approach.

☞ **(Laroui et al., 2021)** Edge computing supports IoT applications that require a short response time.

Problem Statement: How can edge and fog computing address the challenges posed by the enormous quantity of data in IoT and what are the open research challenges and future directions in this area?

The main objectives in (Laroui et al., 2021) are to comprehensively review edge computing technology in the IoT environment, describe the IoT technology and the benefits of edge computing compared to cloud computing, provide an in-depth overview of the issues in the Edge-IoT environment, and discuss the challenges faced by edge computing in IoT applications. Authors highlight the significance of edge computing in managing connected devices, and the need for data processing at the network edge. In general, they provide a comprehensive review of edge computing for IoT, covering various research activities, future directions, recent research activities, future applications, use cases, simulators, open research challenges, and future research directions.

Research work	Problem Statement	Contributions
(Charaf et al., 2021)	What are the challenges in IoT access control and how can they be addressed using Fog Computing?	Proposal of a distributed model for IoT access control using the XACML language in a Fog-Cloud environment.
(Martinez et al., 2020)	What are the implementation aspects required to build a practical large-scale fog computing infrastructure for IoT?	Design and evaluation of a Fog infrastructure for IoT resource management through simulation and emulation.
(Cao et al., 2021)	What are the challenges in resource allocation for 5G IoV architecture based on SDN and Fog-Cloud?	Proposal of a 5G IoV architecture based on SDN and Fog-Cloud, with an optimization algorithm for resource allocation.
(Tufail et al., 2021)	How can Moisture Computing optimize network delays, enhance response time, and reduce infrastructure costs in IoV?	Introduction of Moisture Computing to reduce delays, improve response time, and assist in traffic monitoring and road safety.
(Zhao, 2021)	What are the applications and benefits of fog computing in the Internet of Vehicles?	Analysis of architectures and scenarios of Fog Computing in IoV, with applications in VANETs, big data processing, and security.
(Muneeb et al., 2021)	How can we enhance real-time data analysis systems based on IoT devices through a multi-layer fog computing platform?	Proposal of a Fog architecture for real-time analysis, with simulations showing reduced latency and energy consumption compared to cloud.
(Wang et al., 2022)	How to optimize computation offloading in vehicular edge computing networks to minimize costs?	Proposal of a computation offloading strategy based on cloud-edge collaboration to enhance VEC performance.
(Abbasi et al., 2021)	How can workload distribution be optimized between cloud data centers and edge systems in vehicular networks?	Use of a Genetic Algorithm to optimize energy consumption and reduce processing delays in edge systems.
(Liu et al., 2021)	How can resource management in the IoV be optimized to improve energy efficiency?	Proposal of an IoV architecture based on NOMA and Fog Computing, with optimization algorithms for resource allocation.
(Laroui et al., 2021)	How can Edge/Fog Computing address IoT challenges, and what are the future research directions?	Comprehensive review of Edge/Fog Computing technologies for IoT, with an analysis of current challenges and future research directions.

Table 4.1: Summary of Research Works on integrating Fog/Edge Computing in IoV

Finally, we summarise these research work in the table 4.1. Therefore, we notice that the Fog/edge computing is a key technology for the Internet of Vehicles, enabling reduced latency, optimized resources, and improved real-time services. Recent research explores innovative architectures for:

- IoT access control **(Charaf et al., 2021)**,
- Resource management **(Martinez et al., 2020)**; **(Liu et al., 2021)**,
- Cost and energy optimization **(Abbasi et al., 2021)** ; **(Wang et al., 2022)**,
- Enhancing real-time data analysis **(Muneeb et al., 2021)**.

However, challenges remain, including managing the limited resources and the need for real-world testing. Future research should focus on integrating Edge AI and optimizing architectures for critical applications like autonomous driving, road safety, and traffic management.

4.3 Vehicular Architecture-based IoV and fog-edge computing pradigms for Improving the Urban Traffic systems

The authors of (Qiu et al., 2018) introduce a four-layer framework for the future Internet of Things. We integrate this framework with the paradigm of fog/edge computing and introduce an additional layer, known as the fog-edge servers' layer. Subsequently, we adapt this structure for road traffic systems. Within this section, we offer a detailed description of the proposed architecture.

4.3.1 Layers of the proposed architecture

First, we present the layers of our architecture illustrated in Figure 4.1:

- **Sensing layer:** According to (Al-Fuqaha et al., 2015), this layer is made up of modern sensors, cameras, actuators, and RFID tags that are used to gather, store, and transmit data. In our case, the urban road is the monitoring area where a large number of sensors are deployed. These sensors are used to collect data about the state of the road, such as traffic jams, accidents, or fires. From cars equipped with RFID tags to pedestrians carrying smartphones or internet-connected wearables.

  The captured data from these sensors is sent to the sink node, also known as the master node. The role of the sink node in the Fog/Edge computing layer will be explained.

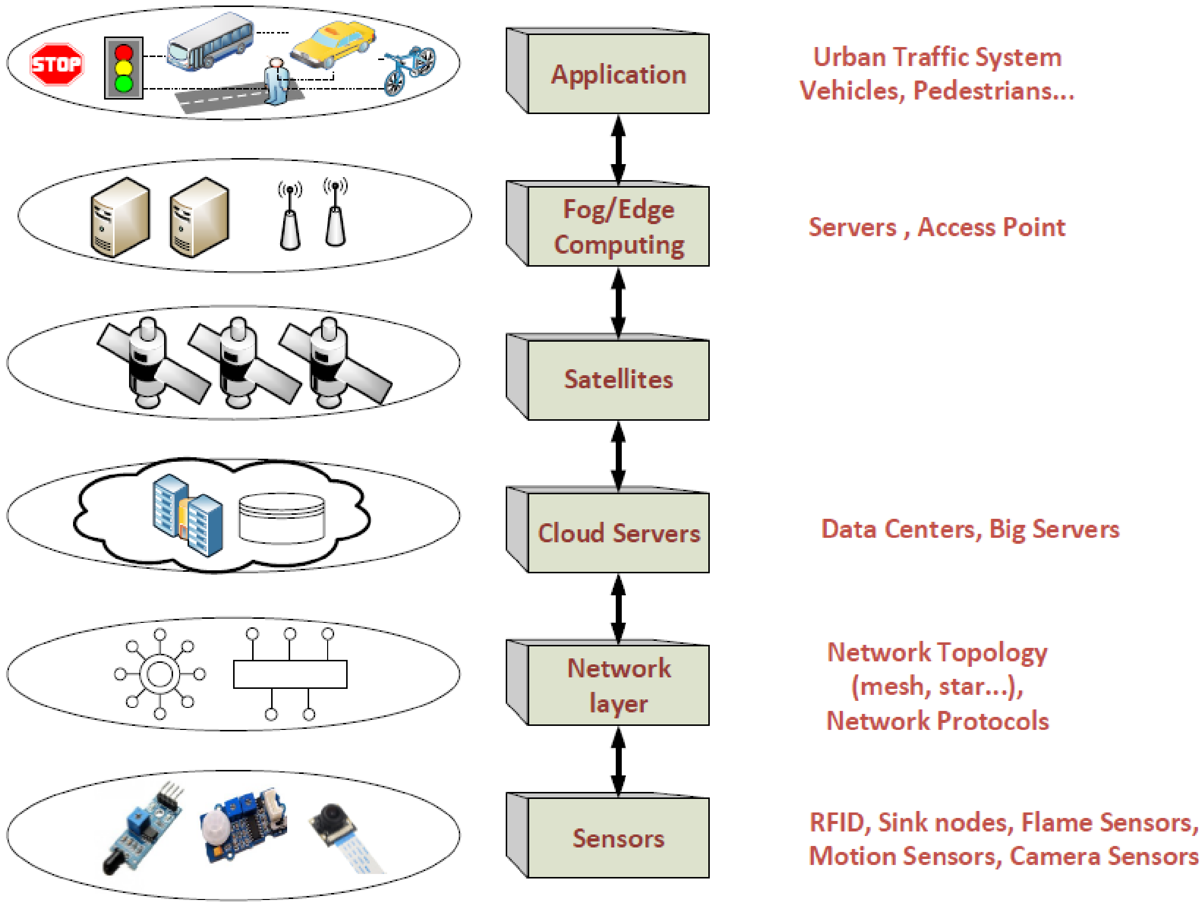

Figure 4.1: The proposed architecture's layers.

- **Network layer:** Within this layer, we use network protocols and their accompanying topologies, such as star topology, tree topology, mesh topology, or hybrid topology, to facilitate communication between vehicles and roadside sensors and units and improve the transmission of data packets (Qiu et al., 2018); Similarly, we prioritize the adoption of self-organizing network protocols to enhance the resilience and effectiveness of network topology construction. One such protocol is ”RPL”, an IPv6 routing protocol developed by the Internet Engineering Task Force (IETF) specifically for low-power and Lossy Networks.

- **Cloud layer:** The role of this layer is crucial in managing the huge amount of data gathered and transmitted by other layers to cloud servers and big data centers for processing, storage, and to make decisions based on data analysis (Qiu et al., 2018; Lin et al., 2017). This is made achievable by the robust analytical computing capabilities offered by cloud servers. Cloud computing has reached a state of maturity and is widely employed to create, store, and use data via the Internet. When there is a need to store, process, and analyze a large volume of data efficiently, the Fog/Edge computing paradigm emerges as a technology that bridges the gap. It extends cloud computing to be in closer proximity to the network of things (Lin et al., 2017).

- **Satellite Sub-layer:** In order to facilitate the transfer of data between Fog/Edge Servers and Cloud data centers and servers, Satellites are employed to optimize time, throughput, and energy consumption.

- **Fog/Edge Computing layer:** Within this layer, there are two distinct categories of devices: the master nodes and the edge servers. Edge servers can be utilized to handle processing, storage, and decision-making in close proximity to the network, rather than relying entirely on cloud servers for all computations. As a result, Edge computing offers faster response times and higher quality compared to cloud computing, particularly in real-time applications such as road traffic (Lin et al., 2017). We perform daily updates to our cloud data centers during nighttime to minimize disruptions during rush hours, ensure availability of resources during low user activity periods, and reduce competition for bandwidth. In contrast, we transmit data from master nodes to Edge servers multiple times and at regular intervals to allow for additional computations and analysis. However, we prioritize high-priority data and immediately send it to the nearest Edge server to maintain real-time functionality in the road traffic system. The master node serves as a centralized point with robust capabilities in processing, energy, and transmission. In comparison to the road sensors, its primary function is to : 1. Gather the data obtained from all the sensors within the same area. 2. Subsequently, it performs computations and data aggregations to minimize the extensive volume of gathered data. This is necessary due to a high probability of redundancy, since the sensors are located in close proximity and may record duplicate information.

- **Application layer:**The application layer responds to the requirements of users by offering services like route optimization and real-time traffic management (Al-Fuqaha et al., 2015). For example, a vehicle driver needs to find the optimal route to reach his destination; he uses our service to obtain the most favorable response. The purpose is to better manage urban traffic by integrating various components such as car drivers, pedestrians equipped with smartphones and smart swatches, road sensors, and other smart devices that are connected to the network. Delivered data is utilized to guarantee the real-time control and supervision of the traffic on urban roads. Therefore, traffic services and applications are heberged in both master nodes and Fog-Edge and cloud servers that may remotely control and monitor objects placed at a certain distance by using sophisticated data analytics techniques and visualization tools. (Qiu et al., 2018).

4.3.2 The functioning of the proposed architecture

Indeed, our design is hybrid in terms of interconnecting devices in the IoV network. This means that objects collaborate and exchange traffic information. Additionally, it is hierarchical, as objects communicate with the master node to transmit data collected by sensors to the Edge Servers. Furthermore, the data processing conducted by the Edge Servers will be transmitted to the cloud centers for analysis and decision-making, as seen in Figure 4.2.

Every car is equipped with a GPS (Global Positioning System) that receives important data, including position, time, and weather conditions, from satellites (Vongsingthong and Smanchat, 2014). Moreover, RFID chips have a vital function in the exchange of information with other cars, pedestrians, and road sensors through the utilization of Zigbee IEEE 802.15.4.

Road sensors have the task of collecting traffic data from both automobiles and pedestrians. This data provides information on the existence of traffic jams, crashes, or other dangers. Afterwards, they send the gathered data to the master node via WiFi (IEEE 802.11).

The master node incorporates communication and data processing modules. The communication component is a wireless antenna that receives and decodes data packets delivered by road sensors or edge servers. In addition, the data processing module is utilized to aggregate the data obtained from the road sensors in order to handle redundancies. Furthermore, data aggregation methods have the objective of minimizing the quantity of data communicated and the consumed energy (Vongsingthong and Smanchat, 2014).

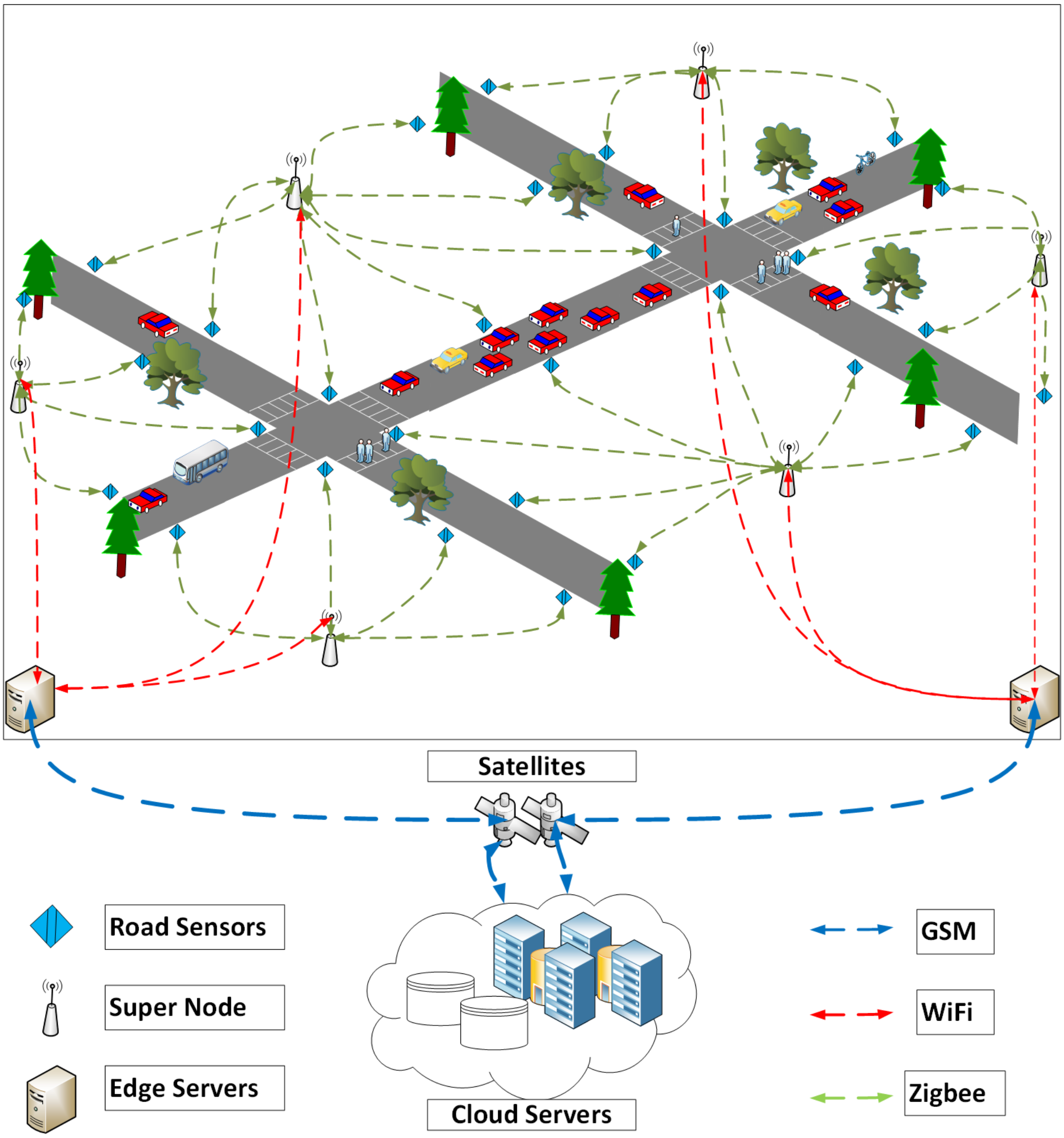

Figure 4.2: The proposed architecture-based IoV

The aggregated data are transmitted to the closest edge server using either LTE-V2X or C-V2X protocol (for more information, see to subsection 2.4.1).

Each Edge Server performs data processing by using information received from Master nodes. It then takes decisions and preventive measures to alert drivers or pedestrians in order to avoid congestion, accidents, and other incidents and to minimize further damage on the road. This process is repeated continuously throughout the day.

Edge servers provide significant storage and processing capacities, enabling them to make better decisions that enhance the quality of mobility in urban regions. They act as intermediaries between cloud servers, data centers, and sensor networks located on the road.

Processed data, decision-making outcomes, and preventive measures will be transmitted to cloud servers via satellites, utilizing 4G-5G technology for data transfer.

The decision to employ pre-existing protocols in the proposed architecture is motivated by the necessity of establishing reliable communication inside the Internet of Vehicles system through the use of any accessible network. This technique is favored due to its effectiveness and compatibility with the existing infrastructure (Vongsingthong and Smanchat, 2014). In our case, we employ WiFi and cellular networks as existing network architectures, thereby eliminating the need for building novel infrastructures.

Cloud centers facilitate extensive global operations that involve heavy data processing and management. With significant processing and storage capacity, virtualization and data analytics are employed to enhance decision-making, implement preventive measures, and store data for optimizing the urban traffic system.

At the end of this chapter, we present a general scheme of the proposed architecture (without the details about connection links), illustrated in the figure 4.3. In this figure, we remark that the edge layer represents the sensing and collecting equipment in IoV networks, like RSUs, smartphones, smart-swatches, sensors, cameras, vehicles, smart homes, etc. In this layer, data processing is done in real-time; as a result, the network latency is low because of the small amount of treated data and the small storage space of the devices. Likewise, in the Fog layer, where we have real and virtualized servers with a medium capacity of data processing and storage, we can extract data analysis and make decisions in less time compared to the cloud data centers. However, it is still limited with a large amount of data, and the cloud layer could replace the fog layer in this case in order to make big processing work, but in more time and with a big delay, using data centers with high capacity of treatment and storage. Therefore, we conclude that the three concepts (Cloud-Fog-Edge) paradigms have complementary roles in an IoV network and should work hand in hand in order to ensure the stability of the network.

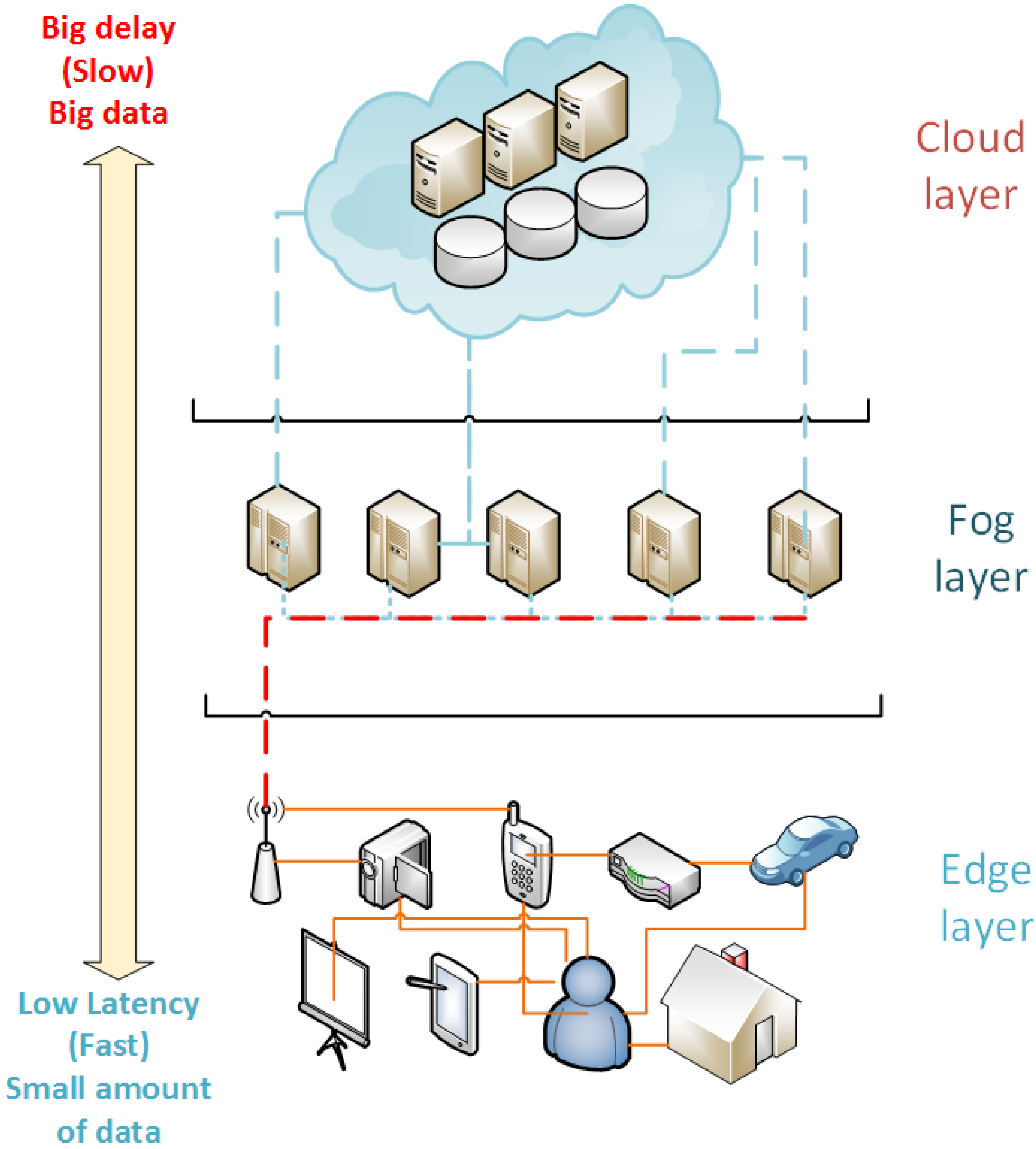

Figure 4.3: General scheme of the proposed architecture

4.4 Conclusion

In this chapter, we present an overview about the fog/edge computing paradigms, in addition to some related works that helped us to propose an efficient architecture-based IoV and Fog/Edge computing concept. Therefore, the proposed architecture is generic and flexible for all urban traffic systems and can be applicable in the real world, because we bring together current and existing IoV and IoT technologies.

Chapter 5

Urban Traffic Flow Management on Large Scale using an Improved ACO for a Road Transportation System

One of the most surprising behavioral patterns exhibited by ants is the ability to find what computer scientists call shortest paths...Ants might be able to run telecommunication networks better than humans...They were able to say to any packet of data with a given destination what the next node it should travel to.

– Marco Dorigo

5.1 Introduction

With the demographic increase, especially in big cities, heavy traffic, traffic congestion, road accidents, and augmented pollution levels hamper transportation networks. Finding the optimal routes in urban scenarios is very challenging since it should consider reducing traffic jams, optimizing travel time, decreasing fuel consumption, and reducing pollution levels accordingly. In this regard, we propose an enhanced approach based on the Ant Colony algorithm that allows vehicle drivers to search for optimal routes in urban areas from different perspectives, such as shortness and rapidness.

Our proposed improvements to the Ant Colony Algorithm to search for optimal paths for urban roads include incorporating multiple factors, such as travel length, time, and congestion level, into the route selection process. Furthermore, random search, elitism strategy, and flexible pheromone updating rules are proposed to consider the dynamic changes in road network conditions and make the proposed approach more relevant and effective. These enhancements contribute to the originality of our work, and they have the potential to advance the field of traffic routing.

This chapter is organized as follows: First, we provide a summary of relevant works related to our contribution and discuss the rationale behind selecting the Ant Colony Algorithm to search for optimal routes in urban areas. In the next section, we present the "Traffic Routing Problem" statement, describe the used graph, present the assumptions and constraints of the studied problem, and explain the proposed approach in detail.

5.2 Related works

Finding optimized paths is significant for vehicle drivers. A lot of scientific research in the transportation field was devoted to selecting the best routes between a source and a destination while considering the travel time, the length of the route, the level of congestion, and thus the safety of the road users. In this section, we summarize some proposed techniques from the literature and introduce the motivations behind using the

ACO meta-heuristic algorithm for solving the traffic routing problem discussed in this manuscript.

(Kumar et al., 2018) proposed a traffic control system based on the ACO algorithm for optimal route search while modeling the heavy traffic collected by the Internet of Vehicles technologies, using Fuzzy logic. Their results outperformed the results obtained from Dijkstra's, Kruskal's, and Prim's algorithms.

Similarly, (Li and Wei, 2020) employed the ACO algorithm to determine optimal urban-rural routes for buses in the Erqi district of Zhengzhou, China. Again, in (Wu et al., 2020), a dynamic path-planning method is proposed to reduce the congestion rate based on the ACO and particle swarm optimization PSO algorithms while considering the road length, the number of lanes, and the current traffic flow. The PSO algorithm is used to optimize ACO parameters for better performance.

With the help of intelligent sensors, (SS et al., 2020) proposed an ACO meta-heuristic-based model to control and regulate the traffic in transportation networks while minimizing travel time and congestion levels. The authors demonstrate that, due to its dynamic nature, the ACO algorithm is suitable for managing high traffic in big cities.

On the other hand, a survey on path search algorithms is presented by (Khekare et al., 2020). The authors suggest an optimal route-finding algorithm with reinforcement learning (ORAWRL), which focuses on traffic density and distance factors. The proposed technique surpasses the genetic algorithm, particle swarm optimization, and artificial neural networks in terms of travel distance, the number of turns, running time, and the optimality of the selected paths. In addition to the later research works, we cite some papers that use other meta-heuristics in other extensions of routing problems.

Therefore, (Abbaszadeh Sori et al., 2020) have formulated a mathematical model for a robot's fuzzy-constrained shortest path problems. They proposed an elite artificial bee colony (EABC) algorithm and simulated it using two fuzzy networks. The comparative results show that the proposed approach outperformed the PSO and GA in terms of convergence speed.

Again, (Ebrahimnejad et al., 2016) have proposed an artificial bee colony (ABC) algorithm for solving the fuzzy shortest path (FSP) problem in a network with fuzzy arc weights. The experimental results have been compared with PSO and GA and are shown to have a faster convergence speed.

Similarly, and with the help of ACO in solving combinatorial problems, (Rezaei Kalantari et al., 2020) propose a dynamic software rejuvenation technique to counteract software aging in web service-based systems using a combination of the ACO algorithm and gravitational emulation local search (GELS), which can decrease the failure rate of web services by 28% in comparison with genetic algorithm and decision-tree strategies.

Motivations

In the context of an urban road network, ACO can be used to calculate the optimal routes between different locations and can lead to efficient and effective solutions that take into account various factors such as distance, traffic flow, and other constraints for the following reasons: One of the main advantages of ACO is that it can handle complex networks with multiple paths and variable conditions because it is a constructive algorithm. By using a pheromone-based approach, the algorithm can adapt to changing traffic conditions and find alternative routes if necessary (SS et al., 2020). Additionally, ACO is a scalable algorithm that can be applied to networks of varying sizes, making it well-suited for urban road networks that can be quite large and complex (Di Caprio et al., 2022). Therefore, ACO can be an effective method for calculating the optimal routes in an urban road network, as it mimics the natural behavior of ants and can converge on an optimal solution over time. In other words, searching for the optimal route from a source to a destination point is very similar to seeking the shortest path from the nest of a colony of ants to a food source. This analogy between ACO and the foraging behavior of ants makes ACO a promising approach for solving traffic routing problems in road networks.

Overall, it is a powerful technique for finding the optimal route in an urban road network because it can adapt to changing traffic conditions, find efficient paths that may not be immediately apparent to human planners, and change to alternative routes if there are road closures, accidents, or traffic jams (Li and Wei, 2020; Di Caprio et al., 2022).

Furthermore, our decision to use the ACO meta-heuristic for solving the traffic routing problem is supported by experimental results and studies from other researchers in the field. For instance, authors (Bedi et al., 2007; Di Caprio et al., 2022; SS et al., 2020; Jiao et al., 2018), recommended ACO as the most suitable algorithm to fix traffic routing problems, like the Traveling Salesman Problem (TSP) (Zukhri and Paputungan, 2013; Le and Peechatt, 2019), Vehicle Routing Problem VRP (Bell and McMullen, 2004; Jiang et al., 2021), path planning and avoiding obstacles for automated vehicles(Wang et al., 2019), for robots (Liu et al., 2017; Cong and Ponnambalam, 2009), for Unmanned Aerial Vehicles UAV (Duan et al., 2009; Chen et al., 2022), for Autonomous Underwater Vehicle AUV (Mirjalili et al., 2020), and for submarines (Fu et al., 2022; Ma et al., 2020).

Unlike the genetic algorithm (Lightner-Laws et al., 2016) which requires the solutions set to be at the initial state, the ant colony meta-heuristic has a constructive algorithm, which assembles elements to construct the solution. This motivates the use of ACO meta-heuristic in real-time applications and stochastic environments (Guettiche and Kheddouci, 2018), like in our case, where the congestion level in each road keeps changing while calculating the best route. Besides, the ACO algorithm has demonstrated its effectiveness in the literature, for finding optimal paths in urban areas (Chowdhary and Kaur, 2017). Indeed, it has outperformed other algorithms, such as Genetic Algorithms in (Putha et al., 2012; Srivastava et al., 2015; Le and Peechatt, 2019; Di Caprio et al., 2022), Dijkstra, Kruskal, and Prim algorithm in (Kumar et al., 2018), firefly in (Chowdhary and Kaur, 2017), Particle Swarm Optimization and Artificial Bee Colony algorithms in (Di Caprio et al., 2022) in terms of reducing execution time, travel time, travel distance and risk prediction in road transportation of hazmat (Achouri et al., 2022).

Ant Colony Optimization is a highly innovative population-based meta-heuristic. The artificial ants work cooperatively to solve hard combinatorial problems and find the best solution. Artificial ants act like real ants by using artificial pheromones as a communication medium (Bedi et al., 2007; Wang et al., 2019; Dorigo et al., 1999; Sabbani et al., 2019;

Nourmohammadzadeh and Hartmann, 2019). Moreover, it is a constructive algorithm that uses a probabilistic seeking method. Artificial ants create solutions by assembling elements and using a probability function that considers the concentration of artificial pheromones and the value of heuristic information (Dorigo and Stützle, 2019; Nourmohammadzadeh and Hartmann, 2019). The ant moves along the pheromone density from the nest to the food sources. As a result, the shortest path is created (Figure. 5.1). The ants use a decentralized method of communication called *Stigmergy* (Korošec and Šilc, 2009), defined as ”an indirect way to communicate through a chemical substance”, that ”offers many advantages when a great number of individuals exchange much information” (Sabbani et al., 2019).

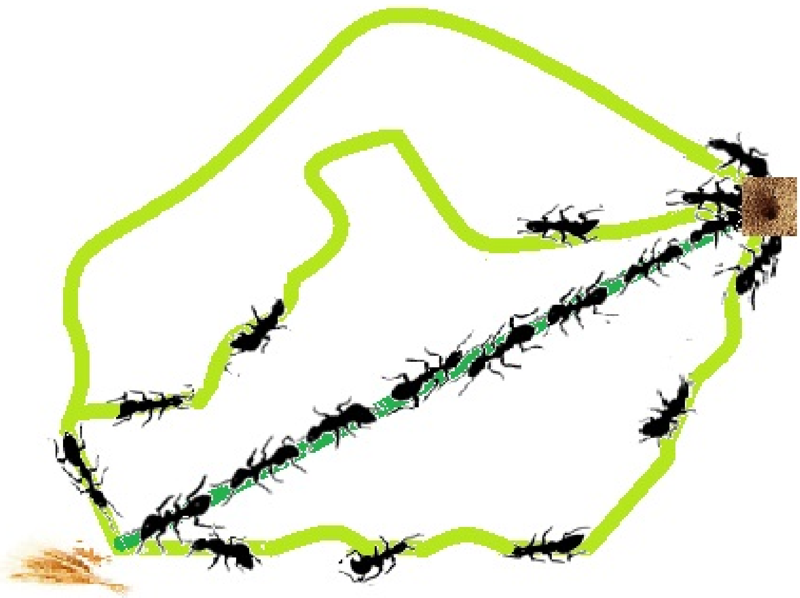

Figure 5.1: Ants looking for the best path.

According to (Dorigo and Stützle, 2019), the ACO meta-heuristic is widely applied over the world, especially in academic scenarios. Besides, AntOptimaEntreprise offers very promising real-world systems to their clients based on the ACO meta-heuristic. In addition, (Dorigo and Stützle, 2019) claimed that “ACO can be applied to any discrete optimization problem for which some solution construction mechanism can be designed”. Furthermore, it was used to solve the problem of melody creation and harmonization (Geis and Middendorf, 2008).

Meta-heuristic algorithms can be considered a subset or a specific category within the broader field of optimization methods. They focus on solving complex optimization problems by exploring the large search space effectively. Deterministic optimization methods, such as linear programming, aim to find the exact optimal solution based on mathematical models and algorithms (Gunantara et al., 2019; Kvasov and Mukhametzhanov, 2018).

Furthermore, the problem treated in our thesis is an NP-hard combinatorial optimization problem (Yu and Yang, 1998; Handler and Zang, 1980) which could not be resolved using traditional algorithms or exact methods, that may fail to find optimal solutions in a reasonable period (Yang, 2020; Goel and Maini, 2018). In the worst cases, the execution time increases exponentially, especially when augmenting the number of variables (nodes) (Dorigo and Stützle, 2019; Colorni et al., 1996; Mirjalili et al., 2020; Mirjalili, 2019). So, we have opted for heuristics and meta-heuristics to reach near-optimum results within an appropriate execution time since meta-heuristics are used whenever there are countless possibilities for solutions (Kim and Bae, 2016).

Ant Colony Optimization ACO is among the most efficient meta-heuristics to solve NP-hard combinatorial problems (Srivastava and Sahana, 2020; Mirjalili et al., 2020; Dorigo and Stützle, 2019). Therefore, it has attracted the attention of scientific researchers in optimization fields and has been widely used in several domains. Moreover, real ants teach us that very small creatures, very weak alone are stronger than we can imagine when they work, interact, and communicate together (Calabrò et al., 2020). More importantly, these cooperation and teamwork principles give ACO dynamism, robustness, and powerful seeking capacity (Li and Wei, 2020).

Research work	Methods	Results
(Kumar et al., 2018)	ACO + Fuzzy Logic for traffic control.	Outperforms Dijkstra, Kruskal, and Prim.
(Li and Wei, 2020)	ACO to optimize bus routes in urban-rural areas.	Improved bus routes.
(Wu et al., 2020)	ACO + PSO to reduce congestion (length, number of lanes, traffic flow).	Effective congestion reduction.
(SS et al., 2020)	ACO model to minimize travel time and congestion.	Suitable for large cities.
(Khekare et al., 2020)	ORAWRL algorithm (reinforcement learning).	Outperforms GA, PSO, and ANN in distance, time, and optimality.
(Abbaszadeh Sori et al., 2020)	EABC for shortest path problems.	Outperforms PSO and GA in convergence speed.
(Ebrahimnejad et al., 2016)	ABC for shortest path problems.	Faster convergence than PSO and GA.
(Rezaei Kalantari et al., 2020)	ACO + GELS to reduce web service failures.	28% reduction in failures compared to GA.
(Bedi et al., 2007)	Recommendation of ACO for routing problems.	Supports the efficiency of ACO.
(Di Caprio et al., 2022)	Supports the use of ACO for urban routing problems.	Shows ACO's superiority over GA, PSO, and ABC.
(Zukhri and Paputungan, 2013)	ACO for the Traveling Salesman Problem (TSP).	Optimal results for TSP.
(Bell and McMullen, 2004)	ACO for the Vehicle Routing Problem (VRP).	Improved vehicle routes.
(Wang et al., 2019)	ACO for path planning and obstacle avoidance.	Superior performance for autonomous vehicles.
(Achouri et al., 2022)	ACO for risk prediction in hazardous material transport.	Reduced risks and improved safety.
(Jiao et al., 2018)	ACO to solve complex routing problems.	Demonstrates ACO's efficiency in complex scenarios.
(Liu et al., 2017)	ACO applied to robotics.	Promising results for path planning.
(Duan et al., 2009)	ACO for drones (UAV).	Optimized trajectories for drones.
(Mirjalili et al., 2020)	ACO for autonomous underwater vehicles (AUV).	Improved AUV performance.
(Fu et al., 2022)	ACO for submarines.	Optimized submarine routes.
(Putha et al., 2012)	Comparison of ACO vs GA.	ACO outperforms GA in execution time and distance.
(Srivastava et al., 2015)	Comparison of ACO vs GA.	ACO more effective for routing problems.
(Chowdhary and Kaur, 2017)	Comparison of ACO vs Firefly.	ACO outperforms Firefly in terms of performance.

Table 5.1: Summary of Research Works on Traffic Routing Optimization

5.3 Routing Problem in a Road Traffic System

In this section, we introduce the studied traffic system. For that, we briefly define the traffic routing problem. Then, we describe the used graph, its edges, and the nodes' attributes. After that, we present the vehicle traffic count methods in a smart city, which may also be adapted to calculate huge traffic in big cities. Finally, we present the assumptions and constraints considered while trying to solve the problem.

5.3.1 Traffic Routing Problem Statement

Traffic routing problems (TRP) are common in several fields of networking research. For instance, we can apply traffic routing in wireless or wired communications to route information packets in a telecommunication network or transportation network, like in our work. In general, its principal goal is to find a short, fast, and optimal path in a weighted graph (oriented or non-oriented, multiple or single lanes). Usually, the selected path is an ordered list of nodes and edges that start from a particular source node and end at a specific target node, taking into consideration the weights of each arc (or road, in our case) to ensure an optimized solution.

In our research, the TRP has a finite set of variables, which are the IDs of the graph nodes with discrete values that represent the intersections, turns, traffic signals, and stop signs. The search space is all combinations of those variables, which constitute the feasible solutions or routes in our case.

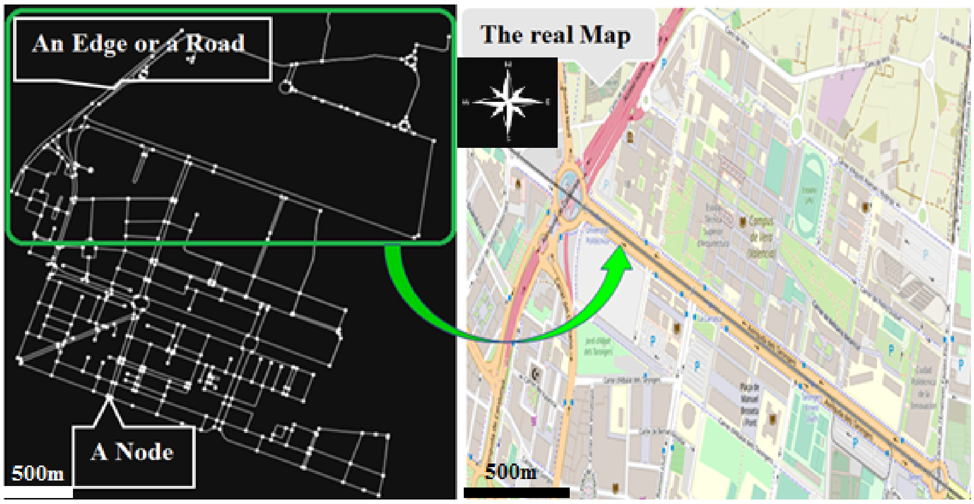

Figure 5.2: Road Network Graph of “Algiros-Valencia-Spain” extracted from OpenStreetMap.

We assume that G(I, R) is a weighted, multi-lanes, directed (oriented) graph, where I refers to the set of intersections that interconnect a set of roads R (Figure. 5.2). In addition, every road r has its features determined by these attributes:

- IDr: is the ID of the road.
- IDs: is the ID of the start node.
- IDe: is the ID of the end node.
- name: is the name of the road.
- lanes: is the number of the road lanes.
- length: is the length of the road (given in meters).
- travel_time: is the time required to pass through this road (given in seconds).
- speed_kph: is the free-flow travel speed of the road r (given in kilometers per hour).
- capacity: estimates the number of vehicles that can occupy the road r at the same time. The capacity of the road can be calculated as follows:

$$Capacity = \frac{length}{(AvgLenV + DistV)} * lanes \tag{5.1}$$

In which:

- $length$: is the length of the road
- $AvgLenV$: is the average length of an urban vehicle (AvgLenV = 4m)
- $DistV$: is the distance between two vehicles ($DistV = 3m$)
- $lanes$: is the number of lanes of this road

Inspired by the Nagel Schreckenberg Microscopic Traffic Model (Nagel and Schreckenberg, 1992; Treiber et al., 2000) and the Highway Capacity Manual (Manual, 2000), we assume that the average length of an urban vehicle is four meters (4m) and the practical safe inter-vehicle distance $DistV$ is three meters (3m).

- Congestion_rate: is the congestion level on a road and is estimated as follows:

$$Congestion\_rate = \frac{NbrV}{capacity} * 100 \tag{5.2}$$

Where: $NbrV$ is the total number of vehicles on the road provided in real-time.

5.3.2 Vehicle Traffic Count methods

Transportation authorities and traffic management systems can effectively manage traffic by collecting comprehensive and accurate data through a diverse range of sensors. Advanced data processing and analysis techniques, in combination with using various types of sensors located on both sides of the road, such as radar sensors, cameras, and laser beams (Inductive Loop Detectors, Ultrasonic sensors, microwave sensors, infrared sensors, and acoustic sensors), as illustrated in Fig. 5.3; offer valuable insights into traffic flow patterns, congestion levels, and overall road network performance. We conduct periodic measurements of the flow entering and exiting the road over a specific period of time. These measurements enable us to monitor traffic flow dynamics and gain insights into the movement of vehicles within the road network. Therefore, accurate traffic flow measurements and Vehicle Traffic Flow Control Systems must be implemented to create a complete traffic management system for improving efficiency and reducing traffic issues on urban road networks.

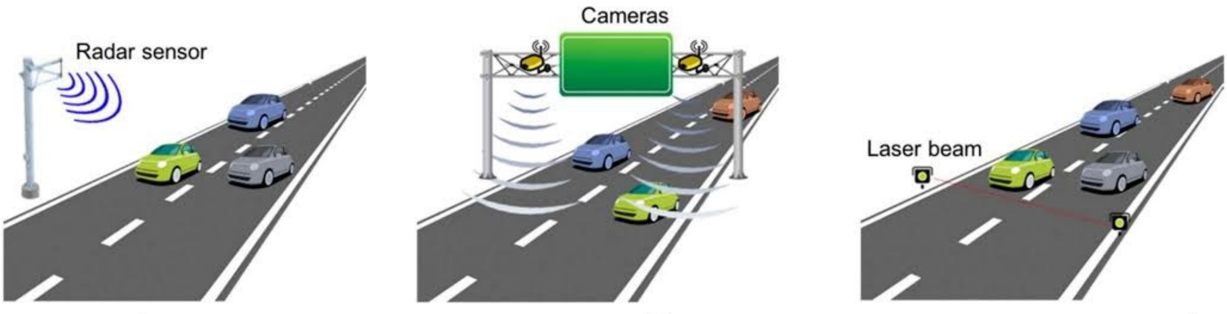

Figure 5.3: Vehicle count in road traffic ((Guerrero-Ibáñez et al., 2018))

In practice, we employ the graph presented in Figure. 5.4-a; which represents the traffic network of Valencia City, Spain. Figure. 5.4-b represents some possible routes from the start node s in the north to the destination node d in the south of Valencia City, with different fitness values. As illustrated, we can find thousands of solutions for the same source and the same destination because this is a big road network with 7976 nodes and 14742 edges. Therefore, selecting optimal roads in terms of short distance, time, and less congested routes is a very challenging task for path planners in large cities like Valencia, (Zambrano-Martinez et al., 2017), “which is the third largest metropolitan area in Spain” (Calafate et al., 2015).

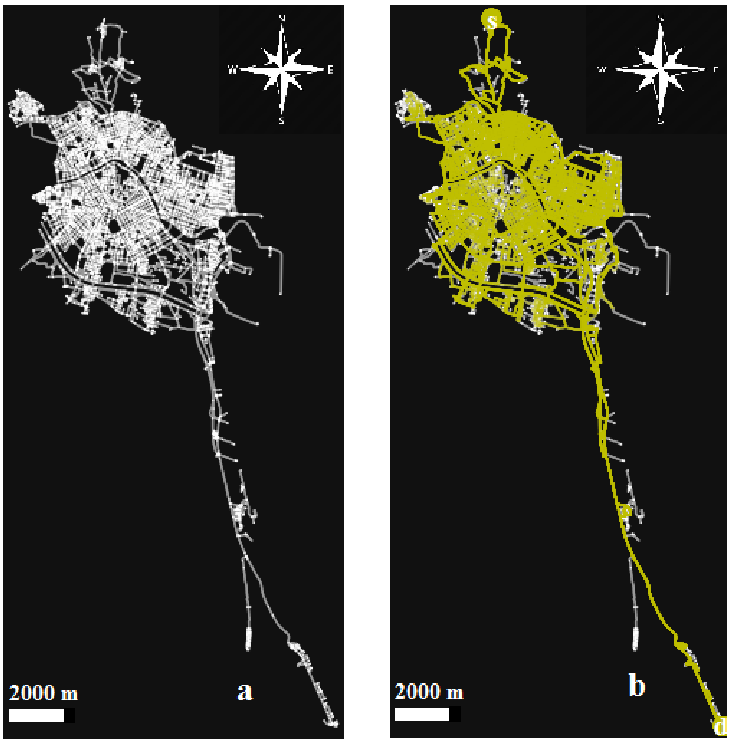

Figure 5.4: a- Road Network Graph of Valencia-Spain / b-Some possible routes from origin to destination.

To give an example of the intensity of traffic in rush hours on a primary avenue, we introduce Table. 5.3. It summarizes the traffic counts measured on Monday 31st May 2021 during a 15-minute window, over the avenue “Blasco Ibañez” in the district of Algiros-Valencia City, Spain, during a peek hour (from 8 am to 9 am). For instance, at 8:15 am, the number of vehicles passing through that road between 8:00 am and 8:15 am is 2880.

ATA	Latitude	Longitude	Lanes	Max Speed	Time	Nb Vehicles
A47	39.4753702	-0.3524861	6	50	08:15	2880
					08:30	3150
					08:45	3150
					09:00	3405
A50	39.4709916	-0.337497	6	50	08:15	2355
					08:30	2033
					08:45	1925
					09:00	2148
A52	39.470121	-0.3345176	6	50	08:15	450

					08:30	1560
					08:45	1230
					09:00	1950

Table 5.3: The traffic counts measured in rush hours, in Algiros-Blasco Ibañez street, Valencia City, Spain.

[1] The source: https://www.valencia.es/dadesobertes/es/dataset/?id=intensitat-de-transit-per trams

Every node connects two roads and represents places on the real map, such as intersections, turns, traffic signals, stop signs, etc. Therefore, it can be characterized by three parameters (or attributes):

- IDn: the ID of the node.
- X, Y: the coordinates x and y of the node.
- visited: a Boolean attribute to indicate if the current node is already visited by the current agent or not.

5.3.3 Problem assumptions and considered constraints

Problem assumptions

We assume that:

☞ All road segments in the network are open and accessible to traffic.

☞ The number of vehicles in the network and their starting positions are known and fixed and do not vary during the process of routing.

☞ The road network is fixed and does not change during the routing process.

☞ All vehicles have the same priority level.

☞ All vehicles can follow the recommended routes without any external obstacles or road closures.

- ☞ All vehicles are equipped with GPS devices and are capable of communicating with the system to receive traffic information.
- ☞ Road sensors are functioning correctly and providing accurate traffic information.
- ☞ The communication infrastructure between the vehicles and the road infrastructure is reliable and always available.

Considered constraints

- ☞ User preferences: The algorithm should consider user priorities, such as minimizing travel time and distance and, as a result, fuel consumption.
- ☞ Capacity of each road segment: each road (edge) in the graph has a maximum number of vehicles that can occupy it in the same period. The capacity of the road should be calculated at the time of initialization using Equation 1.
- ☞ The used graph should reflect the real nature of a road network (multi-lane and oriented). This is the reason behind using a multi-lane directed graph.
- ☞ Short running time and resource constraints: the proposed algorithm may require significant computing power to process and analyze large amounts of traffic data in real-time while at the same time having a short response time. This constraint is important and is assured by the assumption that the road network contains reliable Internet of Vehicles with powerful base stations and fog/edge servers.
- ☞ There are no isolated areas that cannot be reached by vehicles because the entire road network is connected.

5.4 Proposed Methodology

In this section, we describe our proposed approach in detail. Firstly, we determine the fitness function as well as the considered methodology assumptions. After that, we present the rules and equations, and the different steps of the proposed algorithm.

5.4.1 Fitness Function

To make use of the Ant Colony Optimization Meta-heuristic, the road network should be presented with a graph (as illustrated above). The graph presentation allows us to apply the steps of the ACO algorithm, including the calculation of the probability equation to orient ants to the best paths, as well as the deposit, the evaporation of the pheromones, etc. Therefore, we add two important attributes to the list of graph edges' attributes presented in the section. 5.3:

- Pheromones: represents the amount of pheromones deposited by ants while passing on that road. This quantity will be changed for each colony by evaporating and updating pheromones, according to specific equations (explained below).
- Desirability: represents the quality of the road. It changes according to the preferences of the user (such as the distance, the travel time, the congestion level, or a combination of those metrics).

The main idea of our work is to find an ordered set of roads that begins from a specific start node to a specific destination node, based on roads and nodes' attributes (travel length, travel time, road speed, congestion level, the amount of pheromones, and the road quality, etc.). To achieve this, we have suggested the following fitness function:

$$MinF, F = \psi * L + \gamma * T + \theta * C \tag{5.3}$$

Where:

- L: represents the path length
- T: represents the travel time
- C: represents the congestion level
- ψ, γ, θ: represents their weights respectively, while : $\psi + \gamma + \theta$ =1

Weights are adjusted according to the defined objective, taking into account the principal parameters: the path length, the travel time, and the congestion level.

Methodology assumptions

The methodology assumptions are presented as follows:

- ☞ The initial pheromone levels on all road segments are equal.
- ☞ Each colony of ants follows the same set of rules and parameters.
- ☞ The algorithm does not consider external factors such as weather conditions and safety that may affect traffic flow.
- ☞ The algorithm has access to traffic information and can update pheromone levels accordingly.
- ☞ The algorithm has access to accurate road network data, including road topology, segment lengths, capacity, maximum speed, and travel time.
- ☞ We assume that there is sufficient computational power and memory available to run the algorithm on the base stations and the fog and edge servers.

5.4.2 Rules and Equations of the improved ant colony system

We assure the following rules:

- ☞ 1^{st} Rule: All ants have the same start node and the same destination node.
- ☞ 2^{nd} Rule: Every ant cannot visit a node in the graph more than once.
- ☞ 3^{rd} Rule: Every ant selects the next node by calculating the probability $P_{ij}^{a}(t)$, which is given by 5.4.

$$P_{ij}^{a}(t) = \begin{cases} \frac{\tau_{ij}^{\alpha}(t) * \eta_{ij}^{\beta}(t)}{\sum_k \tau_{ik}^{\alpha}(t) * \eta_{ik}^{\beta}(t)} * r & ifk \in \text{unvisited nodes} \\ 0 & \text{Otherwise} \end{cases} \tag{5.4}$$

Where:

- τ_{ij}: is the amount of pheromones deposited on the road *ij*.
- η_{ij}: called the desirability or the visibility, or we can call it the heuristic value*ij*.
- α: is the pheromone's exponential parameter.
- β: is the desirability exponential parameter.
- r: is a random number between [0,1] to explore more routes that have not been visited yet and have good fitness values.

☞ 4^{th} Rule: η parameter

The η parameter, or the desirability of each road (edge in the graph), is calculated as follows:

$$\eta_{ij} = \frac{1}{\psi * l_{ij} + \gamma * t_{ij} + \theta * c_{ij}} \tag{5.5}$$

Where:

- l_{ij}: is the road length, in meters.
- t_{ij}: is the travel time required to pass over this road in seconds.
- c_{ij}: the congestion level of this road on time t.
- ψ, γ, θ: represent their weights respectively, where: $\psi + \gamma + \theta$ =1

We can see from 5.5 that the quality of the chosen roads is inversely proportional to the road length, the travel time, and the congestion level of this road on time t (Table. 5.5).

In addition, there are two static types of information (road length, and travel time), and one dynamic type of information that changes in real time, which is the congestion level. Furthermore, taking into consideration all those important elements helps ants suggest suitable solutions that conform to the preferences of the users of our system. Table. 5.5 provides three examples of η parameter computation based on 5.5.

l_{ij}	t_{ij}	$c_{ij}(t)$	ψ, γ, θ	i	j	$\eta_{ij}(t)$
438	52.6	79 %	1/3	6879129586	107171979	0.0061
229	18	48 %	1/3	7501079086	253235813	0.0121
103.4	12.2	43 %	1/3	6879129587	6879129586	0.0258

Table 5.5: examples of η parameter computation.

☞ 5^{th} Rule: Update of pheromones

We provide an enhanced method of updating pheromones on the graph. In each iteration, ants deposit pheromones to trace their chosen paths, and we calculate the ratio q_a between the fitness of the best queen ever f_{bq} (the best queen relative to the queens of all colonies), and the fitness of the current ant f_a. We can deposit pheromones on the route selected by the ant a if and only if the ratio q_a exceeds a certain threshold "*thr*". This strategy is called the *elitism strategy* by (Dorigo and Stützle, 2019). Instead of using the entire set of solutions found by all ants, the elitism strategy allows us to deposit pheromones from ants that have fitness values near the best fitness by the *thr* threshold. For example, we can fix it to 60%, so we will keep only the solutions that are 60% (and more) close to the best solution found until the current iteration. Moreover, the quantity of the pheromones is proportional to the appropriateness of the solution, as follows:

$$q_a = \frac{f_{bq}}{f_a} \tag{5.6}$$

$$\Delta\tau_{ij}^{a} = \begin{cases} q_a & if((q_a \geq thr) \wedge (ij \in \text{a chosen roads})) \\ 0 & if((q_a < thr) \vee (ij \in \text{a chosen roads})) \end{cases} \tag{5.7}$$

Then, the global amount of pheromones that must be deposited on the road ij is calculated as follows:

$$\Delta\tau_{ij} = \sum_{a=1}^{m} \Delta\tau_{ij}^{a} \tag{5.8}$$

Where: m is the total number of ants in one colony.

After calculating the global amount of pheromones on the road ij, we add it to the pheromones attribute of this road:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij} \tag{5.9}$$

We can add more elitism to the previous strategy by depositing more pheromones with the queen of each colony, as follows:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + (\Delta\tau_{ij}^{q} * Q) \tag{5.10}$$

Where q is the queen of the current colony, and Q is a constant multiplied by the quantity of pheromones deposited by the queen, thereby helping our system to converge rapidly to good solutions.

☞ 6^{th} Rule: Evaporation of pheromones

At the end of each iteration, we evaporate a predefined amount of pheromones, $\rho * \tau_{ij}(t)$, for every edge ij in the graph. The evaporation equation is defined as follows:

$$\tau_{ij}(t+1) = (1-\rho) * \tau_{ij}(t), \forall ij \in R \tag{5.11}$$

Where: $\rho \in [0, 1]$ is the evaporation rate.

We do this operation in each iteration to avoid stagnation and rapid convergence to bad solutions and to explore more regions not yet visited (Dorigo and Stützle, 2019).

Flexible Pheromone Deposit-Evaporate Mechanism

In our research, the stochastic problem refers to the dynamic and uncertain nature of urban traffic network conditions, which can change due to various factors such as congestion, accidents, pollution, road works, and other unpredictable events. We employ a flexible pheromone deposit-evaporate method to tackle this stochastic problem, enabling our proposed algorithm to adapt dynamically to changes in the congestion rate of each road and, as a consequence, improve the effectiveness of searching for the optimal routes. The explanation of the flexible pheromone deposit-evaporate mechanism is as follows: during the pheromone update process, we calculate the number of vehicles in each road segment. After that, using equation (2), we calculate the congestion level of that road. Then, if the congestion level is under 50%, we deposit more pheromones on that road segment. On the contrary, we evaporate more pheromones, according to the congestion rate on that road. For instance, if we find that at the edge (i, j), the congestion rate is 70%, we will evaporate 70% of the pheromones from that edge, and on the contrary, if the congestion rate is 20%, we will deposit 80% of the pheromones on that road.

- If [congestion_rate$(i, j) \leq 0.5$], then:
  - ✓ deposit $(i, j,$ (1-congestion_rate(i,j)) $*$ pheromones$(i, j))$.
- Otherwise:
  - ✓ evaporate $(i, j,$ congestion_rate(i,j) $*$ pheromones$(i, j))$.

We explain the mechanism in more detail as follows in the algorithm:

Algorithm 1 Flexible pheromone deposit-evaporate mechanism

```
1: if C(i,j) ≤ 0.5 then
2:     P(i,j) ← P(i,j) + (1 − C(i,j)) × P(i,j)        ▷ Deposit pheromone
3: else
4:     P(i,j) ← P(i,j) − C(i,j) × P(i,j)              ▷ Evaporate pheromone
5: end if
```

Figure 5.5: Flexible pheromone deposit-evaporate mechanism.

Where:

- C(i,j) = congestion_rate(i, j)
- P(i,j) = pheromones(i,j)

☞ 7^{th} Rule: The stopping condition is reaching the maximum number of iterations (or colonies) and proposing the solution with the maximum fitness value, or the route chosen by the best queen ever.

5.4.3 The proposed algorithm-based ACO

Our improved approach-based ACO proceeds through the following steps (Figure 5.6). Furthermore, to clarify the implementation of our proposed algorithm, we present its pseudo-code in Appendix 7.2:

Step 1: Extract the Multi-Lane Directed Graph “G”, and prepare its roads

- Extraction, from the OpenStreetMap OSM, of the map corresponding to the region of the user and construction of a Multi-Lanes Directed Graph (MLDG) G.
- Simplification of G and adjustment of the network topology by eliminating nodes that are not useful to facilitate the search process (Boeing, 2017) (for more information about simplifying and correcting network topologies, please refer to (Boeing, 2017)).
- Computation of attributes for each road r in the graph G. All attributes are extracted from OSM, except for the road traffic parameters that are calculated using

5.1 and 5.2 and the desirability calculated by 5.5. Also, the pheromone attributes are calculated using algorithmic equations.

Step 2: Create a new Colony

- Creation of a new colony of n ants, and for each ant, an *ID* is assigned. The route is calculated using the probability equation 5.4 and the Roulette Wheel method (Lipowski and Lipowska, 2012).
- Calculation of the fitness value using equation 5.3 for each ant in the colony.

Step 3: Search for the queen of the current Colony

- After the construction of the colony, the queen, which is the ant that has found the optimal route compared to other ants, is determined. In other words, the ant that has a higher fitness value assessed by 5.3 is added to the Queens' list.

Step 4: Find the best queen ever

- The best solution is the one found by the best queen or the queen that has the best fitness value compared to others from other colonies.

Step 5: Update Pheromones

- This is the most important step in our algorithm. The information extracted from steps 3 and 4 is used to decide how to update pheromones and trace the trails of ants of the current colony. Calculation of the threshold by equation 6, and according to its value, which trails to trace is determined using equation 9.
- Calculation of the threshold is done by equation 5.6, and according to its value, we determine which ants to trace their trails using equation 5.9.
- More pheromones can be added to trace the path constructed by the best queen ever and to orient the next colonies to the best possibilities in the search space using equation 5.10.

Step 6: Evaporate Pheromones

- Evaporation of a certain quantity of pheromones, using equation 5.11 for all roads of the graph, to ensure more exploration of the search space at the end of each iteration.
- Go to Step 3 until reaching the maximum number of iterations (colonies).

Step 7: Repeat the same process for all users

- Go to Step 1 until finish all users' requests.

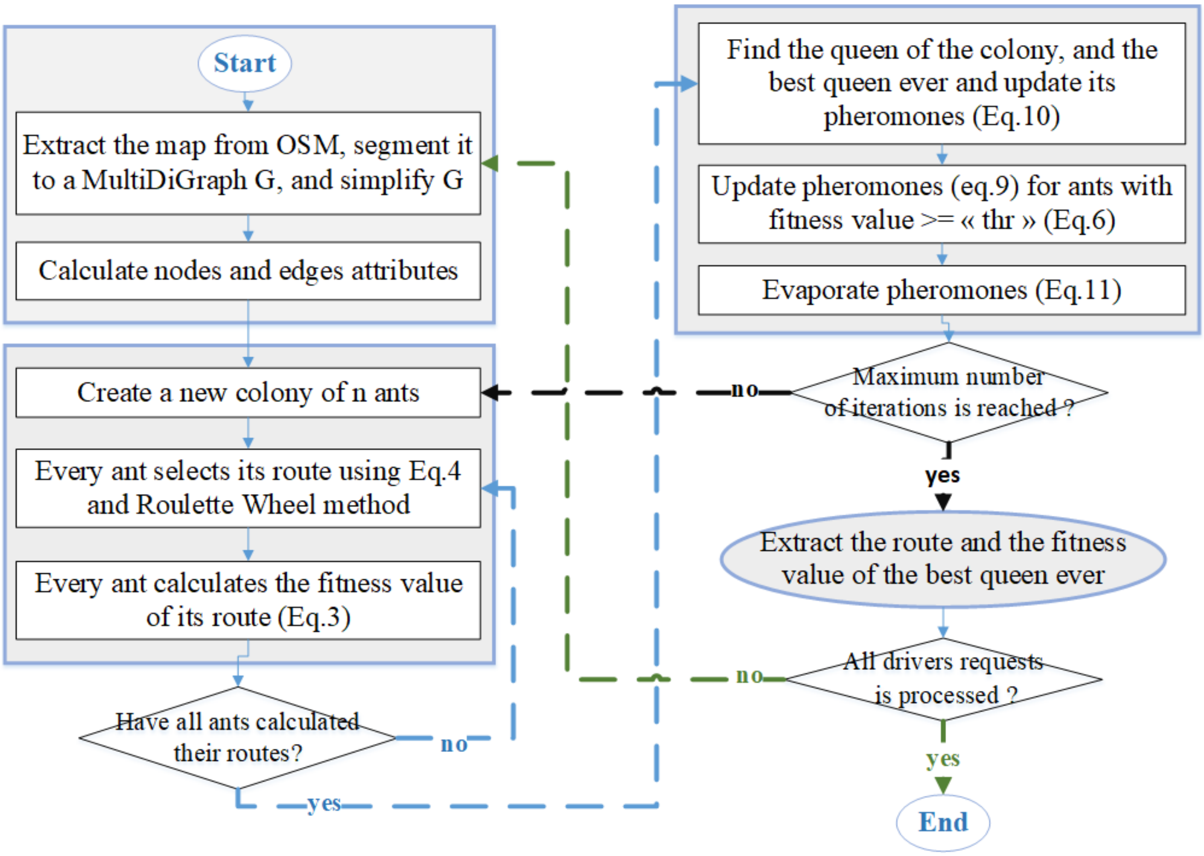

Figure 5.6: Flowchart of the proposed Algorithm.

5.5 Conclusion

In this chapter, improvements to the Ant Colony Algorithm are proposed to search for optimal routes from a start position to the desired destination by considering travel length, travel time, and congestion level as the principal factors in the route selection process. Additionally, incorporating a random search method, elitism strategies, and dynamic pheromone updating rules in order to take into account the dynamic changes in road traffic conditions and make the proposed approach more relevant and effective. The proposed algorithm, which integrates these additional elements into the ACO algorithm, is a novel approach that advances the state of the art in solving TRP in road networks and has the potential to advance the field of route optimization.

Chapter 6

Evaluation and Results

Experience without theory is blind, but theory without experience is mere intellectual play.

– Immanuel Kant

6.1 Introduction

In the previous chapter, we present the improved Ant Colony Algorithm which is applied to calculate the optimal routes in an urban road network by adopting an elitism strategy, a random search approach, and a Flexible Pheromone Deposit-Evaporate Mechanism, In order to make a trade-off between route length, travel time, and congestion level.

Experimental tests show that the routes found using the proposed algorithm improved the quality of the results by 30% in comparison with the ACO algorithm. In addition, we maintain a level of accuracy between 0.9 and 0.95. Therefore, the overall cost of the found solutions decreased from 67 to 40. In addition, the experimental results demonstrate that our improved algorithm outperforms not only the original ACO algorithm but also popular meta-heuristic algorithms such as the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) in terms of reducing travel costs and improving overall fitness value.

In this chapter, we provide the parameters used to simulate the proposed algorithm. After that, we describe the different scenarios, and report the obtained results that demonstrate the effectiveness of the proposed algorithm, and the comparison with other meta-heuristic algorithms.

6.2 The parameters of the proposed algorithm

Before evaluating the performance of our proposed algorithm, we properly evaluate the right set of parameters' values. Therefore, after the execution of several scenarios and tests, we decided to adopt the following parameters' values:

Number of ants	**Number of colonies**	ρ	α, β	ψ, γ, θ	**Q**
30	200-500-1000	0.5	1	1/3	2

Table 6.2: Parameters of the proposed algorithm.

We vary the number of colonies between 200, 500, and 1000 to show the impact of increasing the number of iterations on the goodness of the results and the convergence speed. In addition, we choose a medium number of ants, which is 30, to make a balance between the calculation cost and the exploration process. Besides, we adopt 50% for the evaporation rate in order to avoid the big influence of bad results on the decision-making of the next colonies. Moreover, we select the same value (1) for α and β parameters to give the same importance to the pheromones' intensity and the quality of each road. We also maintain the same value for ψ, γ, θ, because, according to (Pang et al., 2002), making a ”trade-off” between routes' metrics is highly preferable for the majority of drivers. Finally, we choose 2 as the value of Q, to double the number of pheromones deposited by the best queen ever.

To implement the proposed algorithm, we have used the OSMnx Python Library (Boeing, 2017), to extract the map requested by the user, segment it, and transform it into a multi-lane directed graph G. Finally, we simplify the graph G by excluding nodes that are redundant and not useful to do calculations with only effective nodes. For example, to test our script using different scenarios, we have used the graph presented in Figure 5.4-a, which has (**43246** edges interconnecting **31647** nodes) before graph simplification and (**14742** roads interconnecting **7976** nodes) after simplifying the graph. So, (**28504** edges/**23671** nodes) are eliminated from the search process, which helps to decrease the complexity of the algorithm and speed up the program execution. The result of the simplification of the road network graph of the district of Algiros-Valencia-Spain before simplification and after simplification is presented in figures 6.1 and 6.2.

We use Valencia City as a case study to test our proposed algorithm, even though this methodology is quite general and could be applied to other regions and cities as well.

6.3 Experimental tests

In this sub-section, we describe the different tests and the obtained results.

1. (With/Without) Elitism Strategy (EL 0%, EL 50%, EL 100%): This strategy facil-

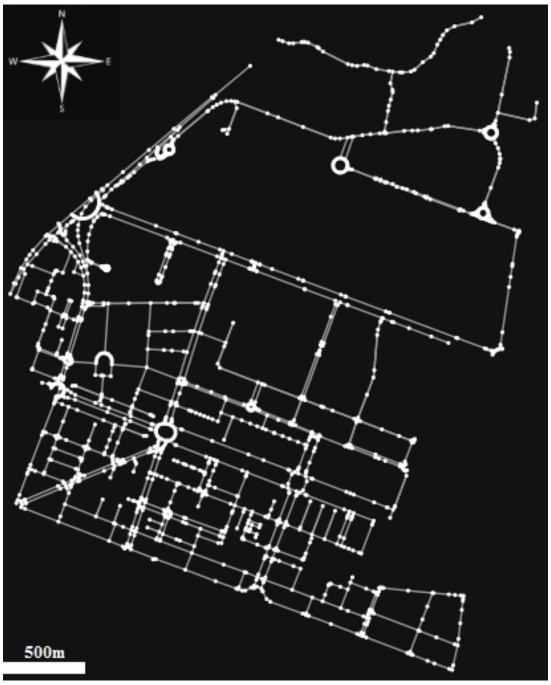

Figure 6.1: Road network of Algiros-Valencia-Spain before graph simplification

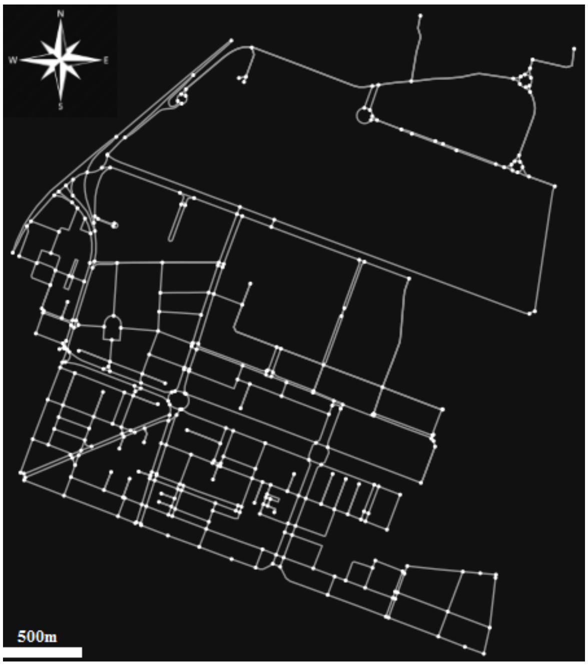

Figure 6.2: Road network of Algiros-Valencia-Spain after graph simplification

itates the convergence of the algorithm to the best results because only pheromones of the best solutions according to a certain threshold (EL 50% to EL 100%) are deposited. In addition to the elitism of the Best Queen Ever, its pheromones will be added in each iteration to improve the quality of the results of the next colonies.

2. (With/Without) Random Strategy: The elitism strategy can cause premature convergence in the first iterations and fall into a local optimum early. To fix this problem, we added a random search strategy. This strategy enables ants to discover new regions and explore nodes and edges that have not been visited yet. In addition, it avoids falling into bad local optimum solutions. To apply and test this method, we consider two options:

    - Random 100%: the total number of ants that choose their routes following the probability given by 5.4, divided by a random number between [0, 1].
    - Random 50%: the first half of the number of ants uses the probability given by 5.4, without the random number, and the second half of the number of ants chooses the option Random 100%.

- Without Random Strategy means in 5.4 we assume that, $\{r = 1, \forall\ ID_a \leq$ Colony size$\}$

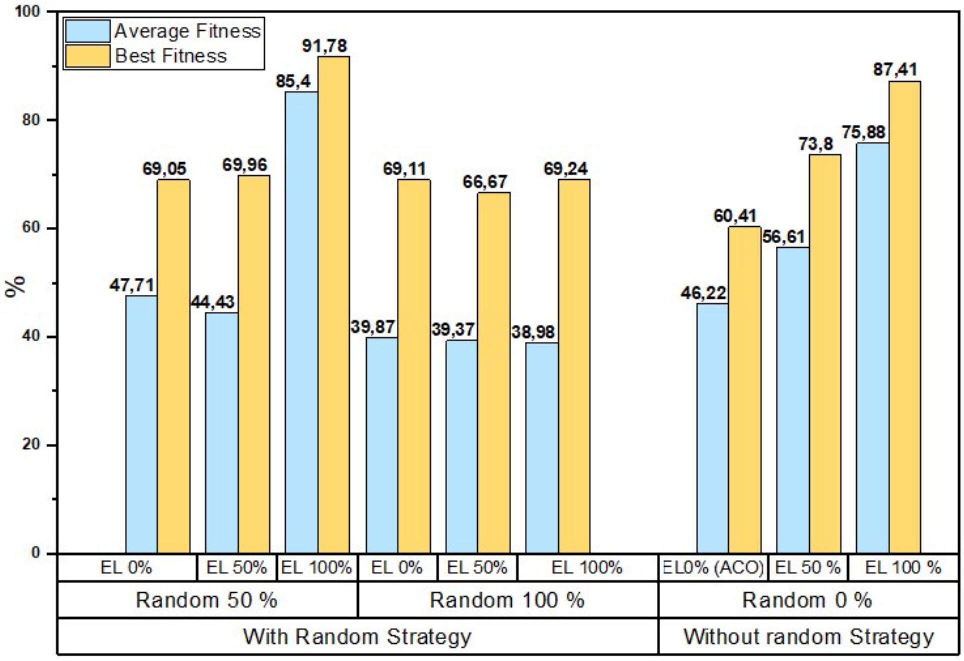

Figure 6.3: Results of testing the proposed algorithm using different scenarios.

After testing the previous scenarios more than 20 times, with the source node s and its coordinates (x_1, y_1) = (-0.3889, 39.5368), and the destination node d and its coordinates (x_2, y_2) = (-0.2768, 39.277), we report the obtained results from the improved ACO algorithm in figure. 6.3. In addition, table. 6.4 and figure. 6.4 summarize some details of the results presented in the figure. 6.3:

Algorithm	ACO			The proposed algorithm		
Iterations	200	500	1000	200	500	1000
Length (km)	53	56	53	38	36	35
Travel time	74min	79min	75min	53min	50min	41min
Average Speed (km/h)	41	41	41	43	44	46
Average Density (%)	91	79	74	53	50	44
Number of nodes	518	494	574	285	266	221
Cost	73	71	67	48	45	40

Table 6.4: The comparative table between the costs of ACO and the proposed algorithm

The cost of the algorithms is calculated as follows : $Cost = \psi * L + \gamma * T + \theta * C$
Where: $\psi = \gamma = \theta = 1/3$

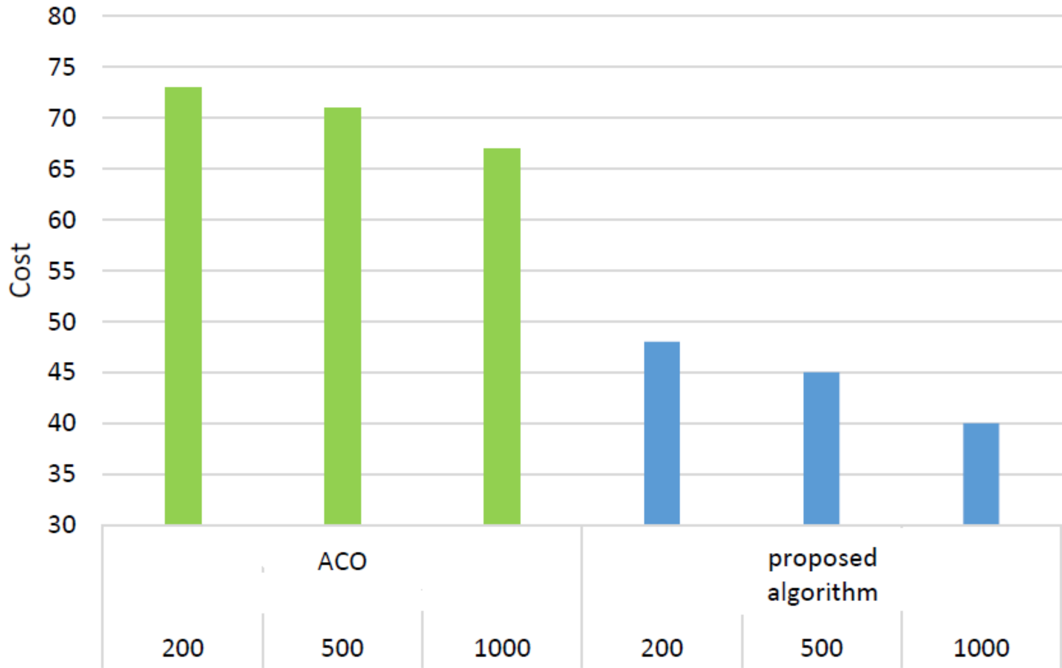

Figure 6.4: The comparative histogram between the costs of ACO and the proposed algorithm

6.4 Performance Evaluation

The qualitative and quantitative evaluation of our algorithm can be measured by calculating several performance metrics; the most popular are ”precision” and ”recall”. These measures are widely used in the field of information retrieval and are given as follows:

- The precision refers to the accuracy of the results returned by the system. The higher the precision value, the better the quality of the results.

- The recall measures the efficiency of the system; the higher its value, the more the results of the system cover most of the relevant results.

- To properly calculate the performance of algorithms, we often combine these two measures into a single measure called the "$F_{measure}$", which is given by:

$$F_{measure} = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{6.1}$$

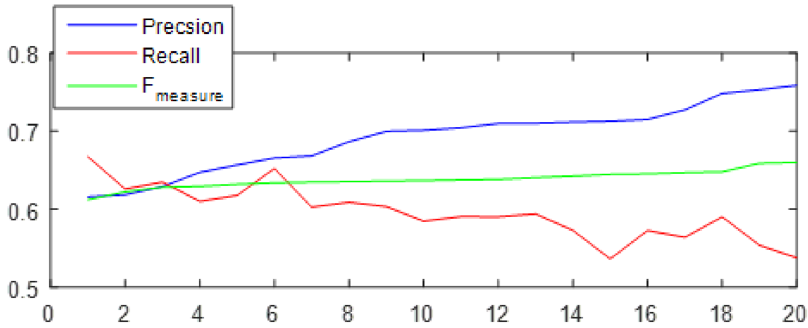

Figure 6.5: Performance of Precision, Recall, and F-measure under different route search queries using ACO.

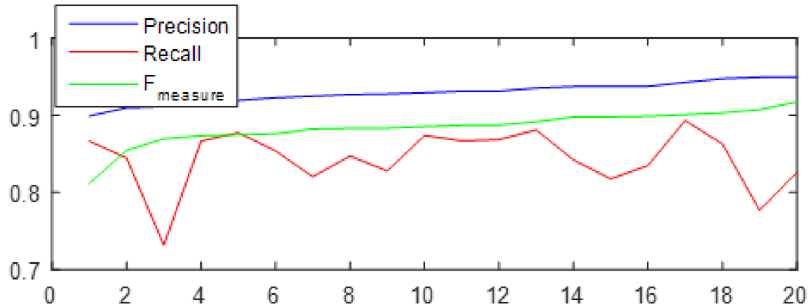

Figure 6.6: Performance of Precision, Recall, and F-measure under different route search queries using our proposed approach.

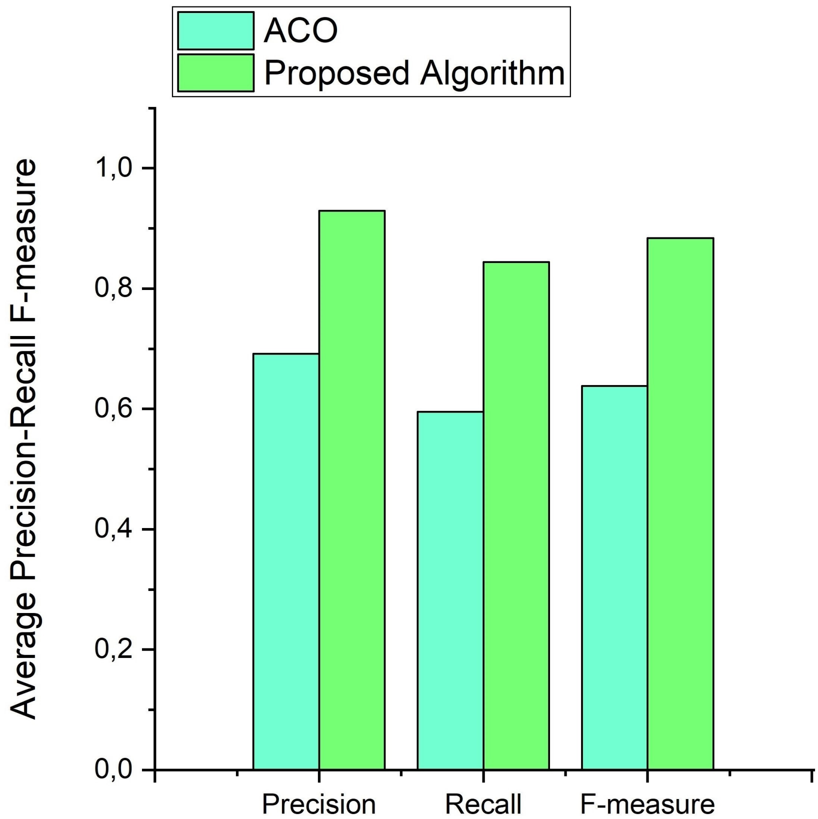

Figure 6.7: Comparative histogram between the average Precision, Recall, and F-measure of the proposed approach and the ACO.

In order to measure the performance metrics of our algorithm, we executed 20 different route search queries in the city of Valencia (different sources, different destinations) using the same simulation parameters, presented in Table. 6.2.

For each search query, we launched several tests (more than 20 tests). Therefore, we were able to extract the following curves that represent the three performance metrics and compare the precision and efficiency of our improved algorithm to some state-of-the-art works that use the ACO to search for optimal routes, like (Mirjalili et al., 2020; Le and Peechatt, 2019; Liu et al., 2017; Srivastava et al., 2015), to just cite a few research works.

We can see from these comparative curves in Figure. 6.5 and Figure. 6.6, and from the comparative histogram 6.7 that we achieved the highest precision and F-measure values, which reflect the precision and efficiency of our algorithm. It is clear from both figures that the precision of ACO does not exceed 80%, while our approach can reach 95%. Similarly, we can observe the same outcome concerning the F-measure metric, which surpasses 90% in our algorithm and does not exceed 70% in the case of using the ACO algorithm to search for optimal paths in an urban road network.

In addition, the F-measure is a harmonic factor between the recall and precision metrics, which reflects the efficiency of the proposed algorithm. Again, we can observe from the curves of our proposed algorithm that both recall and F-measure have practically the same variations. Finally, we conclude that the results obtained by our improved algorithm are very encouraging and could be extended and generalized to larger road networks, like those of continental size. In addition, it can be used in Internet of Vehicles systems to assure more rapidity in the treatment of search queries, which is considered the next step of this research work. Therefore, the scalability ensured by the fog and edge servers in an IoV system (Nazir et al., 2020) allows us to test the novel ACO using real data from the road traffic network.

6.5 Results and Discussion

Figure. 6.8-b represents the best path found by the ACO and the proposed algorithm using 1000 colonies of ants each. From the plotted paths, it is evident that the route suggested by our proposed algorithm is shorter compared to the route found by the ACO. In addition to the corresponding convergence curves in Figure. 6.9 with 1000 iterations, Figure. 6.10 with 500 iterations, and Figure. 6.11 with 200 iterations, all of those curves confirm the effectiveness of the improved algorithm in comparison to the ACO algorithm.

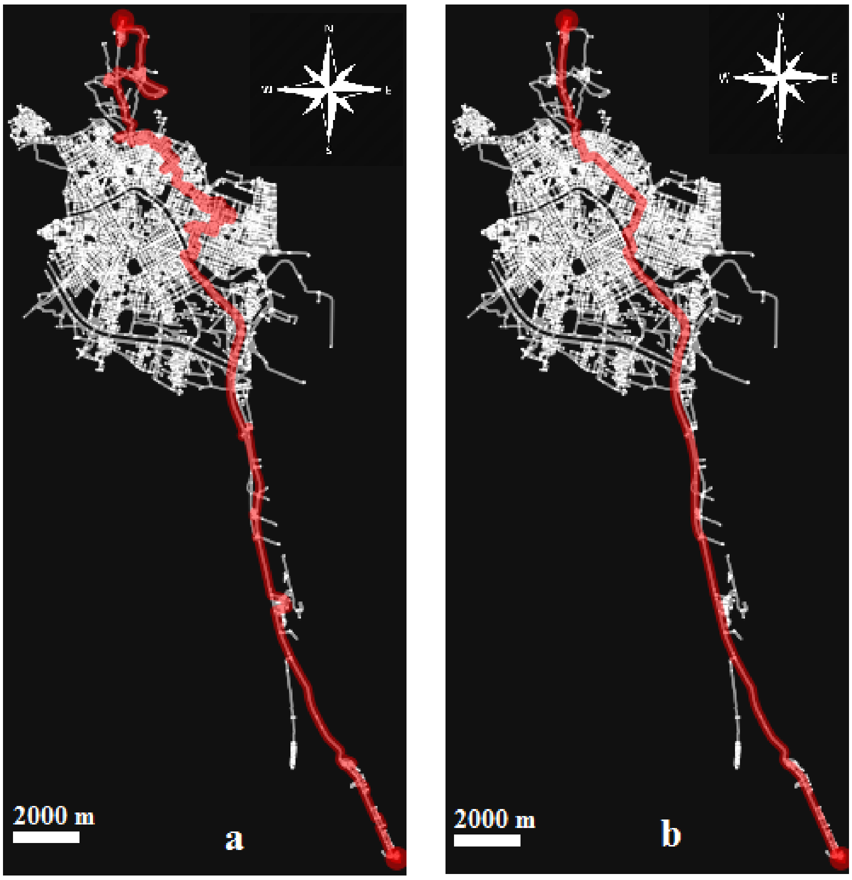

Figure 6.8: Plotted Best Routes after 1000 iterations Found by a- ACO / b- The proposed algorithm.

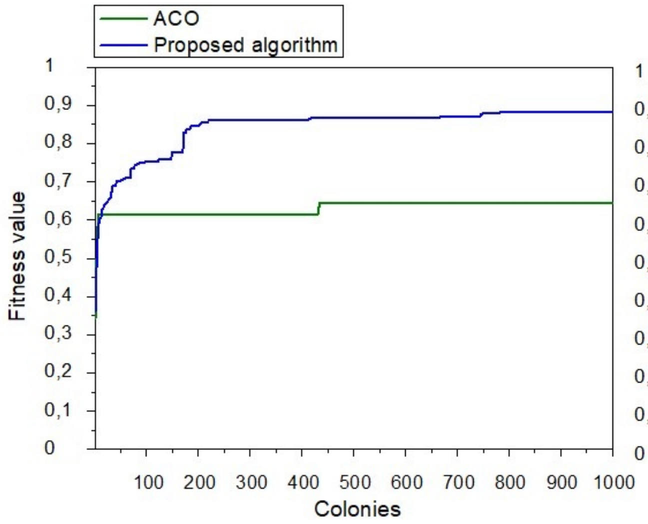

Figure 6.9: Convergence Curve of ACO vs the proposed algorithm for 1000 colonies.

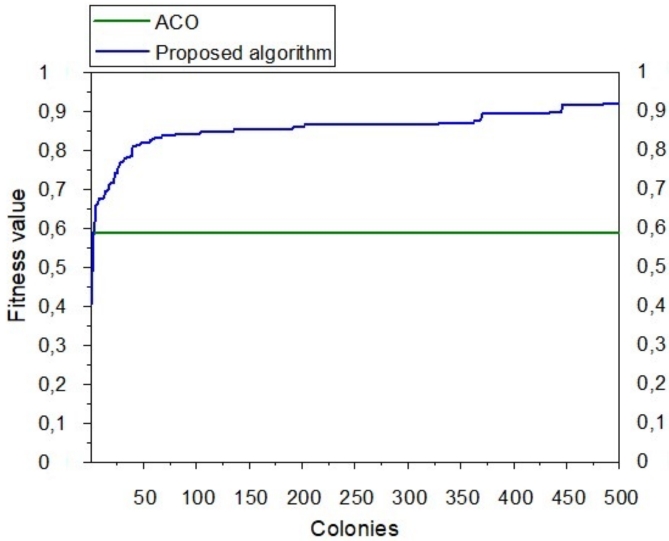

Figure 6.10: Convergence Curve of ACO vs the proposed algorithm for 500 colonies.

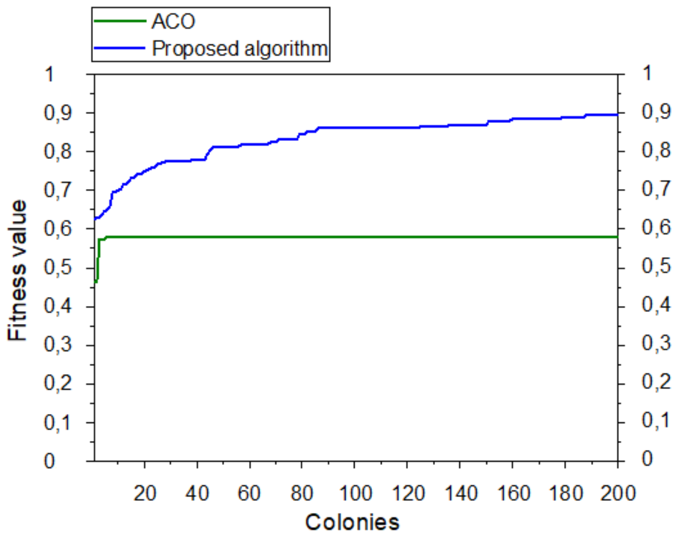

Figure 6.11: Convergence Curve of ACO vs the proposed algorithm for 200 colonies.

From the experimental results in Figure. 6.3, it is clear that the proposed algorithm has the best fitness value. An improvement from 60.41% which is the degree of optimal path approximation found by ACO, to 91.78% which is the degree of optimal path approximation obtained by our proposal, is observed. So, our proposed algorithm improves the optimality of the best solution by 31%, and the average solution of all ants by 39% (from 46.22% which is the average result found by the ACO, to 85.4%, which is the average fitness found by our proposed algorithm).

This improvement is caused by the integration of the elitism strategy and the random search to the ACO. In other words, we get benefits from the two strategies, in which, we avoid tracing trails of bad paths (elitism strategy). At the same time, we offer some randomized results to avoid converging too quickly to the wrong regions and exploring more possibilities by exploiting the random technique, as the elitism strategy can offer optimal solutions, but the opposite is also possible. In other words, the elitism strategy can cause premature convergence in the first iterations and fall into a local optimum early, like in figures 6.9, 6.10, 6.11 where the ACO algorithm converges too quickly from the first colonies in figures 6.10, and 6.11, and from colony number 450 in figure 6.9. To fix this problem, we added a random search strategy to ensure more exploration of other not-visited zones in the network.

In addition, we can observe from the experimental results in Figure.6.3, that the random 100% has given poor results in terms of average and best fitness values compared to the random 50%. This remark is explained by the fact that, if the random 100% technique does not get good paths and the operation of updating pheromones does not influence the choice of the ants in the colony, we will always have poor results. On the other side, if we allow 50% of the ants to choose their routes randomly, the other half of the ants will choose their routes according to the probability given by 5.4. So, according to pheromone trails and the desirability of the roads, we can make a balance between random results and the results given by calculating the ACO equations.

Moreover, if we add more elitism to the random 50% technique, we will get the best fitness value (Figure. 6.3) compared to the other scenarios. Indeed, the elitism strategy will trace pheromone trails of good paths only, conforming to a certain threshold (100% has the best fitness value). Accordingly, the scenario [random 50% with elitism 100%] has the best fitness value and the best average fitness value. So, we adopt it as the best scenario to execute the novel ACO algorithm to search for optimal paths in traffic networks, taking into consideration the travel length, travel time, and congestion level of the roads.

It is important to note that the majority of methods that calculate the optimal path in road networks use only the ”distance” as the principal factor of the research (Mirjalili et al., 2020; Le and Peechatt, 2019; Liu et al., 2017; Srivastava et al., 2015). However, in our work, we use three important metrics to search for the optimal path in a road network: the length of the road, the time required to pass over this road, and the density of traffic on each road. Moreover, in a real-time application, and by using our improved algorithm to search for optimal paths in a road network, the vehicle driver can choose the requested metric by modifying the weight of each one (travel length, travel time, congestion level). However, in our numerical tests, we give the same value to the metric's weights (Table. 6.4) in order to make a trade-off between the short route, fast route, and optimal route in terms of avoiding congestion.

Finally, according to Table. 6.4 and Figure. 6.4, we can clearly conclude that our proposed algorithm outperforms the state-of-the-art works that use the ACO algorithm to find optimal paths, such as (Mirjalili et al., 2020; Le and Peechatt, 2019; Liu et al., 2017; Srivastava et al., 2015), in terms of minimizing the cost of the found solutions. In this manuscript, we focused on improving some properties of the ACO algorithm to get more sophisticated results. Furthermore, ants in each colony select paths according to the road length, the time required to pass over each road, and the degree of congestion on each road to avoid congested roads. So, the result is minimizing the length of the selected route from 53 km while using the ACO algorithm to 35 km while using the novel ACO (Table. 6.4 and Figure. 6.4). Also, the travel time passes from 1 hour, 15 minutes to 41 minutes, and the average density of the route found by the ACO is 74%, which is minimized to 44 % by our proposed algorithm. In conclusion, we have improved the total cost of traveling by passing from 67 to 40 (Table. 6.4 and Figure. 6.4), i.e., from 60% to 90% near the exact solution (Figure. 6.3).

6.6 Comparative Analysis of our Improved Algorithm Versus ACO-GA-PSO

We agree that comparative analysis is an important aspect of our research. Therefore, in order to significantly prove the efficiency of the proposed algorithm, we conduct in-depth computational experiments to evaluate the performance of the proposed approach and compare it with relevant meta-heuristics, namely Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). To do so, we measured the best and average fitness values of each approach over 20 runs and obtained the histogram 6.12 that presents the average fitness of each method over 200–500–1000 colonies/iterations/generations. In addition to the comparative convergence curves of ACO-PSO-GA against the proposed algorithm for 200 colonies, iterations, and generations are presented in figure 6.13. Furthermore, we ensure that the comparison is fair and comprehensive by conducting it using identical implementation conditions: the same road network and keeping the parameters' values, such as colonies/iterations/generations, number of ants, number of particles, and number of chromosomes. By doing so, we aim to provide a clear and meaningful comparison study between the performance of our proposed approach against ACO, GA, and PSO.

The results presented in the histogram 6.12 show that the proposed approach outperformed ACO, PSO, and GA for 200-500-1000 colonies/iterations/generations with an average fitness value of:

- The proposed approach : 66%, 75%, and 81% respectively, compared to:
- ACO: 52%, 56%, 61% respectively.
- PSO: 42%, 47%, 50% respectively.
- GA: 40%, 42%, 44% respectively.

The comparative curves of the proposed approach against ACO, PSO, and GA are shown in Figure 6.13. It is clear that the convergence curves highlight the superiority of the proposed approach. These results are justified by the following reasons:

- The distributed nature of the ACO algorithm and its scalability to large road networks, due to its decentralized search mechanism, make our proposed approach more suitable for searching for optimal paths in a road network. However, PSO and GA may face challenges in scalability due to their global information search processes, which may not scale well to large road networks.
- The adaptability to changes in traffic conditions in real-time. This flexibility is assured by the fact that the ACO algorithm is a constructive algorithm that relies on local information. Therefore, it is able to change the chosen next node according to the most up-to-date traffic information. In addition to the ”Flexible Pheromone Deposit-Evaporate Mechanism” that we add in our proposed algorithm. On the other hand, PSO and GA typically operate based on global information and may require more computational search processes to adapt to such changes and find near-optimal paths.
- Past experience-based approach, by using pheromone trails and the elitism strategy, to guide the search process towards promising results. Also, the elitism strategy helps to converge on good paths more efficiently compared to ACO, GA, and PSO. Especially in PSO and GA, maintaining such memory-based information can be more challenging and may require additional mechanisms.

In addition to our experimental comparative results with PSO and GA, a recent research work (Di Caprio et al., 2022) presents a fuzzy-based ACO algorithm to solve the shortest path problem with fuzzy weights. Authors in (Di Caprio et al., 2022) have made a comparative study between the proposed algorithm-based ACO and the ABC, PSO, and GA in terms of running time and convergence time. The results show that the ACO-based algorithm performs better than the other algorithms, particularly when the complexity of the graph increases.

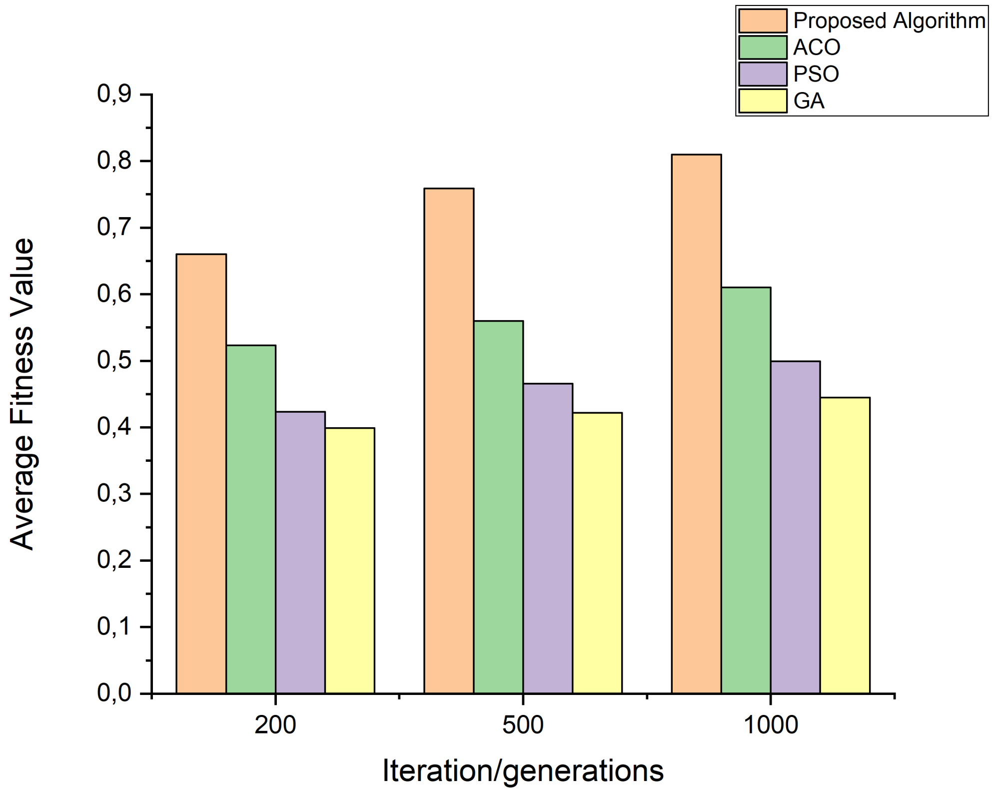

Figure 6.12: Comparative histogram between the average fitness values of the proposed algorithm, ACO, PSO, and GA.

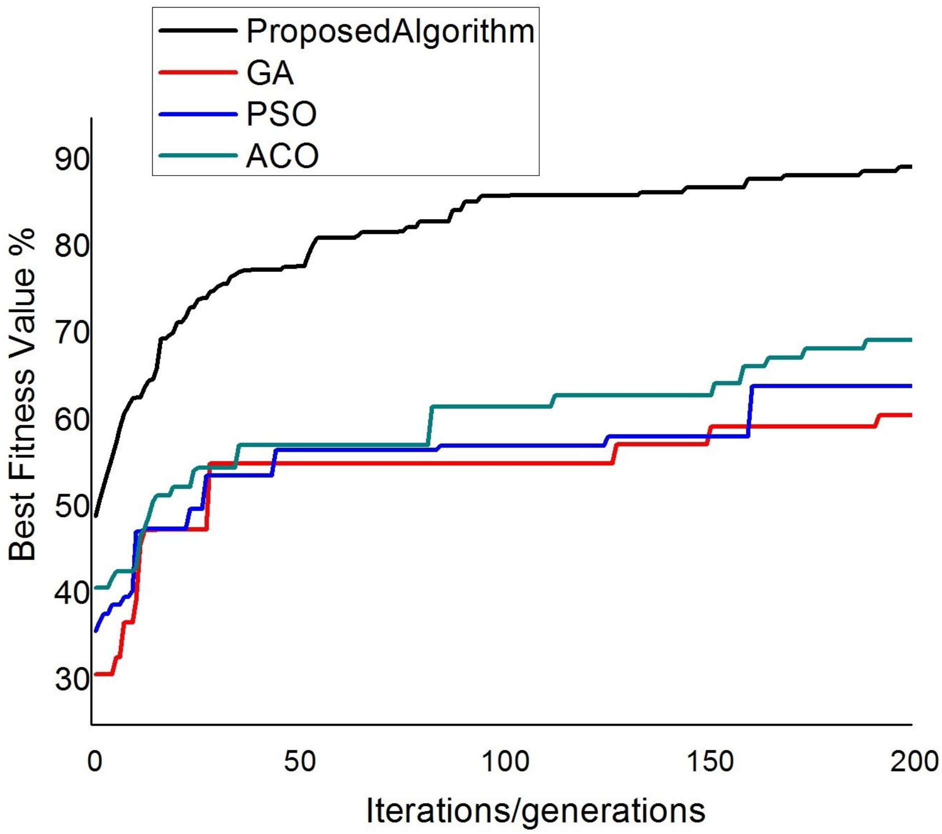

Figure 6.13: Comparative convergence Curves of ACO-PSO-GA vs the proposed algorithm for 200 colonies/iterations/generations.

6.7 Conclusion

In order to conclude this chapter, and based on the experimental tests, our proposed algorithm outperforms the state-of-the-art works that solve the TRP problem using the ACO in terms of minimizing the cost of the found solutions. The cost of traveling is improved from 67 to 40 (Table. 6.4) and Figure. 6.4), i.e., from 60% to 90% near the exact solution (Figure. 6.3). Similarly, the experimental results prove the superiority of the proposed method in terms of average fitness values and best fitness values under the same network conditions compared to PSO and GA, which are reliable meta-heuristics used by researchers in different fields.

Chapter 7

Conclusion and perspectives

I have seen people spend days, if not months, researching and gathering data, but only at the end did they finally figure out what they were really looking for; then they have to redo a lot of stuff. If after a day or so you force yourself to put together your tentative conclusions, then you'll have guidance for the rest of your research.

– Robert Pozen

7.1 General Conclusion

While driving, vehicle drivers require information about the most suitable path in terms of time, minimum distance, and less congested zones to arrive at their destination. Therefore, the use of information technology for transportation is primordial.

In the current thesis, we conduct an overview of the intelligent transportation systems and the impact of their integration in the field of transport. Then, we offer some insights about vehicle networks, especially VANETS and the Internet of Vehicles, and their incorporation in intelligent transportation systems. After that, a brief overview of the fog/edge computing paradigms is provided, detailing their potential in supporting advanced transportation solutions.

Furthermore, we propose layered architecture-based IoV and Fog/Edge computing concepts to efficiently manage urban traffic systems. Overall, the proposed architecture aims to improve coordination and communication among the road network entities, leading to significantly ameliorating urban transportation networks.

In the second part of this thesis, increased effectiveness is achieved by using a well-known meta-heuristic to solve the traffic routing problem in a road network. Therefore, we make some improvements to the original Ant Colony Optimization (ACO) algorithm in order to find the optimal route in urban areas. The improved algorithm includes elitism strategies to orient the next ant colonies to select the best paths. However, the elitism strategy can cause premature convergence in the first iterations and fall into a local optimum early. To fix this problem, we added a random search strategy to ensure more exploration of other unexplored roads in the network. In addition, we propose a flexible deposit-evaporate mechanism to further enhance the performance of the found solution. In addition, to make a trade-off between short routes, fast routes, and less congested routes, we give the same value to the metrics' weights (time, distance, and congestion level). Furthermore, we have conducted extensive experimental tests and demonstrated that our proposed algorithm outperforms existing state-of-the-art works (chapter VI).

7.1.1 Practical implications

This research work is of great civil, social, environmental, and technical importance across various functional domains and research areas in both wireless and wired networks (see figure 7.1). In the field of telecommunications, the algorithm can be applied to efficiently route information packets, improving the performance and reliability of communication networks. In intelligent transportation systems (ITS), the algorithm can be used for vehicle navigation, reducing travel time and fuel consumption and leading to decreased pollution levels in cities, especially in sensitive sectors such as civil protection, fire trucks, ambulances, and other emergency and security services. Additionally, the algorithm can be applied in the fields of trading and shopping, where efficient routing can optimize logistics and transportation operations, leading to cost savings and improved supply chain management. These social, economic, and environmental benefits highlight the practical value and real-world impact of the proposed algorithm.

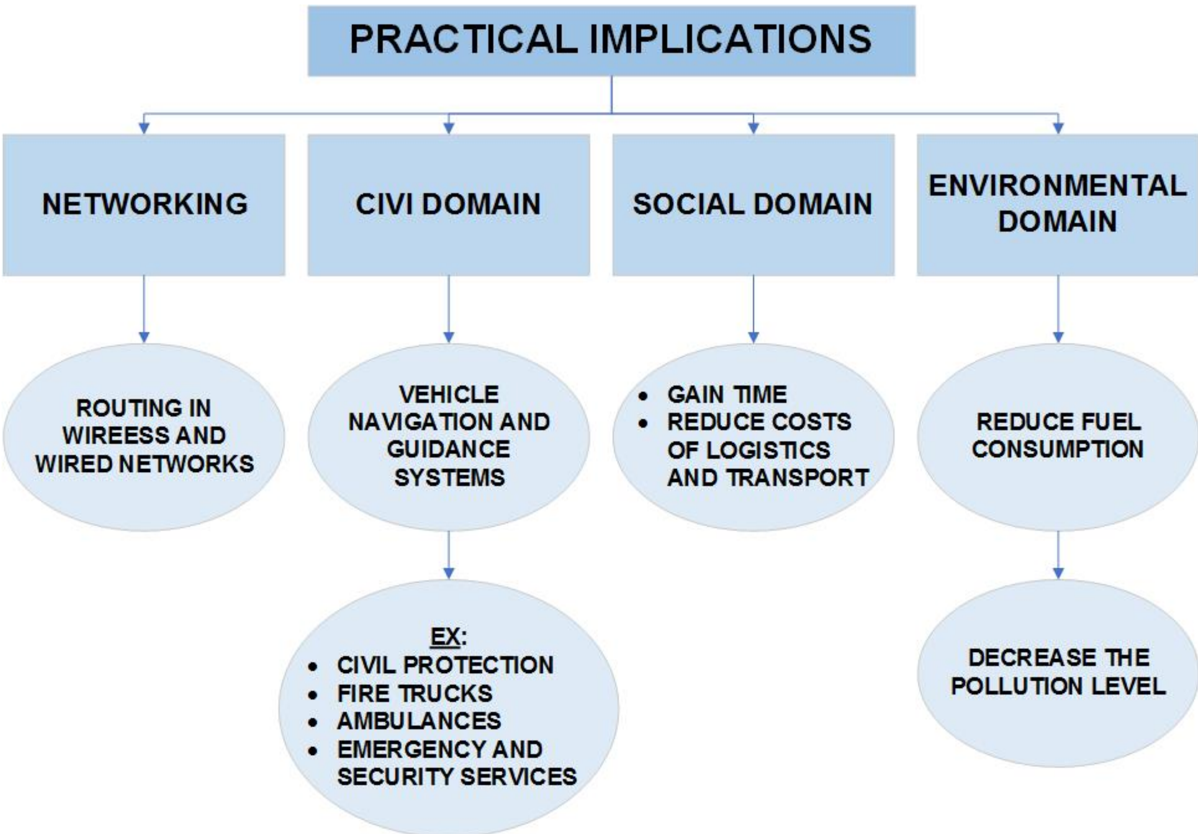

Figure 7.1: Practical Implications of the proposed approach.

7.1.2 Challenges

During the implementation of our proposed algorithm, we faced several obstacles while coding and extracting results. Firstly, we have confronted the problem of algorithm convergence and infinite cycles as we work with a probabilistic approach and a random strategy. After several tests, we fixed this problem, and the algorithm started to converge in all cases. On the other hand, we were opposed to the problem of hardware due to the big workload executed on an ordinary machine like the used PC (DELL Intel(R) Core(TM) i3-3217U CPU @ 1.80 GHz 1.80 GHz - 8Go RAM / Windows8.1-64 bits) to develop the algorithm and extract the results. Therefore, it will be more sufficient to use higher layers and new technologies of the Internet of Vehicles, like the Fog/Edge servers, and parallel computing (Nazir et al., 2020) with virtual machines to assure the scalability and generality of the proposed approach, which is considered the next step of the current research work. Finally, we faced the problem of using real traffic data from Valencia in our tests and scenarios. The data that we have is in raw format and needs important pre-processing operations before being able to use it.

7.2 Limitations and Future Works

Finally, although our proposed algorithm shows promising results, there are certain limitations that need to be acknowledged.

One limitation is that the proposed architecture-based IoV and Fog/Edge computing is global; we work to detail it more and more, using IoT and IoV technologies, in addition to the use of Artificial Intelligence (AI) tools to detect patterns and predict traffic congestion and problems in the urban traffic flow based on real-time data. Furthermore, future work could be the implementation of the proposed architecture in the near future; once successfully implemented, the reduction of damages, collisions, congestion, and pollution in the urban road traffic will certainly benefit the quality of people's lives in urban areas.

Another limitation is that the proposed algorithm currently focuses on optimizing travel length, travel time, and congestion level as the main criteria for path selection. However, there are other factors such as safety, road conditions, weather states, and user preferences that may also affect the optimal path choice. Future work could consider integrating these additional factors into the algorithm to make it more comprehensive and adaptable to different real-world scenarios.

Another limitation is that the proposed algorithm assumes homogeneous colonies of ants, where each ant follows the same set of rules and parameters. However, in real-world traffic scenarios, drivers may have different driving behaviors, preferences, and choices. Future work could incorporate heterogeneity in the colonies of ants to provide more realistic results and better reflect the diversity of human driving behavior.

The last perspective of this research work is to extend it to parallel processing and distributed computing in base stations, fog/edge servers, and cloud servers in an Internet of Vehicles network to guarantee the scalability of the solution in real-world road networks and increase the efficiency of the algorithm.

Despite these limitations, our proposed approach has shown promising results that demonstrate its superiority over the ACO, GA, and PSO algorithms in terms of finding optimal paths in traffic networks. Further research and improvements could enhance its performance and applicability in real-world traffic management scenarios.

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Annexes

Annexe A

Pseudo-code for the Proposed Algorithm

The proposed algorithm

Improved Ant Colony Algorithm to find optimal routes:

Declarations

```
TYPE node =  ID : integer
             X : float
             Y : float
             Visited : boolean
             END
TYPE road =  ID : integer
             start node : node
             end node : node
             name : string
             lanes : integer
             length : real
             traveltime : real
             speed_kph : real
             capacity : real
             C : real %congestionlevel%
             τ : real %pheromones%
             η: real %desirability%
             END
TYPE ant =   ID : integer
             Route : table[..] of node
             Fitness : float
             END
TYPE Multi-lanes Directed Graph = Intersections : table[nbNodes] of node
                                  roads : table[nbEdges] of road
                                  END
TYPE nodeSuccessor = nextNode : node
                     probability : real
                     END
```

Constants: $\Psi = ⅓$, $\gamma = ⅓$, $\theta = ⅓$, $Q = 2$, nbAnts = 30, nbColonies = 100, $\rho = 0.5$, Pr = 0.5, AvgLenV= 4, DistV = 2, $tau_{min} = 0.001$, $\alpha = 1, \beta = 1$

Variables:

u, i, j, l_r, nbUsers, nbNodes, nbEdges, nbV : integer
x1, x2, y1, y2, tau, eta, P, f_a, bestFitness, f_{bq}, F_o : real
rand : real ∈ [0,1]
place : string
G : Multi-lanes Directed Graph
sourceNode, destinationNode, n, currentNode, nextNode : node
r : road
queen, bestQueen : ant
colony : table[nbAnts] of ant
queens : table[nbColonies] of ant
S : table[..] of node
probabilities : table[..] of real
nextNodeList : table[..] of nodeSuccessor

Main algorithm

```
Begin
read('Please, enter the number of users :', nbUsers)
For u ranging from 1 to nbUsers do
    read('Please, enter the research zone as (Algiros, Valencia, Spain) :', place)
    map ← OSM('place')          %Extracting from OpenStreetMap OSM the map corresponding to 'place'%
    G ← Segmenting(map)          %Segmenting the map to a Multi-lanes Directed Graph G%
    G ← Simplified(G)            % Simplifying G by eliminating unuseful nodes%
    read('Enter the coordinates of your current position:', x1, y1)
    read('Enter the coordinates of your desired destination:', x2, y2)
    sourceNode ← nearestNode(x1, y1)
    destinationNode ← nearestNode(x2, y2)
    For each road r in G         %Calculating and adding attributes of each road r to the graph G%
    %all attributes are extracted from OSM except capacity of the road, congestionlevel, pheromones, desirability%
        G.r.capacity ← (G.r.length * G.r.lanes) / (AvgLenV + DistV)
        G.r.C ← (nbV / G.r.capacity) * 100
        G.r.τ ← tau_min                 %To avoid zero and negative values%
        G.r.η ←1/(Ψ * G.r.length + γ * G.r.traveltime + θ * G.r.congestionlevel)
    F
    For i ranging from 1 to nbColonies do
        colony ← newColony(G, nbAnts, α, β, sourceNode, destinationNode)
        queen ← findQueen(colony)
        queens[i] ← queen
        bestQueen ← findBestQueen(queens[nbColonies])
        G ← updatePheromones(G, colony, bestQueen, Pr, Q)
        G ← evaporatePheromones(G, ρ, tau_min)
        write( 'Fitness of the queen',i,'is :', queen.Fitness)
    write('Fitness of the best queen ever is :', bestQueen.Fitness)
    write('The optimal route by taking into consideration length, travel time and
    the congestion level of the roads, is :', bestQueen.Route)
    Draw(bestQueen.Route, G)
End
```

FONCTION newColony(G, nbAnts, α, β, sourceNode, destinationNode**) : table[nbAnts] of ant**

```
Begin
For each node n in G      G.n.Visited ← False
G.sourceNode.Visited ← True
For each ant in colony do
    ant.Route[1] ← sourceNode
    currentNode ← sourceNode
    While (currentNode <> destinationNode) repeat
        S ← successors(currentNode)
        For j ranging from 1 to length(S) do
            nextNode ← S[j]
            if (nextNode = destinationNode) then
```

```
                ant.Route[] ← nextNode
                currentNode ← nextNode
                currentNode.Visited ← True
                exit
            else
                if (nextNode.Visited = False) then
                    nodeSuccessor.nextNode ← nextNode
                    nextNodeList[] ← nodeSuccessor
                    tau ← G[currentNode][nextNode].τ
                    eta ← G[currentNode][nextNode].η
                    probabilities[] ← pow(tau, α) * pow(eta, β)

        For j ranging from 1 to length(probabilities) do
            P ← (probabilities[j] ÷ Sum(probabilities)) × rand
            nextNodeList[j].probability ← P
        nextNode ← rouletteWheel(nextNodeList)
        G.nextNode.Visited ← True
        ant.Route[] ← nextNode
        r ← [currentNode, nextNode]
        f_a ← Ψ * G.r.length + γ * G.r.traveltime + θ * G.r.congestionlevel
        ant.Fitness ← ant.Fitness + f_a
        currentNode ← nextNode
    END WHILE
    ant.Fitness ← F_o / ant.Fitness
END FOR
newColony ← colony
End
```

FONCTION findQueen(colony) **: ant**

```
Begin
queen ← colony[1]
bestFitness ← queen.Fitness
For each ant in colony do
    f_a ← ant.Fitness
    if (f_a < bestFitness) then
        queen ← ant
        bestFitness ← f_a
findQueen ← queen
End
```

FONCTION findBestQueen(queens[nbColonies]) **: ant**

```
Begin
bestQueen ← queens[1]
f_bq ← bestQueen.Fitness
For each queen in queens do
    f_a ← queen.Fitness
```

```
    if (f_a < f_bq) then
        bestQueen ← queen
        f_bq ← f_a
findBestQueen ← bestQueen
End
```

FONCTION updatePheromones(G, colony, bestQueen, Pr, Q**) : Multi-lanes Directed Graph**

```
Begin
For each ant in colony
    f_a ← ant.Fitness
    l_r ← length(ant.Route)
    f_bq ← bestQueen.Fitness
    q_a ← f_bq / f_a
    if (q_a ≥ Pr) then
        For i ranging from 1 to l_r do
            currentNode ← ant.Route[i]
            nextNode ← ant.Route[i+1]
            r ← [currentNode, nextNode]
            G.r.τ ← G.r.τ + q_a
    if (q_a = 1) then                    %updating pheromones of the best queen ever%
        l_r ← length(bestQueen.Route)
        For i ranging from 1 to l_r do
            currentNode ← bestQueen.Route[i]
            nextNode ← bestQueen.Route[i+1]
            r ← [currentNode, nextNode]
            G.r.τ ← G.r.τ + q_a * Q
updatePheromones ← G
End
```

FONCTION evaporatePheromones(G, ρ, tau_{min}**) : Multi-lanes Directed Graph**

```
Begin
For each road in G do
    G.road.τ ← G.road.τ * (1-ρ)
    if (G.road.τ < tau_min) then
        G.road.τ ← tau_min
evaporatePheromones ← G
End
```

Annexe B

Real-time traffic dataset used to test the proposed algorithm

Table: Number of vehicles that passed on Monday 31st May 2021, from 8am to 9am, every 15min, in the district of Algiros, ValenciaCity, Spain

The source is: https://www.valencia.es/dadesobertes/es/dataset/?id=intensitat-de-transit-per-trams

ATA	description	Latitude	Longitude	lanes	type	Max speed	time	n_vehicles
A1	accesobarcelona entre v-21 y rondanorte	39.4828284	-0.349214	8	motorway	50	08:15	7530
							08:30	6912
							08:45	7716
							09:00	6846
A165	avenida de los naranjos	39.4798705	-0.3452837	8	primary	50	08:15	3474
							08:30	3957
							08:45	3009
							09:00	4272
A211	ramonllul	39.4765059	-0.3467292	6	tertiary	50	08:15	1829
							08:30	1965
							08:45	2174
							09:00	2048
A212	ramonllul	39.4798705	-0.3452837	6	tertiary	50	08:15	1833
							08:30	1730
							08:45	1528
							09:00	2134
A230	santosjusto y pastor	39.4700326	-0.3494285	2	tertiary	50	08:15	735
							08:30	885
							08:45	750
							09:00	465
A231	santosjusto y pastor	39.4671	-0.3393899	2	tertiary	50	08:15	641
							08:30	454
							08:45	615
							09:00	590
A253	yecla	39.4714783	-0.3543784	2	tertiary	40	08:15	570
							08:30	420
							08:45	330
							09:00	510
A287	accesobarcelona (paso inferior)entre v-21 y avcataluña	39.4828284	-0.349214	4	Exit	50	08:15	3720
							08:30	3090
							08:45	3600
							09:00	3540
A295	clariano	39.4785606	-0.3511766	6	Primary	50	08:15	1098
							08:30	2124
							08:45	1236
							09:00	1884
A296	accesobarcelona ramal de entrada de v-21 arotonda	39.4828287	-0.3492137	7	Exit	50	08:15	1416
							08:30	1368
							08:45	1560
							09:00	1320

A297	accesobarcelona ramal de salida de paso inferior a v-21	39.4828284	-0.349214	2	Exit	50	08:15	1344
							08:30	1224
							08:45	1536
							09:00	1176
A3	avcataluña de rotonda a primadorreig	39.4822649	-0.3513195	4	Exit	50	08:15	870
							08:30	1410
							08:45	810
							09:00	1260
A359	jose m haro	39.4671	-0.3393899	4	Residential	30	08:15	461
							08:30	335
							08:45	42
							09:00	252
A360	avenida los naranjos	39.4798705	-0.3452837	8	primary	50	08:15	2976
							08:30	3209
							08:45	3120
							09:00	2977
A414	ingenierofaustoelio entre av de los naranjos y c mendizabal	39.4763837	-0.3333488	2	tertiary	40	08:15	1710
							08:30	2010
							08:45	2086
							09:00	1959
A415	santosjusto y pastor entre jose m haro y serreria	39.4671	-0.3393899	2	tertiary	50	08:15	210
							08:30	629
							08:45	461
							09:00	293
A416	av. naranjos entre luispeixo y paseomaritimo	39.4763837	-0.3333488	8	primary	50	08:15	843
							08:30	1038
							08:45	1128
							09:00	1127
A47	blascoibañez	39.4753702	-0.3524861	6	primary	50	08:15	2880
							08:30	3150
							08:45	3150
							09:00	3405
A50	blascoibañez	39.4709916	-0.337497	6	primary	50	08:15	2355
							08:30	2033
							08:45	1925
							09:00	2148
A52	blascoibañez	39.470121	-0.3345176	6	primary	50	08:15	450
							08:30	1560
							08:45	1230
							09:00	1950
A74	clariano	39.4785606	-0.3511766	6	primary	50	08:15	2610
							08:30	2580
							08:45	2790
							09:00	2880
B100	serpis	39.4756382	-0.3470811	2	tertiary	30	08:15	330
							08:30	330
							08:45	300
							09:00	270

B16	campoamor	39.4710371	-0.34698	2	Residential	30	08:15	210
							08:30	300
							08:45	180
							09:00	240
B38	escultolalfonsogabino	39.4741647	-0.3450572	1	residential	30	08:15	165
							08:30	99
							08:45	132
							09:00	66
B40	exploradorandres	39.4720549	-0.3466607	1	residential	30	08:15	180
							08:30	210
							08:45	240
							09:00	240
B74	musicogines	39.4690645	-0.3436817	1	tertiary	50	08:15	291
							08:30	548
							08:45	356
							09:00	620
B86	poeta mas y ros	39.4711451	-0.3508296	1	residential	30	08:15	45
							08:30	111
							08:45	36
							09:00	81