Smart Mobility in Smart Cities: Emerging Challenges, Recent Advances and Future Directions

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Abstract

The world is witnessing a vivid race towards developing advanced solutions to enable smart, fast, affordable and environment friendly mobility for Smart Cities inhabitants. This led to the emergence of the Smart Mobility concept, attracting significant attention from major actors in the mobility sector including policy makers and traffic authorities. Therefore, this survey paper presents an overview of Smart Mobility and discusses the main challenges associated with its key building blocks, parking and traffic management, traffic routing in addition to emissions and road safety implications. Then, the most important works that attempted to address these challenges are presented, and their strengths and limitations are analysed. Finally, the lessons learned from this study and the most promising future directions to tackle these challenges are presented.

1 Keywords

Smart Mobility, Smart Cities, Intelligent Transportation Systems, Traffic Management System.

2 Introduction

Smart Cities offer unprecedented revolutionary services to their inhabitants in terms of enhanced service quality, lower cost, lower impact on the environment, and significantly higher comfort, to ultimately improve the overall quality of life. Achieving this aim is reliant on the efficient use of advanced technologies to monitor and manage cities' critical assets and infrastructure, such as water and energy system, road and rail transport network, to make the city more sustainable while promoting its economic growth. Transforming our cities to Smart Cities, however, strongly depends on several enabling technologies (e.g. Internet of Things (IoT), sensors, Fifth Generation (5G)/Beyond 5G (B5G) networks, connected and autonomous vehicles technology, advances in Artificial Intelligence (AI), etc.) to support their main areas of development, namely e-healthcare, smart government, smart buildings and energy, smart mobility, and sustainability. Moreover, several issues related to the use of these technologies need to be solved to ensure their wide acceptance by cities inhabitants. Among these issues, privacy is a major concern as if it is not protected properly it can lead to the disclosure of sensitive information about individuals such as their health status, tracking their mobility, etc. Another major concern is the fear of cyber-attacks targeting interconnected networks of heterogeneous devices or vehicles, which may lead to devastating consequences, e.g. a hacker taking remote control of an autonomous vehicle, or sending falsified data to IoT actuators, etc. Despite these issues, smart city concept is being translated from theory into practice, in various ways, in many cities worldwide, such as Guadalajara in Mexico, Wuxi in China, Kansas City in USA, Trento in Italy and Casablanca in Morocco.

By 2050, cities will be home for more than two-thirds of the world population Dameri (2014). Although people can buy, search, learn, book their trips online and settle their affairs using Internet facilities, they still need to go to work, school, hospitals and travel; in other words "they must move". Their mobility, using public transport or private cars, generates traffic flow, congestion and air pollution and puts more stress on the available road infrastructure. That is why Smart Mobility (S-Mobility) has emerged as a revolution in the transport sector handling the associated challenges with individuals mobility in Smart Cities in a more efficient way. S-Mobility does not focus on completely building a new infrastructure due to the colossal cost needed and other difficulties, but rather on optimizing the existing infrastructure through the use of Information and Communications Technology (ICT) in a smart way Suske, Tcheumadjeu, Calvin, Sohr, and Xiaoxu (2016). S-Mobility is one of the main building blocks of Smart Cities development because many other services depend on its level of efficiency and robustness. The successful implementation of S-Mobility will make the commuter's journey faster, cheaper, more comfortable and safer.

This survey presents a comprehensive analysis of S-Mobility challenges in the emerging era of Smart Cities, highlights and discusses the most important recent advances in S-Mobility and provides suggestions for future directions. Although a few other surveys addressed several challenges in Smart Mobility, such as Benevolo, Dameri, and D Auria (2016) which focuses on highlighting the role of ICTs in supporting S-Mobility actions and improving the quality of life in the city, none of them has provided a deep analysis and covered the aspects of S-Mobility discussed in this survey. Therefore, to the best of our knowledge, this is the first survey that drew a road-map to assist researchers and traffic managers in efficiently dealing with S-Mobility challenges and thus paving the way to its successful implementation.
The main contributions of this survey can be further summarized as follows:

- Proposing a new classification of parking management systems based on the technologies used for parking spots occupancy detection, and analysing the key contributions in each category.
- Proposing a new classification of traffic data sources using as key classification criteria where (i.e., in vehicles, on road and traffic monitoring equipment, etc.) and how the data is generated or collected. Then, discussing how such heterogeneous data is fused to provide accurate and meaningful data that can be used for traffic flow estimation, and traffic flow prediction, enabling more efficient adaptation of traffic light control timings.
- Proposing a new classification of routing methods in transportation networks based on two metrics, transportation modes (mono, schedule-based, or multiple) and the routing criteria (single or multiple) used to select the best route.
- Highlighting how air pollution is dealt with using alternative but complementary approaches (i.e., on-demand mobility, E-bike, Taxi-drone, etc.).
- Addressing road safety by focusing on both vehicles and pedestrians. For the former, we discuss the techniques developed to make vehicles smarter, cooperative and autonomous to reduce the risks of accidents; while for the latter, we analyze the solutions developed to alert pedestrians about immediate road dangers, etc.

The remainder of the paper is organized as follows. Section 3 gives an overview on Smart City concept and defines the main concepts in S-Mobility. Section 4 addresses the key challenges hindering the achievement of S-Mobility objectives. Section 5 discusses the recent advances in addressing the above challenges in S-Mobility, followed by a presentation of the lessons learnt from this study along with a suggestion of potential future directions in Section 6. Finally, we conclude the paper in Section 7.

3 Mobility in Smart Cities

As places of opportunities where everything is available such as jobs, good schools, hospitals, shopping centers, entertainment services, etc., cities have attracted more and more population during the last few decades Arasteh et al. (2016). This has led to an increased air pollution, traffic congestion and noise, especially in big urban areas. However, the fast expansion of ICT based solutions adoption and IoT sensors deployment in several application domains have assisted these cities to become more intelligent and comfortable for living. In the following, we present the most common definitions of Smart Cities, their categories and dimensions. Then, we provide an overview of the most important dimension, that is S-Mobility.

3.1 Smart City in a Nutshell

According to Benevolo et al. (2016), a city is considered "Smart" if it is a prosperous city in competitiveness, social and human capital, governance, mobility, natural resources preservation, and quality of life, in addition to its reliance "on the smart combination of activities of self-decisive, independent and aware citizens" Dimitrakopoulos (2017).
Many platforms and solutions are proposed for Smart Cities such as CiDAP platform Cheng, Longo, Cirillo, Bauer, and Kovacs (2015) that uses IoT network and focuses on the process of data collection, and OpenIoT platform Petrolo, Loscri, and Mitton (2014) that deals with data management. These two platforms are combined in Santana, Chaves, Gerosa, Kon, and Milojicic (2018) to provide a Unified Reference Architecture. A web platform called "E-City" is also developed in Amado, Poggi, Ribeiro Amado, and Breu (2018) and made accessible to planners, stakeholders, and population with the aim to provide them with more insights on energy consumption in different urban areas.

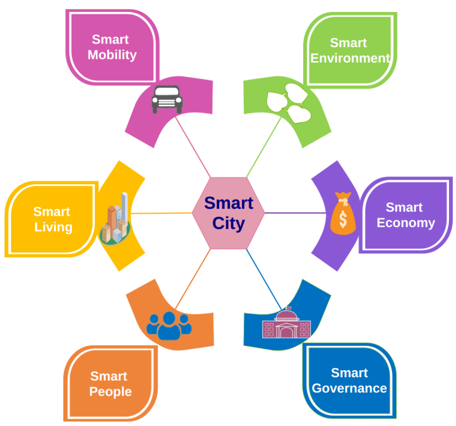

Figure 1. **A Smart City model**

The components of a Smart City model are often grouped into six dimensions Housing and OTB (2018) (see Figure 1): smart environment, smart economy, smart government, smart people, smart living and S-Mobility. This model is adopted by many works in the literature such as Moustaka, Vakali, and Anthopoulos (2017), Letaifa (2015), Pellicer et al. (2013), Moustaka, Vakali, and Anthopoulos (2018), and Housing and OTB (2018). This inspired us to organize the objectives (or the challenges to overcome) of Smart Cities according to the above six components and for each of them we briefly explain how they address one or more of these challenges.

- *Smart environment:* this class addresses how to make cities healthier for living by reducing pollution and achieving efficient resources management such as smart water Lee, Cho, and Kim (2019), Babu, Rao, Boyidi, and Bendalam (2019), smart lighting Brock, den Ouden, van der Klauw, Podoynitsyna, and Langerak (2018), Escriva, Torres-Sospedra, and Berlanga-Llavori (2018), smart building and smart home Jo and Yoon (2018), Do, Martini, and Choo (2018), smart grids Koutitas (2018), waste management Bakas et al. (2018), Windfeld and Brooks (2015), etc. For example, Bigbelly [1] is a smart waste and recycling system and zerocycle [2] is another system that determines recycling rates based on waste data collection.
- *Smart economy:* aims to achieve significant economic growth by looking for the best means to realize that, focusing on entrepreneurship, productivity, flexibility of labour market, digital economy, logistics, etc., Moustaka et al. (2018), Housing and OTB (2018).
- *Smart government:* aims to foster the adoption of the most suitable political strategies and the use of ICT towards better participation in decision-making, improvement of public and social services, and promoting transparent governance, etc.
- *Smart people:* people are the key element of Smart Cities because they can collect and share data using their own devices such as smart watches, tablets, smartphones, etc. Ericsson Mobility Report [3] predicted that 70% of the world population will own smartphones by 2020. With the advent of Smart Cities and the increased usage of smartphones for data collection, the new theme of "crowd-sensing" came to the front. As pointed out by Ma *et al.* in Ma, Zhao, and Yuan (2014), the sensing paradigm has three characteristics: cost effectiveness, scalability and mobility. Both crowd-sensing and crowd-sourcing use mobile sensors for data collection, but the latter needs user input to provide a feedback Pilloni (2018). In the rest of this paper, we do not differentiate between these two concepts. Crowd-sensing is used in different fields such as parking management X. Chen and Liu (2016), traffic management Ning, Xia, Ullah, Kong, and Hu (2017), etc. The main challenges in managing such data sources are security and privacy preservation issues in addition to processing and mining the resulting big data using AI algorithms to extract new knowledge.

[1] http://bigbelly.com/
[2] http://www.zerocycle.co/
[3] https://erticonetwork.com/ericsson-mobility-report-70-percent-of-world-s-population-using-smartphones-by-2020/

- *Smart living:* focuses on the improvement of urban facilities such as schools, shopping centers, universities, hospitals, cultural facilities, and touristic landmarks etc. As an example, a Smart Tourism Dynamic Responsive System (STDRS) framework was developed in Dubai Khan, Woo, Nam, and Chathoth (2017) to pinpoint relevant practices about Dubai's Smart City and smart tourism.

- *Smart Mobility:* mobility in urban areas is a major concern for citizens as well as for companies aiming to achieving timely delivery of goods at a lower cost. Many challenges arise from this dimension, such as, how to satisfy users demand by ensuring comfortable journeys and minimizing trips duration without causing any delay to transport companies and preserving the environment. Several studies have developed different solutions for improving the mobility in cities to reduce traffic congestion and minimize its resulting impact on commuters, environment and the economy. Examples of these solutions include electric cars by Google Car [4], smart velomobility Behrendt (2016), smart parking Pala and Inanc (2007), a traffic information system such as REMON *REMON* (n.d.), bus and train scheduling J. Li (2002), Antsfeld and Walsh (2012). Companies and research centers like Hitachi Okuda, Hirasawa, Matsukuma, Fukumoto, and Shimura (2012), Fujitsu Kawasaki (2015) and German Aerospace Center (DLR) Suske et al. (2016) also developed several solutions in this field. Some governments have adopted new strategies to achieve S-Mobility like the Danish government [5] that has encouraged the citizens to use bikes.

According to Moustaka et al. (2018), S-Mobility is the most investigated dimension of Smart Cities in the literature. It is the most important and crucial component of a Smart City, because it influences all the other dimensions. That is why we are focusing on S-Mobility in this paper.

3.2 An overview on Smart Mobility

The term *Smart* or *Intelligent* Mobility emerged in the early 90s to refer to a city with a mobility system increasingly relying on technology and innovation Papa and Lauwers (2015). As pointed out by the authors of Staricco (2013) and Benevolo et al. (2016), S-Mobility may have two meanings depending on the use of ICT. The first meaning refers to an efficient and cost-effective mobility system, regardless of the role that ICT plays, that makes use of relevant technologies. The second meaning, however, refers to a mobility system that uses ICT in a consistent and regular way. Within a Smart City, S-Mobility is a service that ensures a clean, energy efficient, safe, comfortable and cheap mobility for traffic participants Suske et al. (2016). S-Mobility primary objectives is not to set up new infrastructure, but rather to optimize the usage and operation of the existing infrastructure through the intelligent use of ICTs Suske et al. (2016).

[4] http://www.nytimes.com/2010/10/10/science/10google.html
[5] http://www.cycling-embassy.dk

According to Jeekel *et al.* Jeekel (2017), there are four dimensions of S-Mobility: vehicle technology, Intelligent Transportation System (ITS), data and new mobility services. In Papa and Lauwers (2015), Papa *et al.* have described the main aspects of S-Mobility as either techno-centric or consumer-centric. Techno-centric S-Mobility refers to the use of technologies like ICT in transportation infrastructure while consumer-centric aspect of S-Mobility focuses on providing new products to consumers. In other words, techno-centric focuses on hardware and consumer-centric on people who are a crucial element to enable S-Mobility. Figure 2 illustrates the main objectives of S-Mobility in Smart Cities.

Figure 2. Smart Mobility objectives in Smart City

S-Mobility's main objectives are summarized in the following six points Benevolo et al. (2016):

1. Reducing air pollution through minimizing the number of vehicles on roads and encouraging people to use Eco-friendly means of transport.

2. Reducing traffic congestion: this can be achieved by informing drivers about congested road segments and redirecting them to less congested roads using efficient routing and prediction techniques. In addition, improving the efficiency and flexibility of public transport by adapting the destination served by bus lines, for example, based on the travellers' needs and the usage rate would help in alleviating the traffic congestion.

3. Increasing safety on the road: car accidents are one of the main causes of deaths in the world in addition to the resulting disabilities due to serious injuries, and material damage and their impact on the economy, thus reducing the number of accidents is crucial.

4. Reducing noise pollution: transport noise is one of the main causes of noise pollution that has negative impact on people living in cities. Therefore, designing ICT solution to reduce this noise is compulsory.

5. Improving transfer speed: choosing the optimal path regarding time and minimizing shifting transition

will allow drivers to reach their destination in the desired time.

6. Reducing travel cost will enable more affordable transport for citizens and contribute to economic growth as well. This can be achieved using multi modal transport and ICT based applications.

S-Mobility brought new challenges that cannot be solved using the existing solutions, therefore new architectures, methods and algorithms are required to overcome them. We summarize these challenges in the following five research questions: 1) How to effectively detect parking spots occupancy in order to minimize the search time for a free spot and its associated cost? 2) How to efficiently manage road traffic (estimation and prediction of traffic) to reduce travel time and cost and make travellers' journey more comfortable? 3) How to provide users with the optimal route to reach their destination within the desired time and other additional constraints, if any? 4) How to satisfy users' demand with minimum (or no) impact on the environment in terms of air and noise pollution? and finally 5) How to make our roads safer in the S-Mobility era? Despite the ongoing efforts in developing efficient solutions to face the above challenges, mobility in cities is still suffering from a lot of problems and no solution, to the best of our knowledge, has satisfactory covered the previous five questions. The objective of this survey is, therefore, to answer the above-mentioned research questions.

4 Overview of Smart Mobility Challenges

In this section, we summarize the main challenges facing S-Mobility. These challenges could be classified into the following categories to ease the understanding of their nature and difficulty level: parking management, traffic management, traffic routing, air pollution and road safety related challenges (see Figure. 3). The relationship between these challenges can be explained as follows. Parking management system supports traffic flow management by reducing traffic congestion. An efficient parking management system will enable a reduction in the time spent by drivers searching for a free parking spot. Parking management systems can also support traffic routing systems through efficient coordination between them; if a traffic routing system is made aware of the availability of parking spots at the different car parks managed by a given parking management system, it can more efficiently route traffic in a way that reduces travel time for drivers, achieves better load balancing and maximizes the usage of car parks capacity. Traffic routing systems and traffic flow management systems support each other because the former can help in reducing the creation of traffic bottlenecks through load balancing. The latter can enable more efficient routing by providing accurate traffic flow estimation and evolution prediction. An innovative design and efficient operation of the above three systems will enable significant reduction in air pollution. Finally, efficient traffic flow management can significantly reduce traffic congestion and thus driving becomes safer.

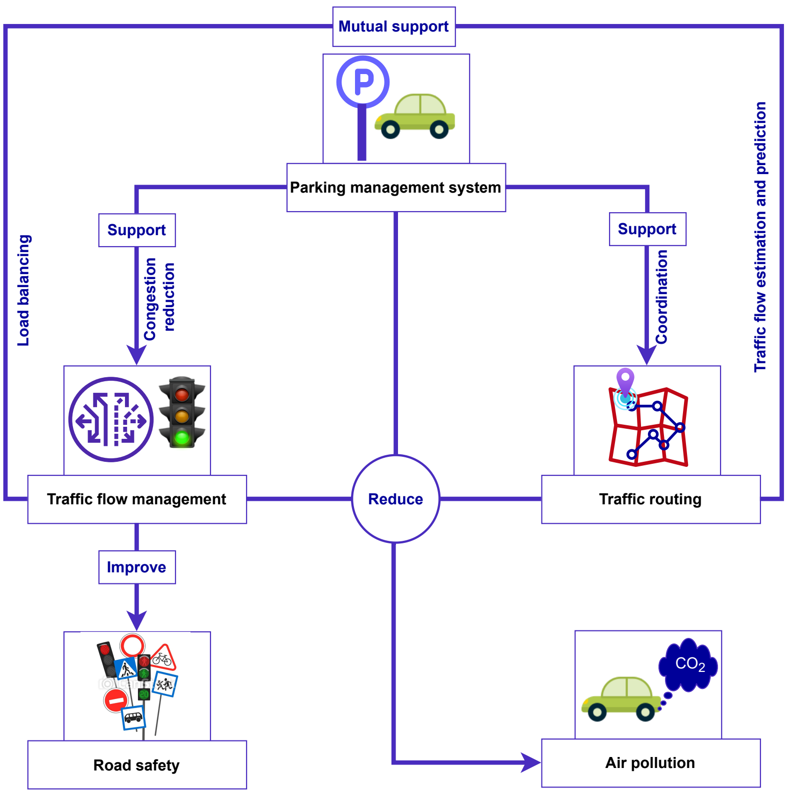

Figure 3. The relationship between the Smart Mobility challenges

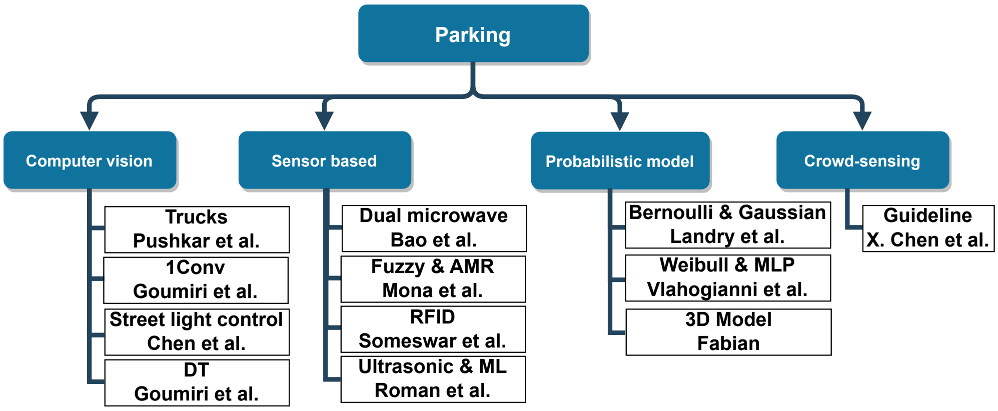

Figure 4. Classification of parking spots occupancy detection methods

4.1 Parking management

Despite the recent innovation in transport, the efficient management of on-street and off-street parking spots has not seen significant advancement in the way the availability of such spots is advertised to drivers, and the tools made available to enable efficient and easy parking P. M. et al. (2019). The inefficiency of current parking management systems is highlighted often, as drivers spend significant time searching for free spots; even though on average only around 80% of spots are occupied according to Research (2013). A study conducted by INRIX revealed that the average UK driver spends around 44 hours a year searching for parking, equating to £733, totalling £23.3 billion for the country INRIX (2017). This study highlighted as well that London was the worst city to park in, with an annual search time of 67 hours or 12 minutes per journey. Moreover, as stated by Admiral; 64% of drivers feel very stressed and anxious when they search for a free parking spot, and 71% complained about the limited number of available parking spaces Frampton (2017). Another study has shown that we waste an average of 17 hours a year looking for a place to park [6].

This wasted time due to parking management inefficiency or insufficient number of parking spots contributes significantly to the increased traffic congestion in cities, as stated in Nawaz, Efstratiou, and Mascolo (2013), as well as the increased greenhouse gas emissions. Therefore, innovative solutions are needed to optimize the parking search time (for both on-street and off-street parking), reduce the parking cost and avoid creating bottlenecks nearby popular landmarks and key locations in the city. To achieve this aim, the real-time parking spots occupancy detection is compulsory along with the awareness of the nearest path to the parking spot location and the price to park. In the present survey, we focus on investigating parking space occupancy detection issues and propose novel classification of the existing works.

In Lin, Rivano, and Le Mouël (2017), the authors classified parking management solutions into three categories based on the target objective: information collection, system deployment and service dissemination. Enríquez, Soria, Álvarez-García, Velasco, and Déniz (2017) leveraged the technology used as source for parking spots occupancy detection to classify the proposed solutions into three classes: infrastructure based solutions where sensor devices are the main source of information, crowd-sourcing based solutions that rely on drivers smartphones input, and hybrid solutions that combine both of the above. In this survey, we propose to classify the techniques used for parking spots vacancy detection in smart parking into the following four categories: computer vision enabled techniques, sensing technologies enabled techniques, probabilistic models enabled techniques and crowd-sensing enabled techniques as illustrated in Figure 4.

4.1.1 Computer vision enabled techniques

In this category, image processing techniques are used to process the data gathered by the cameras to detect the parking spots occupancy. As in Kianpisheh, Mustaffa, Limtrairut, and Keikhosrokiani (2012), we can identify two sub-categories of solutions: the first one counts the number of vehicles entering or exiting the parking without any indicator on the exact location of the vacant spots, while the second captures the exact location of the available spots.

Image processing was used in Pushkar Modi (May 2011), where an automated truck stop management system was developed. This system informs trucks' drivers about the vacant spots and then directs them via a variable message display placed 30 or 40 miles before a stop signal. The proposed system was tested on a sample of videos and the results were promising. Some practical deployment challenges that may reduce the trustworthiness of such a system by its potential users were detected and solved. Examples of such challenges include the occurrence of errors when people cross a parking spot. This problem was solved by introducing a blob tracking to identify moving objects (i.e., people), which has significantly improved the results.

The authors in Goumiri, Benboudjema, and Pieczynski (2021) proposed a method to detect parking spots' occupancy by processing images collected from videos using Convolutional Neural Networks (CNN), see LeCun, Bottou, Bengio, and Haffner (1998). The idea consists of

[6] https://www.usatoday.com/story/money/2017/07/12/parking-pain-causes-financial-and-personal-strain/467637001/

using the images collected by the available CCTV cameras. The proposed model is combined by one convolutional layer hence the name 1Conv. The obtained results highlighted that by using the 1Conv model, 99.84% of accuracy can be achieved , while the mAlexNet network, see Amato et al. (2017), can lead to 98.07% of using the PKLot[7] dataset. The 1Conv model is two times faster than the mAlexNet.

In L.-C. Chen, Sheu, Peng, Wu, and Tseng (2020), Chen *et al*. proposed a method to detect parking spaces. This method uses street light control in where the lights are turned off when there is no vehicle in the street and vice versa. This system was implemented using the Jetson TX2 module, YOLO v3, and MobileNet v2. Experiments were done using the CNRPARK+EXT[8] dataset and another set of images collected with a camera. The advantages of this system are: reducing costs compared to sensor-based methods, optimizing the use of lighting by turning it on and off when needed, and finding out how many parking spaces are available. To evaluate the performance of this system two metrics are used: accuracy and recall. The accuracy of this solution is 99%, while the recall is 95%. YOLO v5 is used in Rafique, Gul, Jan, and Khan (2023) to detect car rather than classify parking spaces into free or occupied.

In Goumiri, Benboudjema, and Hakimi (2022), Goumiri *et al*. used Decision Tree Regressor (DT) to estimate the number of available places in the upcoming time. The DT hyper-parameters were tuned on two public datasets, CNRPARK[9] and KLCC[10]. The authors transform the CNRPARK dataset of parking images to a dataset adopted for a regression problem. The proposed solution was compared to Random Forest Regression (RF) using MSE, MAE, RMSE, and R^2 metrics. The study reveals that the DT proposed gives more accurate results than RF from small and large datasets.

Usually, computer vision based methods have a very high scalability and reliability levels but at the expense of the achieved accuracy, as stated in Fraifer and Fernström (2016). The accuracy of such methods in outdoor parking systems can be affected significantly by bad weather conditions as the captured blurry images can lead to inaccurate results Kianpisheh et al. (2012). Therefore, there is a need to develop a universal method more resilient to weather conditions as well as other factors that may affect the accuracy of parking spots occupancy Yang and Pun-Cheng (2018).

4.1.2 Sensing technologies enabled techniques

These techniques use diverse sensor devices to detect the occupancy of parking spots and can be *intrusive* or *non-intrusive*. Intrusive techniques require excavate holes to host the sensors which include active infrared sensors, inductive loops, magnetometers, magneto-resistive sensors, pneumatic road tubes, piezoelectric cables and weigh-in-motion sensors. Inductive loop detectors [11], for example, are placed in the entrance of parking to count the number of entering and exiting vehicles; then this number is compared to the total parking capacity to determine the number of available spots.

The Magnetometer is another example of sensors in this category and it mainly relies on the measurement of the earth's magnetic field disturbances caused by a vehicle. Its main advantages are its easy installation, low cost and small size. However, the accuracy of Magnetometer is reduced in most cases due to several factors including derivative magnetic field, overlap of close ferromagnetic objects and the variation of cars' manufacturing material Bao et al. (2017).

In Moura and Sussner (2018), a fuzzy approach was proposed to detect spot vacancy using anisotropic magneto-resistive sensor (AMR). This sensor is mainly adopted for wide parking areas like shopping malls and airports. The proposed method identifies as an output three states of a spot: *occupied*, *free* or *in transition* which means there is a vehicle entering or leaving the spot. The authors take into consideration a sliding window centered on the considered spot. To evaluate the solution two parameters are used: *variance* and *difference*. The former mean the variance in the present window. It takes its value in one of the two fuzzy sets, *big* or *small*. The latter, however, represents the difference between the average in the current window and the smallest average in a window before the appearance of a large variance. It is determined manually and can be *positive* or *negative*.

In Bao et al. (2017), Dual microwave Doppler radar transceiver modules were used to detect vacant spots and have been found to achieve an accuracy higher than 98%. RFID was also used in Someswar, Dayananda, Anupama, Priyadarshini, and Shariff (2017) with other technologies to develop an autonomic integrated car parking system. In Roman, Liao, Ball, Ou, and de Heaver (2018), an ultrasonic rangefinder was placed in vehicles' passenger seat side to measure the distance to a roadside obstacles. Then, a supervised machine learning algorithm is used to extract features of parked cars.

4.1.3 Probabilistic modeling enabled techniques

In Landry and Morin (2013), a probabilistic distribution was used to model the occupancy of parking spots. Initially, Bernoulli distribution was used to identify whether a given spot is free or not. In addition, the Gaussian distribution was used to model the spacial distribution of spots. The temporal distribution was chosen in regard to parking of interest because it depends on the behavior of people using that parking. Subsequently, the two distributions spacial and temporal are joined. The main objective of this work is to estimate the expected waiting time for a spot to be released.

[7]https://www.kaggle.com/blanderbuss/parking-lot-dataset
[8]http://claudiotest.isti.cnr.it/park-datasets/CNR-EXT/
[9]http://claudiotest.isti.cnr.it/park-datasets/CNRPark
[10]https://www.kaggle.com/datasets/mypapit/klccparking
[11]https://cdn2.hubspot.net/hub/68630/file-2634251974-pdf/docs/inductive-loop-write-up.pdf

In Vlahogianni, Kepaptsoglou, Tsetsos, and Karlaftis (2016), the authors propose a method for parking forecasting in smart cities. This method uses sensors to collect data related to parking spots. A forecast can be made in two ways short-term parking occupancy forecast in specified areas of a metropolitan road network and the likelihood of a free position being vacant within the next time. The results show that the multilayer perceptrons are the most adopted model for forecasting areas in 30 minutes horizons. While the Weibull regression model gives the most accurate results when estimating the likelihood that a parking place will remain vacant in the next period.

Unlike the two previous works (i.e. Landry and Morin (2013) and Quinn (2008)), that predict the status of a given spot in the future, the solution proposed in Fabian (2013) predicts the probability of the presence of a vehicle in a given spot. This solution trained existing images, related to spot geometry and usual vehicle form, to identify parking spots status. In order to optimize the training phase, a probabilistic 3D car model was proposed. The reliability of this solution was tested under different degrees of illumination. The results show a worst case accuracy of up to 96.4%.

The requirement of prior knowledge of the probability distribution Moura and Sussner (2018) is the main limitation of this category of solutions because it is difficult to accurately determine, in advance, how long a vehicle will occupy a given parking spot, which makes them unsuitable solutions.

4.1.4 Crowd-sensing enabled techniques

In X. Chen and Liu (2016), the authors describe a crowd-sensing based system that helps drivers in finding free parking slots and guide each of them towards a suitable spot. This system consists of a *central server*, *client devices* and *smartparkers*. Three types of drivers are considered in this sytem: *smartparkers* who contribute to the system, *free riders* who use the system without sharing any information with it, and finally *ordinary riders* who are independent and do not interact with the system in any way. The system distinguishes three states of a given spot: *occupied*, *free* or *unknown*. The system annotates all streets by their parking availability and displays such information on a map. Drivers are informed about available free spots when they submit a request for a parking spot. If the indicated spot is found occupied, the driver reports this information to the server which in turn updates its database. Then, it guides the driver to another free spot (ideally, the closest one to its current location) to minimize cruising time. This process is called coordinate crowd-sensing and its main advantage consists in enabling the system to explore unknown areas. To investigate the performance of the proposed approach, two metrics were used: *average walking time* and *average cruising time*. Simulation results have shown that 12% of contribution by drivers give acceptable quality of service, whereas free riders can degrade significantly the quality of the service. Another guidance system is proposed in Chai, Ma, and Zhang (2019).

The curse of sensing was discussed in Montori, Jayaraman, Yavari, Hassani, and Georgakopoulos (2018). In Shoup (2006) Shoup *et al*. have explained how to choose between cruising for curb parking or pay for off-street parking. This technique suffers from free-riders X. Chen, Santos-Neto, and Ripeanu (2012) and selfish liars as stated in Kokolaki, Kollias, Papadaki, Karaliopoulos, and Stavrakakis (2013) and Kokolaki, Karaliopoulos, Kollias, Papadaki, and Stavrakakis (2014).

Examples of existing parking solutions include ParkSense [12] and BePark [13].

4.2 Traffic management

Road traffic congestion caused by the increasing number of vehicles using the limited and often deteriorated road infrastructure costs a significant loss of productivity for the society due to its resulting increase in journey times, air pollution and drivers' anxiety. Compared to traveling at a constant speed in free flow traffic, traffic congestion increases CO_2 emissions as well as fuel consumption Barth and Boriboonsomsin (2008) due to Stop-and-go driving. Carbon dioxide (CO_2) is one of the most important causes of greenhouse gases that must be controlled to maintain a healthy environment. A recent study by the Texas A&M Transportation Institute [14], has shown that American commuters spend an average of 54 extra hours a year stuck in traffic congestion. In 2017, commuters wasted an average of 83 hours blocked in traffic. Driving in such conditions increases the anxiety level of drivers, which in consequences can lead to traffic accidents. Similar to the environmental damages caused by traffic congestion, economic losses are also presented. The average cost of extra traffic was $1,010 per commuter. The Texas A&M Transportation Institute expects that in 2025, each commuter will waste 62 hours in traffic, and the cost of national congestion will skyrocket to $200 billion that same year.

According to the TomTom Traffic Index [15], in 2017 Mexico City was the most congested city in the world with 66% of additional time spent by drivers stuck in traffic every day, and up to 101% in the evening compared to a free flow traffic, which reckons up to 227 hours of extra travel time per year. The above statistics highlight the detrimental impact of traffic congestion and call for innovative solutions to efficiently deal with this issue in order to make mobility smarter and greener. To achieve such objective, we need first to deal with the heterogeneity of the generated traffic data, collected from different sources, and their associated challenges.

4.2.1 Traffic data sources

The most important traffic data sources could be classified into three classes: in-vehicle embedded devices, air and ground monitoring devices and data acquisition techniques.

[12] https://www.youtube.com/watch?v=NxihNI8Hxxw
[13] https://www.bepark.eu/en/belgium
[14] https://static.tti.tamu.edu/tti.tamu.edu/documents/mobility-report-2019.pdf
[15] http://corporate.tomtom.com/releasedetail.cfm?releaseid=1012517

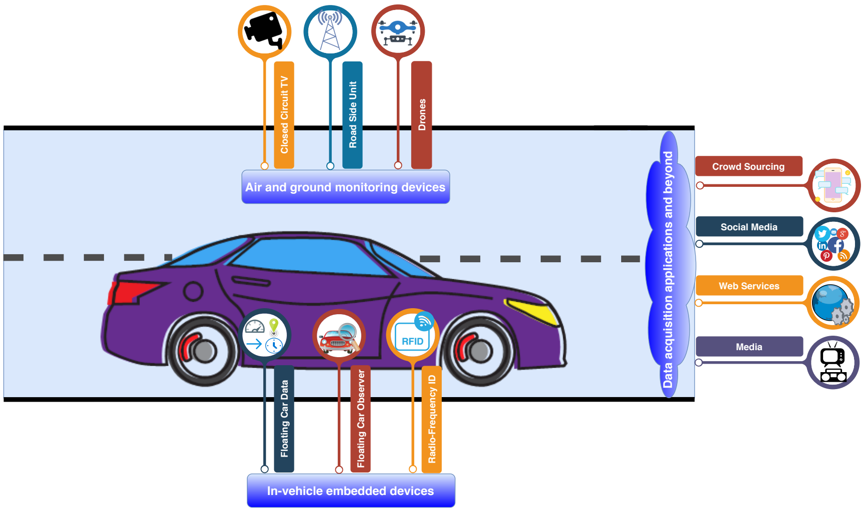

Figure 5. Heterogeneity of traffic data sources in Smart Cities

- In-vehicle embedded devices: this class includes embedded devices in vehicles, such as FCD, RFID and FCO, used to measure and report some useful parameters for accurate traffic estimation.

  – *Floating Car Data (FCD)*: also known as floating cellular data, it is based on speed, localization, direction of movement and the pick up time of information collected from drivers' phones to determine traffic conditions. As stated in Altintasi, Tuydes-Yaman, and Tuncay (2018), despite FCD's reliability issues, its low cost and high coverage make it an important traffic data source. FCD was used in Kong et al. (2018), to generate a realistic mobility dataset for vehicular social networks validation. This method is used to estimate and predict traffic conditions in the short-term The detection of crucial traffic patterns in urban areas was investigated in Altintasi, Tuydes-Yaman, and Tuncay (2017) and an FCD based approach was proposed. Results have demonstrated that using only average movement speed outcome from FCD is sufficient to identify traffic patterns.

  – *Floating Car Observer (FCO)*: in this technology, vehicles are able to determine their positions and collect traffic data in both directions of traffic flow regarding time and space dimensions. FCO was introduced in Hoyer, Czogalla, and Naumann (2006) to detect vehicles on a two-lane road using a public transport vehicle equipped with sensors. Recently, Bluetooth-based FCO has emerged as a new data source in which FCO is used for monitoring and the Bluetooth module for transmission. This technology is able to detect traffic participants such as cars, bicycles, buses, etc., equipped with a Bluetooth device. The German Aerospace Center (DLR) has developed an ITS approach called DYNAMIC Tcheumadjeu et al. (2017) in which Bluetooth-based FCO was used. Collected data is processed, fused and visualized to extract information such as: trajectories of vehicles, origin/destination matrix, travel time, etc. Gurczik *et al.* inGurczik (2015), used Bluetooth-based FCO to supervise traffic participants owning an activated Bluetooth.

  – *Radio-Frequency Identification (RFID)*: this technology consists of a chip and antenna and aims at identifying a vehicle by a unique ID. It can be used to count the number of vehicles entering or leaving a road segment. This information is useful to determine traffic conditions. The impact of days of the week, road layout and vehicle types on the increase in traffic during peak hours has been investigated in Wemegah, Zhu, and Atombo (2018). To study the influence of vehicle movements, Structural Equation Model (SEM) was used. Vehicle movements data is obtained using RFID devices. This method can assist decision makers to propose effective solutions that enhance travel time and reduce congestion.

- Air and ground monitoring devices: this class includes the monitoring equipment integrated into the road infrastructure, such as RSUs and CCTV, or used to monitor the traffic flow from the air such as Drones and helicopters.

  – *Road Side Unit (RSU)*: is a device placed on the road side and is able to monitor and communicate with vehicles when they are within its communication range. It is often used as a source of data traffic such as in Goudarzi, Kama, Anisi, Soleymani, and Doctor (2018) where time series data gathered by the deployed RSUs are used to build a traffic flow prediction model. In Kaul, Xue, Obraczka, Santos, and Turletti (2018), RSUs were also used as a second level controller in a Dynamic Distributed Network Control for ITS, or D2-ITS. The aim of this framework is to manage and control resources in VANETs (Vehicular Ad hoc Networks).

  - *Closed Circuit TV (CCTV)*: it consists in using a video camera to monitor a specific area primarily for surveillance and security purposes. In Ki, Choi, Joun, Ahn, and Cho (2017), Urban Traffic Information System (UTIS) and CCTV have been used to estimate travel speed. A model to predict Electric Vehicles (EV) charging-power demand is proposed using CCTV.
  - *Drones*: using drones as a flying carrier of RSUs or cameras could enable better traffic monitoring and faster reaction to bottlenecks and traffic incidents. Menouar *et al* discussed in Menouar et al. (2017) a number of use cases for drones usage in transportation such as supervising and reporting accidents or unusual traffic situations, managing dynamic traffic signals, acting as RSU, etc. Moreover, drones could be used as well for fast delivery of first aid kit and other necessary tools in case where the incident location is difficult to access using an emergency vehicle or through a helicopter. A fleet of drones could also be dispatched to cooperatively accomplish specific missions related to traffic monitoring and congestion relief. In Figure 5 we illustrate the most common data sources used for road traffic management.

- Data acquisition applications and beyond: this class covers any other source of traffic data that does not belong to any of the previous two classes, thus it includes crowdsourcing, social media, and inputs from citizens witnessing road incidents for example etc.

  - *Crowdsourcing*: pedestrians and passengers can provide information, using a smartphone or any device connected to the Internet, that help drivers to avoid blocked or congested roads due to unpredictable events. Such information will also help the traffic authority to identify the root causes of sudden traffic congestion occurrence, especially in road segments not covered by monitoring equipment. In Tafidis et al. (2017), the authors have used crowdsourcing as an alternative or additional data sources to predict the impact of traffic on air pollution. In Kumarage, Rajapaksha, De Silva, and Bandara (2017), a machine learning method was used to develop a model that estimates traffic flow using crowd sourced data.
  - *Social Media* data from social media like Facebook and twitter could be filtered and analyzed using data analytics methods to extract useful information about traffic such as congested areas, accidents, road construction works and so on. This source of traffic data is rarely used in practice but has attracted a lot of attention recently as stated in Kuflik et al. (2017) where tweets are used to learn relevant transport information such as: identifying areas where transport is most needed and to assess the quality of service provided by different transport modes. This work has also investigated the main challenges for large scale exploitation of this source of traffic data.
  - *Web Services*: Applications that can gather information and display data about the traffic or the events that can affect it (e.g., weather conditions) such as the traffic evacuation path control system developed in X. Li and Hsiao (2018). Another example of a web service is the data analysis tool developed for big data in Ahrabian, Kolozali, Enshaeifar, Cheong-Took, and Barnaghi (2017).
  - *Media*: Radios and TV can announce information about traffic conditions in real-time.

Usually, more than one data source is used to enhance the accuracy of traffic flow estimation. For example, in Pratelli, Petri, Ierpi, and Di Matteo (2018) Bluetooth sensors data, traffic counts data and transport modeling results were used as data sources to investigate travel time, origin/destination, etc. In Byon et al. (2018), different data sources consisting of GPS probes, loop detectors, radio broadcasts and the traffic department's websites were fused to extract traffic information on a highway segment. According to Byon *et al*., setting up an effective traffic monitoring system requires a combination of both quantitative and qualitative data. Therefore, data fusion is a compulsory process that needs special attention to efficiently exploit the wealth of existing heterogeneous traffic data sources.

4.2.2 Data fusion

The above-mentioned heterogeneous sources generate a huge amount of heterogeneous data that need to be fused in order to extract reliable and accurate information. Data fusion is a process that has been widely studied and is usually defined as the process of combining information from different sources in order to provide an advantageous and richer data. One of the most common definition has been proposed by Mitchell *et al*. in Mitchell (2007): "the theory, techniques and tools which are used for combining sensor data, or data derived from sensory data, into a common representational format ... in performing sensor fusion our aim is to improve the quality of the information, so that it is, in some sense, better than would be possible if the data sources were used individually". The main objectives of data fusion process are summarized as follows Bachmann (2011):

- Achieving higher reliability since information are gathered from different sources instead of relying on a single source only.

- Achieving higher accuracy because information acquired by combining readings from several sources is more accurate than one reading, or several readings from one source, which avoids information ambiguity.
- Achieving better completeness, coverage and complementarity because using multiple data sources provide a more complete data, specially when we deal with spacial and temporal information where the entire zone of interest must be covered. These information can complement each other to provide useful data.
- Achieving more cost effectiveness: sometimes using several sensors each of which is dedicated to one function is cheaper than using one sensor that ensures different functions. Moreover, the sensors, RSUs and CCTV, etc., are already deployed on roads for different purposes.
- Achieving better data representation: dealing with big data increases the decision time, however by fusing such data the response time is reduced because the processed dataset is optimized.
- Achieving better timeliness because the time required to acquire information from multiple sensors is lower than that taken for a single sensor, specially if parallelism is used.

Once traffic related data are collected and fused the resulting information will be used to accurately estimate or assess the traffic conditions, react efficiently to minimize traffic congestion and its impact and predict how the current situation will evolve to take optimal decisions. In the following, we will discuss the main techniques used for traffic flow estimation and prediction in addition to the algorithms that control the traffic lights and ensure their synchronization.

4.2.3 Traffic flow estimation

The traditional methods used to measure traffic flow, such as loop detectors and CCTV, are expensive to deploy, suffer from some operational limitations, their accuracy is affected by the weather conditions and requires complex processing of the generated data. New methods have been recently proposed to overcome the above limitations by adopting or using the aforementioned new traffic data sources. We will classify these methods into three categories based on the level of details provided when describing the traffic flow Burghout (2004): microscopic, mesoscopic and macroscopic. Macroscopic models describe the traffic at a high-level of aggregation as flow (i.e., the number of vehicles per hour that pass through a certain location or a point in the road network), without considering its constituent parts (the vehicles), whereas microscopic models describe, in detail, the behavior of the entities forming the traffic stream (the vehicles) as well as their interactions. Mesoscopic models provide an intermediate level of detail, for instance describing the individual vehicles but not their interactions as stated in Burghout (2004). Figure 6 illustrates the three classes of traffic flow estimation methods.

Figure 6. Details level of traffic flow estimation methods

Microscopic The microscopic model is the most widely used in traffic flow estimation solutions in the literature. It is usually complicated to implement but gives accurate results. A machine learning based solution was proposed in Lefebvre, Chen, Beauseroy, and Zhu (2017) to estimate traffic flow using acoustic sensors, it is characterized by its low cost and processing complexity and its privacy preservation guarantees for road users. This solution has lower cost and processing complexity and guarantees privacy preservation of road users. This solution has been experimentally evaluated during 11.5 days, which is a very short testing duration because the traffic flow varies significantly during different periods of the year (e.g., teaching terms, vacation, Christmas break, special and unpredictable events, etc).
In Frias-Martinez, Moumni, and Frias-Martinez (2014), it has been proven that passive cell phones network information could be used to estimate traffic flow using a linear regression model. This method can be effective in some traffic conditions. A neural network based model was also proposed in Habtie, Abraham, and Midekso (2016) to estimate traffic flow for urban road network. The architecture used in this work is Multi-Layer Perceptron (MLP) neural network. Traffic data is collected from drivers' mobile phones and used as prob vehicles. The performance of the developed model is evaluated using both simulation and real world experimentation and the obtained results have proven its accuracy.

Macroscopic This class of models is less widely used compared to the previous one but it is easier to implement. It consists in discretizing the space and the time of interest. It is usually based on models like Cell Transmission Model (CTM) Dr. Tom V. Mathew (2017), Link Transmission Model (LTM) Yperman, Logghe, and Immers (2005), and Network Transmission Model (NTM) V. L. Knoop and Hoogendoorn (2014), which is based on Microscopic Fundamental Diagram (MFD) Geroliminis and Daganzo (2008) that has been renamed later as

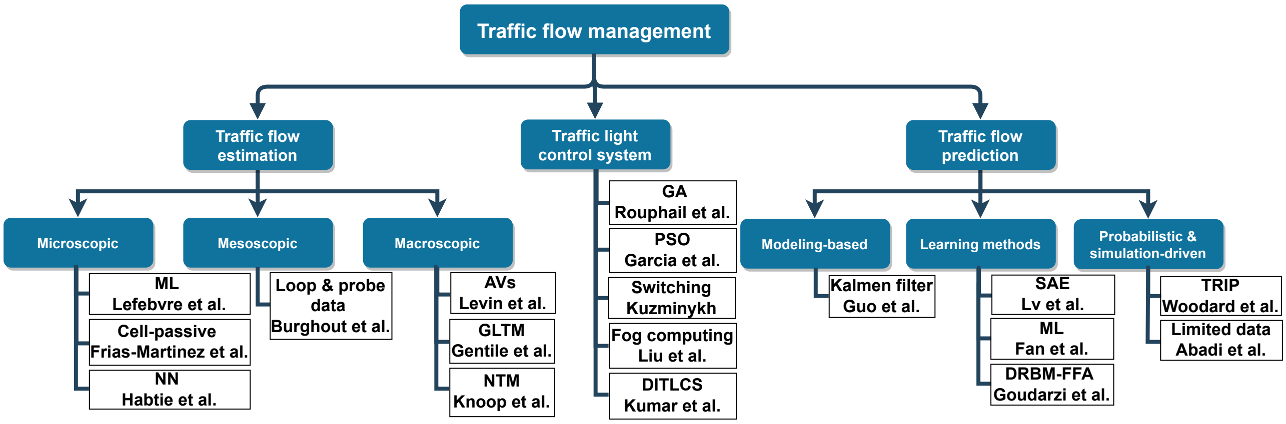

Figure 7. Classification of traffic flow management systems

Network Fundamental Diagram (NFD) Keyvan-Ekbatani, Kouvelas, Papamichail, and Papageorgiou (2012).
A Dynamic Traffic Assignment (DTA) model was developed in Levin and Boyles (2016) for roads shared between autonomous vehicles (AVs) and human driven vehicles. Shared Autonomous Vehicles (SAV) is a new concept that was investigated via a simulation framework in Iacobucci, Donhauser, Schmöcker, and Pruckner (2023). Several variants improving LTM have been proposed such as: General LTM (GLTM) Gentile et al. (2010), iterative LTM Himpe, Corthout, and Tampère (2016) and continuous formulations and analytical properties of the link transmission model Jin (2015). GLTM was used to simulate traffic congestion on urban networks in Gentile (2015) by proposing a framework for modeling DTA. LTM was extended by incorporating ramp metering and variable speed limits in Hajiahmadi et al. (2016). Usually, NTM predicts the congestion in the current cell and generalizes it to the whole network. In V. Knoop, Tamminga, and Leclercq (2016), NTM was used to predict traffic congestion patterns in large scale networks. The impact of route models on a road network has been studied in Leclercq, Parzani, Knoop, Amourette, and Hoogendoorn (2015). traffic dynamics of a road network. Although LTM has n times lower complexity[16] compared to CTM for the same level of accuracy according to Yperman et al. (2005), we have remarked, from the literature review, that CTM is the most used model. It has proven its effectiveness in many systems such as DTA, traffic signals, etc., and recently with AVs. For traffic flow simulation in large scale networks LTM is much more efficient and provides more accurate results than CTM Jin (2015).

Mesoscopic This class of models is new compared to the two other classes and combines the advantages of both of them. In terms of level of detail, it is located between microscopic and macroscopic levels. This class is defined, in Burghout (2004), as: "Mesoscopic models normally describe the traffic entities at a high level of detail, but their behaviour and interactions are described at a lower level of detail". If we are aiming to perform a microscopic simulation in a large road network but with limited resources, then a mesoscopic model is the best choice. A framework for estimating traffic flow using Eulerian data (loop), Lagrangian data (probe) and both of them combined together was developed in Duret and Yuan (2017). For each type of data a method was proposed and tested on the same dataset. To investigate the performance of the proposed framework, experiments were conducted on a freeway segment. Microscopic simulation has given satisfactory results for only 5% of probe vehicles. However, this framework should be tested on a large scale network for more accurate results.

[16] i.e, if CTM has a complexity of O(n*n) then LTM complexity is O(n).

4.2.4 Traffic flow prediction

The results of traffic flow estimation are generally used as an input to predict the traffic state in the future. Predicting the traffic flow state in urban areas is much more difficult than in freeways. This is due to the complexity of urban road network topology and the huge amount of traffic data generated in cities. However, vehicles velocity is problematic in highways because vehicles move at a very high speed which negatively impacts data collection and dissemination process. Several methods have been proposed to achieve short or long term prediction of traffic flows. These methods leverage a number of strategies such as statistical modeling, machine and deep learning, applying probabilistic distribution on mobile phones GPS data and use simulation techniques to complete the missing data, etc. Therefore, we classify these methods, as shown in Figure 7, into three categories: Modeling-based methods, Learning-based methods and probabilistic & simulation-driven methods. In the following, we describe each of these categories.

Modeling-based methods This class relies on a number of models such as statistical models and Autoregressive Moving Average (ARMA) model Weiss (1984) and its variants like Autoregressive Integrated Moving Average (ARIMA) Mohamed S. Ahmed (1979). Stochastic Seasonal Autoregressive Integrated Moving Average (SARIMA) is a generalization of ARMA. In addition, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) has gained a lot of attention for its ability to predict traffic flow states with the corresponding prediction interval. Moreover, Kalman filters have been used for (SARIMA + GARCH) structure implementation. Studies show that this structure is suitable to model the conditional variance traffic flow series Guo, Williams, and Smith (2007). An adaptive Kalman filter approach has been developed in Guo, Huang, and Williams (2014) to predict traffic forecasting in short term, i.e., 15 minutes. Unlike conventional Kalman filters, which use historical data, this model uses real-time data. This approach has shown good performance, can be adapted for very volatile traffic, and its stability can be maintained by increasing its memory size.

Learning-based methods This class involves machine learning, deep learning and neural network methods. A Stack Autoencoder Model (SAE) is a famous model of deep learning, in which the target output is used as input for the next layer. Because the existing models for traffic flow prediction are not deep enough and model traffic shallowly, according to Lv, Duan, Kang, Li, and Wang (2015), the authors of this paper used, for the first time, SAE to model traffic flow features. To use SAE network for traffic prediction, a standard predictor was added in the top layer. The proposed algorithm was tested with 1500 detectors that sent data every 30 seconds, then an aggregation of five minutes interval was performed. The results have shown more than 90% improvement in accuracy compared to other methods for 15, 30, 45 and 60 minutes. The methods to which it has been compared are: the Back-Propagation Neural Network (BP NN) model, the Random Walk (RW), the Support Sector Machine (SVM) and the Radial Basis Function Neural Network (RBF NN) model. This solution is not adopted for low traffic conditions and engineering factors such as accidents, weather conditions, etc., that were not taken into account.

In Fan, Su, Nien, Tsai, and Cheng (2018), a big data analytic based and machine learning driven platform was developed to predict traffic flow state and provide users with traffic state information. Two models have been employed: one-destination travel time prediction (OTTP) for normal traffic conditions and adaptive travel time prognosis (ATTP) for dynamic traffic patterns. The OTTP model is used to choose the adequate beginning time for a journey to steer clear of congestion while the ATTP model aims to reduce travel time.

A short term traffic flow prediction approach named DRBM-FFA was proposed in Goudarzi et al. (2018) to help in reducing traffic congestion impact. This approach makes use of a Deep Belief Network (DBN) with multiple layers of Restricted Boltzmann Machine (RBM) autoencoders. Time series data produced by the RSUs was used as input to build the model and the firefly algorithm (FFA) was used in the training phase. Using Monte Carlo simulations this approach has been shown to be more robust and accurate compared to the following alternative schemes: ARIMA Mohamed S. Ahmed (1979), the conventional MLP neural networks Gardner and Dorling (1998), MLP-FFA, which is a hybridation of MLP Kennedy (2011) with the firefly algorithm (FFA) Łukasik and Żak (2009) as optimizer and ARIMA-PSO that combines ARIMA with Particle Swarm Optimization (PSO) as optimizer.

Several deep learning models have been recently used to predict traffic flow in short and long term among them: a deep Bi-directional Long Short-Term Memory (LSTM) stacked autoencoder (SAE) Essien, Petrounias, Sampaio, and Sampaio (2021), LSTM X. Chen et al. (2021), and graph convolutional with LSTM Peng et al. (2021).

Probabilistic & simulation-driven methods This class involves applying probability distribution techniques and simulation when there is a lack of real-world data. That is the main difference between this class and the previous two classes. Recently, a new method that leverages mobile phone GPS data to predict traffic flow has been developed. This method is called TRIP Woodard et al. (2017), for Travel Time Reliability Inference and Prediction. In TRIP, data collected from mobile phones or vehicles probes are used in real-time to dynamically predict the probability distribution of travel time. TRIP has shown better results in term of reliability compared to Microsoft's engine for travel time prediction used in Bing Maps.

The main challenge in traffic prediction for this class is the unavailability of real-time information for some intersections, but a solution for this issue was proposed in Abadi, Rajabioun, and Ioannou (2015). This solution aims to predict traffic flows in transportation networks with limited data in short time up to 30 minutes. The proposed algorithm works in two steps: "Traffic flow data completion" and "Short-term traffic flow prediction". The former step builds the initial Origin Destination (OD) matrix through simulation, then optimizes it using historical and available real-time data. The results of this step are a Link–to-Link Driving Ratio (LLDR), which gives the link ratio to another adjacent link of traffic flow propagation. The output of the previous step is used in a recursive way to predict traffic flows. The estimated LLDR can be inaccurate due to unexpected events like accidents or closed routes. Therefore, a Monte Carlo experiment was performed where Gravity model was used for transportation forecasting, because of the limited available data, unlike Activity-Based model which is more suitable when more data is available. The proposed algorithm has given accurate results when compared with the measured traffic using only 16% of links with available real-time data. However, it does not provide long-term prediction and the Monte Carlo method used processes in four steps and runs 1000 times for each sample.

4.2.5 Traffic light control system

Traffic light control is an important parameter in the estimation of travel time. With the increasing number of vehicles and road networks expansion, and hence the number of traffic lights deployed on roads, the management of such systems requires smarter and often more complex scheduling strategies.

Metaheuristic algorithms, such as Genetic Algorithms (GA) Rouphail, Park, and Sacks (2000) and Particle Swarm Optimization (PSO) García-Nieto, Alba, and Olivera (2012), are common scheduling strategies used in this

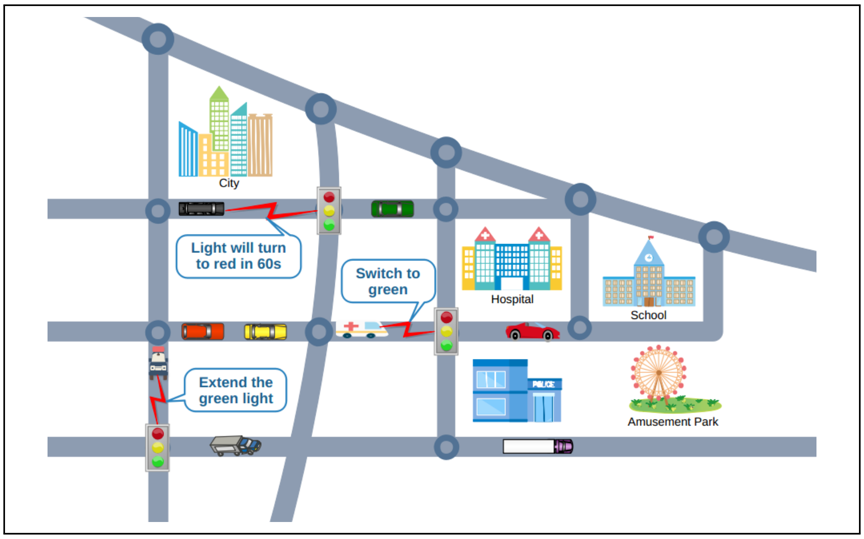

Figure 8. Illustration of advanced traffic light control system operation

context. In García-Nieto et al. (2012), Gracia *et al.* proposed a swarm intelligent method to identify a cycle of successive traffic lights. Simulations were conducted, in Malaga and Cevilla (Spain), using SUMO at the microscopic level. An increase in the number of vehicles that reach their destinations on time and a reduction in global trip times were observed compared to the obtained results with predefined real-world measurements.

The authors of Kuzminykh Ievgeniia (2015) developed a new system capable of switching the traffic light to green upon detection of prioritized vehicles (e.g., ambulances, firefighting trucks, police cars, etc.) to allow them passing without stoppage. This solution assumes that vehicles are equipped with on-board communication and computing capabilities so that they can send their direction to the traffic light control system to switch to the adequate light.

Security is another important aspect that should be considered when designing traffic light control systems because the consequences of a successful attack on such systems would be devastating. In fact, these systems are known to face several problems in communication between the system and vehicles or road monitoring devices such as RSUs. Fog computing [17] was used in Liu et al. (2018) to secure traffic light control systems using two schemes in which the traffic light was modeled as a fog device. The first scheme uses Diffie-Hellman puzzle and is deemed unsuitable for high vehicles density scenarios. The second scheme, however, is based on the hash collision puzzle and is more suitable for high vehicles density scenarios.

In Kumar, Rahman, and Dhakad (2020) a Dynamic and Intelligent Traffic Light Control System (DITLCS) is developed to update traffic light duration in real-time. Vehicles are given probabilities to allow the system to operate in three different modes: Fair Mode (FM), Priority Mode (PM) and Emergency Mode (EM). A model based on reinforcement learning is developed. It selects the color of the light, and s fuzzy inference system chooses the appropriate color among the set proposed by the reinforcement learning model. Experiment results demonstrate that the proposed model gives better results than the other current status of the art solutions.

Figure 8 shows an example of an advanced traffic light control system capable of adapting its cycles based on detected recurrent (or non-recurrent) events on the road. Such a system can also exchange relevant information with smart or autonomous vehicles, such as remaining time for the current cycle, equipped with adequate communication capabilities like IEEE802.11p Patel and Ukani (2012) and/or LTE-A and 5G Jain, Acharya, Jakhar, and Mishra (2018). In such system communication is bidirectional, from the traffic light to vehicles and vice versa. The traffic light control system can send notifications to vehicles about the traffic signal states, such as the light will switch to red in 60 seconds, and/or suggesting the optimal speed to avoid stopping at next intersection. Prioritized vehicles such as police cars, ambulances, and firefighting trucks, can request extending the green light cycle or switching to green if the light is currently red. Another use case would be extending the red light cycle, upon request from police to the road traffic authorities, to delay a suspect or a driver who evaded police control etc.

4.3 Traffic routing

Traffic routing is an old problem that has been extensively studied in the past, however the advent of new technologies and new power sources for vehicles with their associated constraints call for revisiting it to develop suitable routing algorithms for the era of smart mobility. Finding the optimal path to a given destination is one of the most researched problems in the transportation field. The response time is a crucial criteria that is usually bounded for quality of service purposes and must not exceed a few seconds. In addition, the found optimal/best path should be updated dynamically to account for any sudden change in traffic conditions, due to the occurrence of unpredictable events such as accidents and road closure, while the ve-

[17]https://www.networkworld.com/article/3243111/

hicle is moving towards the destination. Meeting these routing constraints is challenging because the decisions made usually require processing a huge amount of heterogeneous data in a short time, which might not be achievable with the existing routing algorithms. Therefore, such algorithms must be upgraded or novel ones should be developed.

In this survey, we only focus on shortest path finding algorithms in transportation systems. The basic algorithms for finding the shortest path, such as Dijkstra Dijkstra (1959) and A* Hart, Nilsson, and Raphael (1968) algorithms, are not suitable for meeting the challenges stated above. In general, these algorithms are divided into two classes: purely search algorithms and preprocessing-assisted algorithms that aim to accelerate the routing process through the use of the preprocessing phase results Antsfeld (2013). To further ease the understanding of the routing process in the era of Smart Cities and their advanced means of transport, we propose a new classification based on the used means of transport and the best route selection criteria (i.e., the constraints to optimize). The means of transport could be: mono-modal, schedule-based or multi-modal as stated in Bast et al. (2016), while the second parameter could be either single criteria based selection or multi-criteria based selection.

The used means of transportation could be tram, bike, private vehicle, taxi, bus, etc., if one transport mode only is used then we are in the *mono-modal* class. *Schedule-based* consists of using any combination of buses, train, subway and tram. Finally, the *multi-modal* class includes a combination of any transportation modes with bicycles, private vehicles and walking. In Figure 9, we illustrate the classification of routing algorithms based on the used means of transportation.

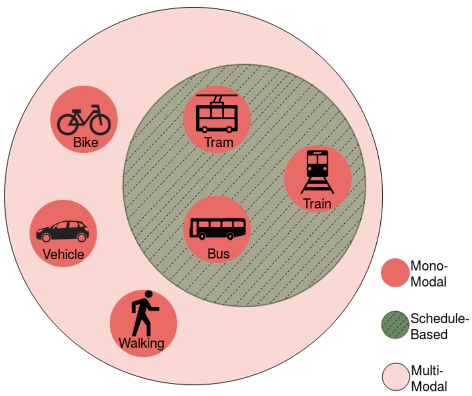

Figure 9. **Classification of routing algorithms based on transportation modes**

Routing algorithms aim to optimize a specific criterion such as: the total travel time or distance, travel cost, safety level, the generated CO_2 emissions and number of shift, etc. If we want to optimize a single criterion then we are in the *Mono-Criteria* class. Combining several criteria gives the *Multi-Criteria* class. Examples of the most commonly used routing criteria are depicted is Figure 10. By combining the two parameters mentioned above we obtain six categories of routing algorithms as illustrated

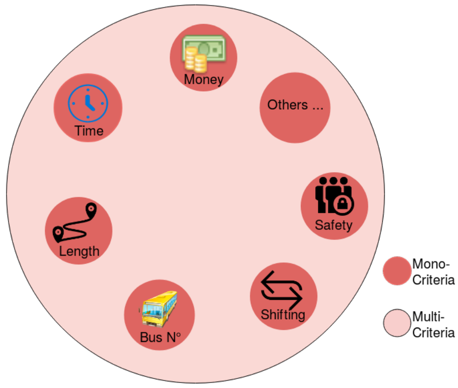

Figure 10. **Examples of the main routing criteria used in S-Mobility**

in Figure 11.

4.3.1 Mono-Modal with Single routing Criterion

This class includes the oldest algorithms proposed for routing such as Dijkstra Dijkstra (1959), A* Hart, Nilsson, and Raphael (1972) and Contraction Hierarchies (CH) Geisberger, Sanders, Schultes, and Delling (2008). CH is a fast technique that consists of contracting a node, meaning that changing this node by shortcuts representing the shortest paths passing by it.

4.3.2 Mono-Modal with Multiple routing Criteria

A bio-inspired heuristic using the travel distance and safety level as main routing criteria was proposed in Osaba, Del Ser, Bilbao, Lopez-Garcia, and Nebro (2018) to find the optimal path for bikes. Moreover, the travel time constraint, which is an implicit consequence of the road length, is also discussed. Open Trip Planner (OTP) [18] was used to calculate the best route that meets the above constraints. The multi-objective bio-inspired approach has been tested on real environment. The obtained results were satisfactory and demonstrated that the developed solution could be used for planning bike rides. Additional constraints could be added to further optimize this solution and, ultimately, testing it with real world open data to accurately assess its performance.

Goods Delivery by lorries in urban areas has been studied in Chou, Hsia, and Lan (2017) where a multi-objective approach was developed to reduce the delivery time, distance traveled and resulting cost. This approach works in two steps: "pre-assigned scheduling" and "route planning". The former identifies the customers requirement, time scheduling and available lorries while the latter plans the route based on the above input. Google Map Application Program Interface (API) is used in the second step to compute the distance and required time to reach a given destination. A feasibility study using a set of lorries was conducted to assess the efficiency of this approach in a real environment. The results were promising and

[18]http://www.opentripplanner.org

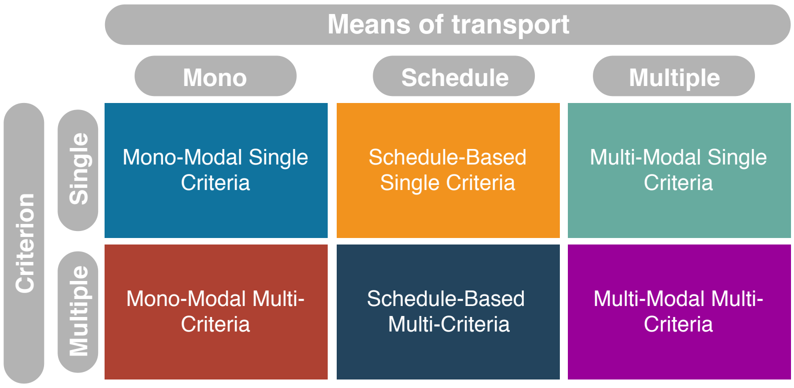

Figure 11. Classification of routing methods in transportation network

showed a reduction of 34.1% in distance and 21.6% in time.
In the case of a disaster, the timely delivery of the needed resources to victims is mandatory to save lives and reduce the resulting damage. The needed resources, required delivery time and the total cost are the three objectives to optimize in Chang, Wu, Lee, and Shen (2014). To achieve this, an algorithm called Greedy-Search-based Multi-Objective Genetic Algorithm (GSMOGA) was designed. This algorithm combines the speed of greedy search with Multi-Objective Genetic Algorithm (MOGA). The evaluation results showed that GSMOGA delivery time is lower than MOGA and Greedy-Search by 63.57% and 46.15% respectively.

4.3.3 Schedule-Based with Single routing Criterion

A traffic regulation system has been developed in Ezzedine, Bonte, Kolski, and Tahon (2008) to coordinate and synchronize departure and arrival times between diverse transport modes. It is obvious that the objective criterion is time optimization. Bus and tram, bi-modal has been used as a case study. This system was integrated with traveller information system to form an Inter-modal Transportation System Management (ITSM). Experiments have been conducted in a realistic simulation environment as part of an urban transportation network project in Valenciennes, France, and the results were promising.

4.3.4 Schedule-Based with Multiple routing Criteria

Genetic Algorithm (GA) and fuzzy set theory were used in J. Li (2002) to attempt solving bus and train scheduling problem. The aim was to minimize the total number of shifts and shift cost. The proposed approach chooses a schedule from a small set of shifts that has been selected from the set of all feasible shifts. The fuzzy set theory was employed for the first time in this work to solve such a problem. The GA, was applied to avoid decomposition of large driver scheduling problems. The developed approach could be used to solve similar scheduling problems and has been generalized successfully.

4.3.5 Multi-Modal with Single routing Criterion

The optimization of the waiting time in multi-modal transportation system has been investigated in Michel and Chidlovskii (2016) where a stochastic program based solution was developed to minimize the passengers' waiting time. Experiments have been conducted in the city of Nancy in France using data collected from buses and trams to assess the performance of the proposed solution. An open source solver called CBC (COIN Branch and Cut) solver *CBC User Guide* (n.d.) and Python were used to implement this solution and the obtained results indicate that the waiting time was reduced by around 42% for short trips and up to 77% for long trips.

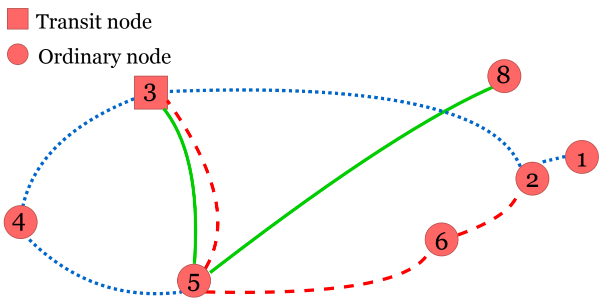

Figure 12. Example of transit nodes

4.3.6 Multi-Modal with Multiple routing Criteria

This category has attracted a lot of attention in the research community as evidenced by the number of proposed works. The concept of transit node routing, inspired from real world navigation, was introduced in Bast, Funke, and Matijević (2006). When we travel between two distant points, we usually pass by some common edges between different shortest paths. Therefore, the end-points of these edges form a set of "Transit Nodes", which is usually a small set compared to the total number of nodes forming the road network. Having the set of all transit nodes of a given location and the travel time needed to reach all its adjacent transit nodes will definitely improve the computation time of the shortest path to the destination. Moreover, using a central unit that collects, updates and shares such information with different means of transport will improve the travel time. Transit

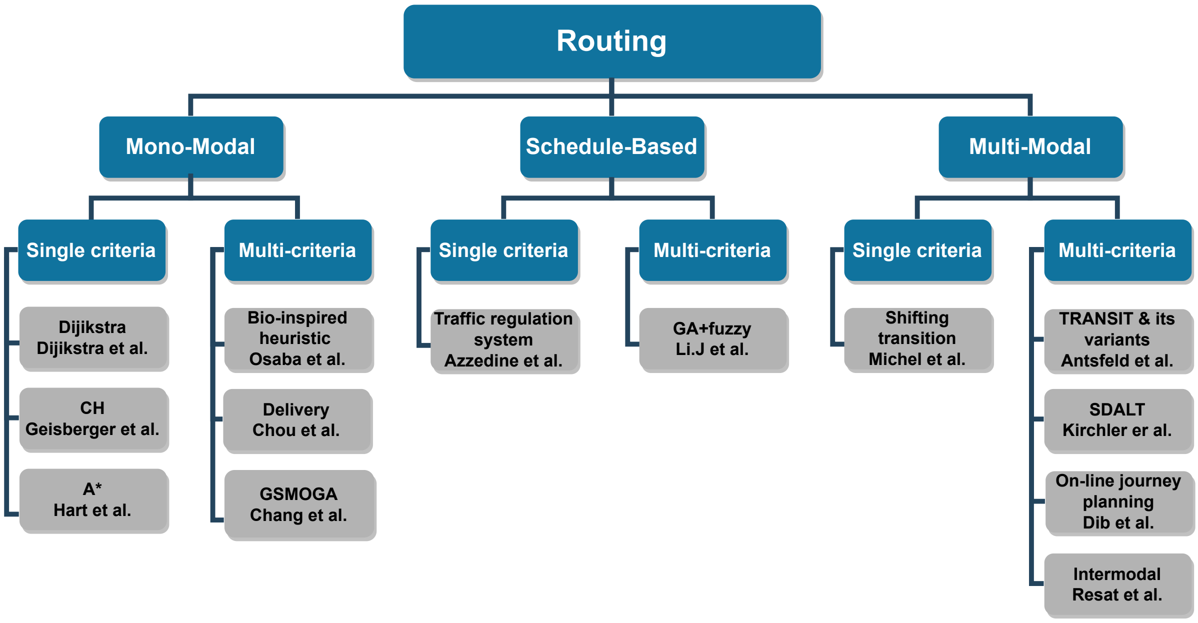

Figure 13. **Classification of routing algorithms in transportation network**

algorithm is among the best algorithms used to find the shortest path in large scale road networks Geisberger et al. (2008). In Figure 12, we show an example of transit nodes. The three paths (pink, green and blue) are shortest paths of different sources and destinations. The green (8,5,3) and pink (2,6,5,3) paths share the edge (5,3) so 3 is the set of transit nodes.

In Antsfeld and Walsh (2012), the authors improve the Transit algorithm proposed in Bast et al. (2006) by including multi-modal transportation. Transit algorithm assumes that the network is static, which is not true in the real world. When a change occurs in the network, the pre-computed values (e.g., transit nodes and shortest paths) are recalculated again despite that some shortest paths are not affected by such change; this was the main motivation of this work. The developed algorithm was called "TRANSIT".

To deal with real world scenarios, such as multi-objectiveness, route alternatives and user preferences, the previous work was improved in Leonid and Toby (2012). The idea is that in reality users might be interested to know the departure time by giving the arrival time. Thus, the same algorithm is applied using backward links. In order to make the system more user friendly, multiple alternative roads are provided by running a query using the starting location and the departure or arrival time chosen by the user. Then, the best five results are selected. To make the system more reliable, the user is asked to indicate how long he is willing to wait before changing a service.

In Antsfeld (2013), a new algorithm called CHAT (Cluster, Hierarchy and Hit) was proposed as an extension to Antsfeld and Walsh (2012) in order to enable faster queries and reduce the memory requirement. The authors have adapted their algorithm to the public transport network by developing a new model that combines and improves the two approaches used to model such a network: Time Dependent and Time-Expanded models. The improvement of the Time-Expanded model led to a reduction in storage space by 30% and lower pre-computation time. With this modeling, the public transport network is seen as a single transport mode instead of a multi-modal. The same algorithm may involve unnecessary waiting time in some stations or several changes of services. A post-processing is, thus, used to solve this issue; the user is redirected to another path, if it exists, that involves less waiting time although the arrival time is the same. Other works include: SDALT (State-Dependent A* search, Landmarks and Triangle inequality) Kirchler (2013), online journey-planning Dib, Manier, Moalic, and Caminada (2017), parking guidance system Gao, Yun, Ran, and Ma (2021) and intermodal transportation Resat and Turkay (2015). Intermodal was defined as: "being or involving transportation by more than one form of carrier during a single journey" *Merriam-Webster Dictionary* (n.d.).

In Figure 13, we summarize the discussed routing algorithms in this section along with their different classes and sub-classes. The main objective of a route or journey planner is not limited to making the user journey more comfortable and smooth but also healthier and safer. This is achieved by reducing the time spent by vehicles on roads, thus reducing CO_2 emission. In the next section we will describe the impact of S-Mobility on reducing air pollution caused by vehicle movements.

4.4 Air pollution

Clean air is extremely important for people to live healthy but it has recently become a dream because of air pollution. Carbon monoxide causes breathing difficulties and cardiovascular problems. Nitrogen Oxides (NO_x) and Hydro-Carbons (HC) affect the lung function of children and asthmatics. The microparticles created by these two

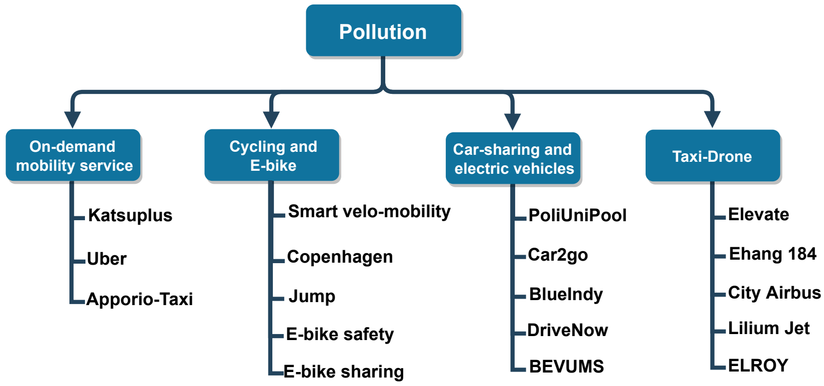

Figure 14. Existing solutions for air pollution reduction using Smart Mobility

elements constitute a cause of mortality Biglia and Belleflamme (2015). Air pollution globally kills more people than malaria and AIDS combined together as reported in [19]. It is mainly caused by manufactories and transport emissions. A new study at the University of Toronto Wang et al. (2015) found that 25% of cars and trucks are causing about 90% of pollution from the vehicle fleet.

Everyone uses the most suitable transport mode for his needs without considering its impact on the society, which sometimes might be devastating. We must, therefore, find a balance between the needs of the users and those of the society. In order to reduce air pollution caused by transportation, the number of private vehicles driven on the roads must be reduced and walking, cycling, carpooling or using eco-friendly public transport should be encouraged. A journey planner is also another solution to reduce CO_2 emissions. Figure 14 shows the existing solutions for air pollution reduction using S-Mobility, which are further discussed below.

4.4.1 On-demand mobility service

On-demand buses is a promising solution that assists in minimizing the number of vehicles on roads. Kutsuplus *On-Demand Public Transportation Changing Human Mobility in Cities* (n.d.), which stands for "call plus" in Finnish, is a transport service used in the capital city of Finland, Helsinki, which is more expensive than regular bus lines but cheaper than regular taxis service. It consists of minibuses of nine passengers where rides are arranged through smartphone applications. Prospective passengers input their points of departure and destination along with the desired arrival time to the application. Then, the application generates instantaneous information on where to get on and off and an accompanying timetable. The system computes the optimal route to meet riders' needs, enabling the bus to truly be operated “on-demand” as required. The actual fares, while being higher than the normal bus services fare, are lower than using a taxi service. Kutsuplus is an example of efficient on-demand buses service that aims to significantly reduce the number of cars on the roads of Helsinki in 10 years. Helsinki's city authorities ambition is to put in place, by 2025, a "mobility on demand" system that integrates all forms of shared and public transports with a unified single payment subsystem.

Uber [20] is an on-demand taxi system that was launched in San Francisco in 2011 and later in London and Paris in 2012. According to Reuters world news [21], in 2017 Uber was operating in more than 90 European cities. This system operates as follows: the rider enters the desired destination and pick up point. Then the driver contacts the rider and picks him from his location. This application offers different services such as: Uber food, Uber companies, travel, etc. Another similar application to Uber called Apporio-Taxi *apporio home page* (n.d.) is developed by Apporio Infolabs to overcome the code complexity of Uber. It is operational in several countries around the world such as Egypt, Kenya, Mexico, France, etc. Such on-demand taxi service was another way of reducing the number of privately owned cars on the roads and thus lowering air pollution.

4.4.2 Cycling and E-bike

Electric bike or simply E-bike is a bicycle with an integrated electric motor. The benefits of cycling for people's health and its positive impact on the society are numerous such as improving people health and fitness and reducing air pollution and the excessive demand on different transport modes. Several countries, such as the Danish government, give a lot of importance to improve cycling and encourage their citizens to use bikes for their short to medium distance travel, especially within urban areas. The danish government aims to make Copenhagen the world's best city for cyclists and to achieve that it sets a number of objectives to reach by 2025 [22]. Among these objectives, we briefly discuss those related to reducing air pollution:

- Increase the percentage of people using bicycle for their daily travel to 50%. Bicycles are known as a

[19] https://www.smithsonianmag.com/science-nature/air-pollution-kills-more-3-million-people-every-year-180956638/?no-ist

[20] https://www.uber.com

[21] https://www.reuters.com/article/us-uber-britain-europe-factbox/factbox-uber-operates-in-more-than-90-european-cities-despite-legal-battles-idUSKCN1BX1WX

[22] https://cyclingsolutions.info/cycling-embassy/

non-motorized transport that preserve environmental sustainability. Cycle tracks, parking facilities for bicycle, valet parking for cyclists, surface treatment for cobblestones, bike repair, weather reports, etc. will encourage people to use bicycles.

- Increase the number of cycle tracks in the Copenhagen PLUS-net by 80%. PLUS-net is a network of “Bicycle Superhighways” for extremely busy roads. By 2025 this system will be extended to Green Routes, Bicycle Superhighways and the most congested bicycle routes.
- Average travel time must be reduced by 15%. An extra focus on creating shortcuts for cycling network will improve the travel time. Establish new bike lanes, traffic calming and speed pumps will minimize the cycling times.
- Increase to 80% the share of cyclists who find that bike paths are well maintained. The Shared bicycles arise as a new transportation mode to go to work, to school, universities, etc. It is mainly used by children. Safety bike lanes will encourage parents to allow their children to cycle in their way to school.
- Increase to 80% the number of citizens who think that cycling culture has a positive impact on the atmosphere of the city. Being aware of the benefits of cycling will definitely encourage people to use it.

Despite the multiple benefits of cycling, it is still neglected in most countries, unlike other modes of transport. In Behrendt (2016), a system, named *“smart velomobility”*, is developed to take advantage of Smart Cities and the Internet of Things (IoT) to boost the use of bicycles. According to Koglin and Rye (2014), “Smart velomobility considers how networked cycling practices and experiences fuse physical and digital aspects, including aspects of physical mobility, infrastructure, power relations, representations and every day experiences and practices”. An open source platform, named SEMS (Smart E-bike Monitoring System), is used for data acquisition necessary to monitor bikes use and locations without the riders’ input. An interface is available for all riders and SEMS team for data visualization. Uber offers a service for on-demand electric scooters called Jump *JUMP home page* (n.d.). The rider selects a bike or a scooter, then identify and unlock it and finally ride it. Once his trip is finished, he parks and locks the bike or the scooter again.
The influence of COVID-19 on electric bicycle safety in China was investigated in Yan and Zhu (2021). The study has demonstrated that the epidemic might dramatically improve e-bike safety concerns in areas with a higher rate of e-bike fatalities and injuries. In the suburbs of Velenje, Slovenia, the authors of Bruzzone, Scorrano, and Nocera (2021) looked at the feasibility of employing e-bike sharing and demand-responsive transportation systems. They came to the conclusion that implementing such a system would expand the number of villages with daily and regular access to railway and bus terminals, as well as public services in the city center.

4.4.3 Car-sharing and electric vehicles

A new report published by the International Energy Agency (IEA) in 2018 [23] announced that more than one million electric car were sold in 2017, with more than half of global sales in China. The global number of electric cars on the roads exceeded three millions worldwide, with an expansion of more than 50% compared to 2016.
Carpooling is an innovative transportation concept that relies on the shared use of personal cars. PoliUniPool Bruglieri, Ciccarelli, Colorni, and Luè (2011), is an example of a carpooling system developed for students studying in Milano’s universities. An algorithm was developed to minimize an objective function of numerous parameters. One of them is "*the total route length*", which will certainly reduce air pollution. One of the characteristics of this system is that it supports the use of environmentally friendly means. This is done by choosing railway and subway stations as destination of the carpooling trip for the user. The environmental-friendly characteristic is ensured by the fact that 17% of students use subways and railways for their trips.
The proposed algorithm is able to provide results in a short time (i.e. four minutes). The developers of this system believe that a successful carpooling service would definitely be helpful in relieving congestion in Milano’s urban areas.
Car2go *CAR2GO hame page* (n.d.) is another example of a carsharing service adopted in many countries such as: Germany, Canada, Italy, etc. With car2go, drivers are monitored along their trips. Unlike other carsharing services, in this system, the user pays only for the period of use of the vehicle. Cars are available on the street in specific locations around the city where the users car unlock them and drive away. Auto Bleue *auto-bleue home page* (n.d.) is an electric car rental service based on carsharing concept. It can be used via a reservation service (ZEN service) or without prior reservation (FLEX service). This service is offered in Nice, France. This project was closed permanently on December 31, 2018. Another carsharing service operating in France is Communauto *Communauto home page* (n.d.) which advocates that each carsharing car replaces nine personal cars and releases eight parking spaces. Carsharing users drive less, walk and use public transportation more, thus significant greenhouse gases will be avoided. Other examples of carsharing services include BlueIndy *blueindy home page* (n.d.) in Indian and DriveNow *DriveNow Car Sharing & Car Club* (n.d.) operating in Germany and seven other European countries.
A free-floating carsharing is a system that aims to fulfil the mobility needs of the inhabitants of a given area in a city. The choice between electric and hybrid cars in this system was investigated in Wielinski, Trépanier, and Morency (2017). Results showed that hybrid cars are more popular for journeys longer than 24 km. Moreover, cold weather and a male user are two factors that influence negatively the choice of electric cars while higher energy levels (i.e., higher battery capacity) increase the probability of choosing them by the users.

[23] https://www.iea.org/gevo2018/

In Brendel, Lichtenberg, Brauer, Nastjuk, and Kolbe (2018), a framework was developed to better manage batteries in E-cars. It consists in a Battery Electric Vehicle Utilization Management System (BEVUMS). This framework uses E-carsharing that reduces CO_2 emission and urban traffic. To assess the performance of this framework, simulations were carried out on a dataset of 2000 and 20000 car rental data points, respectively, and the obtained results were promising. This framework provides a guidance to implement a BEVUMS that encourages the use of shared electric vehicles. Algorithms dedicated to electric vehicle are being actively developed and tested such as Jang, Kwag, and Ko (2023).

4.4.4 Taxi-drone

Taxi-drone or flying taxi is the future of urban mobility as it will reduce traffic congestion and therefore air pollution. The Uber Elevate team *Uber Elevate* (n.d.) plans to integrate air transport with Uber services by 2023 and thus Uber passengers will be able to fly over congested ground traffic. It is currently being tested in Dallas and Los Angeles. Uber took advantage of Consumer Electronics Show[24] (CES) in 2019 *CES Fact Sheet and Logo* (n.d.) in Las Vegas to present its first drone taxi prototype. It can carry four passengers plus the pilot. It is fully electric with a speed up to 175 mph.

Ehang 184 Margaritoff (n.d.), is an electric flying taxi in China which has been successfully tested more than a thousand times. Ehang 184 can run at 100 km/h for 23 minutes carrying a single passenger weighing up to 100 kg. Other examples of taxi-drones include Workhorse Surefly *WORKHORSE home page* (n.d.), Kittyhawk Flyer *KITTYHAWK home page* (n.d.), Kittyhawk Cora *KITTYHAWK home page* (n.d.), Volocopter 2X *VOLOCOPTER home page* (n.d.), City Airbus Passenger Drone von Kursell (n.d.), Lilium Jet *LILIUM home page* (n.d.), Astro Aerospace Passenger Drone (ELROY) *astro home page* (n.d.), Bell Helicopter *BELL home page* (n.d.), etc.

Surefly *WORKHORSE home page* (n.d.) is a hybrid aircraft that can carry a pilot plus one passenger or cargo. It uses gasoline generator and an electric battery that can hold out for 10 minutes. Surefly can run up to 70Knots [25]. Safety is ensured by a parachute that can be used in case of emergency. Kittyhawk Flyer *KITTYHAWK home page* (n.d.) is a personal flying car with speed of 20 mph. It is autonomous and fully electric, designed for one passenger. Kittyhawk Cora *KITTYHAWK home page* (n.d.) is a two seats Autonomous Aerial Vehicles (AAV). It is all-electric and self-driving. Its maximum speed is 180 km/h. In case of emergency a parachute is present to save passengers' lives. The German aviation company Volocopter designed Volocopter 2X *VOLOCOPTER home page* (n.d.), self-driving Vertical Take-Off and Landing (VTOL). It runs completely on electricity with a velocity of 100 km/h. The two seaters VTOL has a parachute for passengers safety. Airbus has also designed its VTOL called City Airbus Passenger Drone von Kursell (n.d.). The four passengers aircraft will be flown by a pilot during testing then it will be completely autonomous. The fully electric aircraft has a speed of 120 km/h. Lilium Jet *LILIUM home page* (n.d.) is an on-demand air taxi in Germany. It is designed for five passengers. It will initially be driven by a pilot then become self-driven after a few years. This aircraft can travel 70 km in 15 minutes and its maximum speed is 300 km/h. It is completely electric. ELROY is an electric VTOL (eVTOL) designed by Astro Aerospace *astro home page* (n.d.). This passenger drone is autonomous or manually. Carrying two people, it can run with a maximum speed of 70 km/h. Bell Helicopter *BELL home page* (n.d.) is an on-demand mobility solution designed for package delivery. The four passengers drone is electric with a speed of 150 km/h. It operates by a pilot and anticipates to be self-piloting. In Table 1, we summarize the above discussed taxi-drone solutions.

In addition to air pollution, another major cause of people's death is road accidents. Therefore, drivers and passengers safety on road will be discussed in the next section.

4.5 Road safety

According to the World Health Organization [26], every year nearly 1.25 million people die as a result of traffic accidents. Approximately 50% of those dying by road traffic crashes are "vulnerable road users": pedestrians, cyclists, and motorcyclists. From 20 to 50 millions other people are seriously injured and suffer from sustainable disabilities. Moreover, road crashes cause huge economic losses to individuals, their families and nations. They cost each country 3% of its Gross Domestic Production (GDP).

Low and middle income countries are the most vulnerable to traffic accidents with more than 90% of the total deaths in the world, despite having a small percentage of the world's fleet of vehicles, or nearly 54%. African countries are suffering from a high rate of road traffic deaths. Even in developed countries, people from poor backgrounds are more likely to cause traffic accidents. For young people, females are less likely to have traffic accidents than males. About 73% of deceased young males are under the age of 25, the probability of their dying from traffic accidents is three times more compared to young females.

According to the World Health Organization, without sustained actions road traffic crashes are predicted to become the seventh major cause of death by 2030. The newly adopted 2030 Agenda for Sustainable Development has a plan to minimize the number of road deaths and injuries by 2020 by 50%. Thus, road users safety is an important issue that should be solved by S-Mobility. We group the solutions proposed to increase road users safety into: vehicles oriented solutions and pedestrian oriented solutions (see Figure 15).

[24] is an international yearly trade show organized by the Consumer Technology Association (CTA)

[25] Knot is a measure of speed. 1Knot = 1.852Km/h

[26] https://www.who.int/en/news-room/fact-sheets/detail/road-traffic-injuries

Table 1. A comparative study of Taxi-Drone solutions

	Capacity	Power source	Operation	Target service	Max speed
Uber Elevate	4	Electric	Pilot then autonomous	Carrying passengers	240km/h
Ehang 184	2	Electric	Autonomous	Carrying passengers	100km/h
Surefly	1	Gasoline and Electric battery	Pilot	Carrying passengers and Cargo	130km/h
Kittyhawk Flyer	1	Electric	Autonomous	Personal flying car	32km/h
Kittyhawk Cora	2	Electric	Autonomous	Carrying passengers	180km/h
Volocopter 2X	2	Electric	Autonomous	Carrying passengers	100km/h
City Airbus	4	Electric	Autonomous	Carrying passengers	120km/h
Lilium Jet	5	Electric	Pilot then autonomous	Carrying passengers	300km/h
ELROY	2	Electric	Autonomously or manually	Carrying passengers	70km/h
Bell Helicopter	4	Electric	Pilot	Package delivery	150km/h

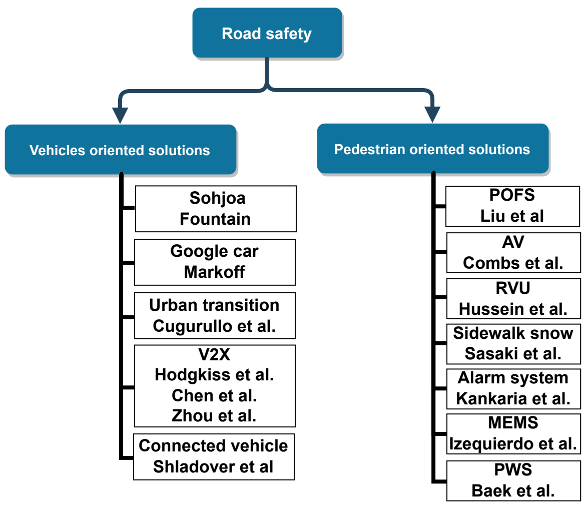

Figure 15. Classification of road safety solutions

4.5.1 Vehicles oriented solutions

Autonomous cars' advanced technology aims to eliminate the driver's intervention which is often the main cause of accidents. For example, a small electric bus chugged called Sohjoa Fountain (n.d.) is a promising solution in Helsinki. It represents a slow ride toward the future of public transportation. Running at 7 mile/h without a driver, it operates using sensors and software components but currently a person is stationed on board ready to hit a red "stop" button if any emergency situation arises. In 2010, Google presented a prototype of a driveless vehicle called later Google Car Markoff (n.d.). According to the U.S.NEWS BEST CARS Kurczewski (n.d.) published on October 2018: "Fully autonomous cars are currently undergoing testing in several areas of the country, but none are yet available to the general public". "This first generation of autonomous vehicles will, in most cases, not be offered for sale or lease to the general public, but instead would be reserved for commercial use by ride-hailing fleets and delivery services" Topics (n.d.). By 2021, the first totally autonomous vehicles introduced by Ford will be in sales. Despite their advanced features, autonomous vehicles bring additional challenges related to privacy issues and their potential vulnerability to cyber attacks, where a remotely controlled autonomous car can be used to launch a terrorist attack, disturb the traffic in highly congested areas, etc.

In Yaqoob et al. (2019), the authors presented a taxonomy of emerging technologies, requirements, and potential issues for autonomous driving vehicles in smart cities. Huang *et al.* in Huang and Chen (2020) have also investigated deep learning-based technologies used to enable autonomous driving features, while Yurtsever, Lambert, Carballo, and Takeda (2020) discussed recent trends and unsolved issues of automated driving.

Cities are gradually integrating autonomous automobiles driven by artificial intelligence into their transportation portfolios, with significant consequences for the design and sustainability of the built environment. In Cugurullo, Acheampong, Gueriau, and Dusparic (2020), the authors discuss the urban transition to autonomous transportation, depending on three-axis. The first ax is to provide a theoretical framework for comprehending the spread of autonomous vehicles in cities. The second ax depends on the results of a thorough inquiry conducted in Dublin. In the last ax, they utilize the survey's empirical findings to examine various urban futures, with an emphasis on the changes in urban design and sustainability that the transition to autonomous transportation expects to bring about.

Cooperative and connected vehicles is another solution to enhance road safety through enabling the exchange of data between the vehicles, using Vehicle-to-Vehicle (V2V) communication, or the vehicles and the road infrastructure, using Vehicle-to-Infrastructure (V2I) communication, as well as between the vehicles and other road users such as pedestrians and cyclists using V2X communication. To minimize the risk of accidents when performing manoeuvres, such as lane change, vehicles need to coordinate their actions using V2V communication to improve the manoeuvre efficiency and safety level J. Hodgkiss, Djahel, and Hadjadj-Aoul (2019). Vehicles can also report relevant data about accidents, congestion, state of the road, drivers status, etc. This data can be very useful in enabling faster reaction to incidents, minimizing the number of casualties, and timely traffic information delivery to drivers to avoid congested areas, thus reducing further travel delays and the risk of accidents since drivers who are stuck in congestion tend to drive faster to compensate the experienced delay. This critical data must be routed efficiently in order to provide drivers with timely accurate information.

In Ye, Chen, Li, Ma, and Liu (2021) a microscopic model was proposed to predict vehicle speed using V2X communication. This model uses multivariate time series arrays to model the traffic. The contribution of this work is an energy conservation control system. When compared to the standard logic threshold-based control technique, the suggested strategy increases vehicle energy economy by 13.02% and reduces Carbon dioxide emission by 16.04% under real-world driving circumstances. In Djahel, Doolan, Muntean, and Murphy (2015), the authors discussed in detail vehicular communication and proposed a classification of the existing routing protocols based on the use or not of two parameters: road map network and vehicles mobility model. In Shladover (2018), Shladover *et al*. provide a survey on connected and automated vehicles technology. Another more recent survey is Zhou, Xu, Chen, and Wang (2020), where the authors discussed the challenges and the issues in progressive V2X innovations for the Internet of Vehicles (IoV).

4.5.2 Pedestrian oriented solutions

Pedestrian alert system has proved its efficiency for collision avoidance. A pedes-trian-oriented Forewarning System (POFS) was proposed in Liu et al. (2015). It aims to alert pedestrian distracted by smartphone about imminent risks of accidents. The system is composed of three modules: Communication module, collision estimation module and alert module. In the first module, a V2X communication system is developed to support vehicle-to-vehicle, using Wireless Fidelity (Wi-Fi), and vehicle-to-smartphone communication. Long Term Evolution (LTE) is the most adopted for vehicle to smartphone communication because of the limited coverage range of WI-FI and the speed of moving cars. An LTE DATA PUSHING (LDP) algorithm is developed to enable downloading data from the server to the pedestrian smartphone in case of a risk of collision with a vehicle in its future path. In the second module, a collision estimation algorithm is proposed to predict the risk of accidents occurrence. The third module alerts pedestrians depending on the smartphone status, which can be: screen-centric state, voice-centric state, screen-voice state and silent state. For each state, there is a different alert mode. This system can warn the pedestrians with a probability of at least 90%.

In Combs, Sandt, Clamann, and McDonald (2019), a study is conducted to highlight the impact of AVs on pedestrian fatalities on the roads in United States. In this study, a number of scenarios are simulated where ordinary vehicles are replaced by AVs to study how this would affect pedestrians fatalities. A Fatality Analysis Reporting System is used to extract statistics about pedestrian fatalities. Then, the maximum number of pedestrian fatalities that can be avoided using AVs equipped with sensors is identified. The obtained results show that in-vehicles sensors along with other advanced features of AVs can assist in preventing from 30% and up to 90% of pedestrians and vehicles collisions. However, achieving the same results in real world requires high penetration rate of AVs, which is still a futuristic dream and the cost of AVs might be another obstacle towards achieving this dream.

A collision prediction algorithm for pedestrians and Vulnerable Road Users (VRU) is proposed in Hussein, García, Armingol, and Olaverri-Monreal (2016). It is based on Vehicle-to-Pedestrian (V2P) and Pedestrian-to-Vehicle (P2V) communication. It aims at increasing visual situation awareness of VRU for both AVs and regular vehicles, in addition to reducing potential danger on the road and advocating the adoption of AVs by drivers. Two systems are developed to operate on smartphones and vehicles. The Time To Collision point (TTC) is also computed using the GPS position of the pedestrian's smartphone. Warning and vibration messages are displayed on the smartphone screen alerting the pedestrian about the direction of the oncoming vehicle. The same process is repeated in vehicle. Experiments are performed using an electric autonomous vehicle from the iCab project Gomez, Marin-Plaza, Hussein, Escalera, and Armingol (2016). It operates by an on-board embedded computer that can be controlled manually. To assess the performance of the proposed solution two metrics are used: "distance to collision point" and "collision danger index against time". The results are promising and show high detection rate and users were satisfied by the system. Also this system has proved the feasibility of using V2P and P2V communication instead of sensing devices. However, this solution suffers from inaccurate localization data obtained by GPS.

In Sasaki, Emaru, and Ravankar (2021) an innovative pedestrian recognition system for sidewalk snow removal cars was proposed. It is especially useful for night driving scenarios. Using LiDAR point clouds, the information in front of the snowplow is gathered by grouping and categorizing objects. Support vector machine (SVM) is used to implement this system for recognition and classification of pedestrians. Experiments in real scenarios proved the robustness of this method where the accuracy of classification is high.

In Kankaria, Jain, Bide, Kothari, and Agarwal (2020) a vehicle-specific alarm system was developed to safeguard the safety of individuals operating the vehicle. It should not only safeguard the safety of drivers but also that of all pedestrians and animals by detecting them. YOLO was chosen to implement this system due to its efficiency in image processing and object recognition accuracy, even with bespoke datasets. Traffic Signs, Human Detection, and Traffic Light Detection were evaluated using GTSRB, COCO, and Bosch datasets, respectively. The model was trained using 80-classes of the already pre-trained YOLO dataset. The execution achieves an accuracy of 91.12% at a processing speed of 30 frames per second, outperforming all the state-of-the-art approaches. The accuracy listed

above is the average of the three custom datasets, each of which has substantially better accuracy when trained on YOLO.
The authors in Izquierdo, del Val, and Villacorta (2021) developed a new sensor based on a Micro-Electro-Mechanical System, MEMS, Microphone Array to detect the presence of pedestrians. This sensor is not based on brightness, has a low cost, and has a high accuracy detection. In this study, tests were conducted with various persons, and in various ranges, true detection and false alarm detection of the system have been calculated in each scenario. The acquired findings demonstrate that the proposed system can identify and estimate the position of pedestrians, allowing a vehicle going up to 50 km/h to stop and prevent a collision.
A proximity warning system (PWS) was designed for employees in construction and mining sites to prevent collision in Baek and Choi (2020). This system uses smart glasses to detect heavy equipment in proximity. A Bluetooth beacon is installed in the equipment to transmit information collected. In construction and mining sites, personal PWS with smart glasses provides the following notable benefits. For starters, because smart glasses are worn on the face, workers may freely utilize both hands. Second, pedestrians can be given immediate visual proximity alerts, allowing them to swiftly assess unsafe circumstances and flee as fast as possible. Finally, the suggested personal PWSs might be deployed and used in mining and construction sites by distributing numerous pairs of smart glasses and Bluetooth beacons to workers, regardless of their magnitude. Another solutions for pedestrians safety include Zavodjančík, Kasanickỳ, and Demčáková (2021) where automated road vehicles was used to decrease pedestrians-vehicles accidents.
Sensors signalization for blind people and elderly, special lines for cyclists, mobile applications for accidents announcement to speed up the rescue teams intervention, and upgrading the road infrastructure to make pedestrian crossing safer are some other solutions to increase road safety for pedestrians and commuters.

5 Recent advances in Smart Mobility

During the last decade, the major industrial players and stakeholders in the mobility sector have shown significant interest in investing in the development of the cutting-edge technologies needed to power revolutionary solutions for Smart Cities citizens' mobility. This led to an unprecedented race towards building innovative S-Mobility solutions to overcome the above discussed challenges. Their efforts vary from designing an easy to park small vehicle Fountain (n.d.), an autonomic integrated parking system Saka A.A. and Glassco (2001), a smart connected vehicle Siegel, Erb, and Sarma (2018) that informs the driver about its state as well as road traffic conditions, and electric cars Markoff (n.d.) that take away fuel consumption and reduce air pollution. Manufacturers have also recently invested in flying taxis *Uber Elevate* (n.d.), also known as passenger drones or taxi drones to reduce ground traffic congestion. HITACHI, FUJITSU, BMW, among others, are example of big companies which have developed revolutionary solutions to enable S-Mobility. In this section, we will discuss the most prominent technological solutions dedicated to S-Mobility.
Table 2 summarizes S-Mobility challenges addressed by a number of technological solutions in the market. We can notice the importance given to air pollution due to the increasing awareness of climate change issue and its root causes. In contrast, traffic routing features have not been included in most of the solutions, except of Kutsuplus. Ensuring efficient traffic management is neglected by E-cars and Sohjoa. This latter could also create traffic congestion due to the low speed of its buses which is 7 miles/h on average. Although eliminating or alleviating parking related issues were considered in most of the solutions, E-cars still suffer from this issue in addition to their recharge scheduling and the range anxiety problem. Most manufacturers of recent innovative mobility means, such as Sohjoa, Google cars and E-car, developed enhanced safety and security measures for their passengers.
The advent of new technologies, like the aforementioned ones, have inspired researchers to develop new systems and architectures for S-Mobility, some of which are described in the following.

5.1 Systems and architectures

In this subsection, we briefly discuss a selection of systems developed by major actors to support S-Mobility.

5.1.1 Urban Management Infrastructure (Hitachi)

In order to find the best trade-off between individual users mobility needs and constraints and the impact of the chosen transportation means on the society and the environment, Hitachi Okuda et al. (2012) proposed the concept of "smooth and sustainable" S-Mobility. This implies that the mobility service must run "smoothly" for the users without causing damage to the society. Okuda *et al*. proposed an architecture to implement this concept, in which all transportation companies of Japan are involved. To collect and analyze data from different companies and provide each of them with the required data to run their service, an efficient coordination between these companies is required. To achieve that, Hitachi has developed a solution that consists of five layers: transportation user experience layer, transportation services layer, information collection layer, information management and control layer, and transportation company coordination layer. To optimize the whole system, three types of optimization are used: service optimization, intra-company optimization and optimization of coordination between different transportation companies. This solution, however, does not support multi-model transportation and requires an active participation from users and transportation companies, which might limit its impact and applicability in other contexts where such participation is not at the expected level. This is true as most companies are reluctant to share their data unless there is a clear incentive or benefit for them.

Table 2. The main focus of major technological solutions for Smart Mobility

	S-Mobility challenges covered				
	Parking management	Traffic management	Traffic routing	Air pollution	Road safety
Kutsuplus	Yes	Yes	Yes	Yes	No
Sohjoa	Yes	No	No	Yes	Yes
Google car	Yes	Yes	No	Yes	Yes
E-bike	Yes	Yes	No	Yes	Yes
E-car	No	No	No	Yes	Yes

5.1.2 Cyber Physical System (Fujitsu)

Fujitsu Kawasaki (2015) considers that multifaceted solutions are needed to develop an efficient mobility service because this latter depends on several factors such as the stage of economic development of the country and the region where the solution is used. In 2012, two recommendations have been made by the Transportation Policies Council of the Japanese Productivity Center in order to achieve a S-Mobility society. The first consists in creating a system that connects in-vehicle devices to users smartphones, and developing new technologies for indoor/outdoor data collection that can be adapted to work with the Japan's Indoor Messaging System (IMES) [27], which is an indoor GPS. The second recommendation is to make elderly mobility run smoothly through encouraging personal mobility vehicles (PMVs), developing new systems, in addition to creating parking and paths for bicycles.

By using the location data service provided by Fujitsu Intelligent Society Solution Smart Mobility SPATIOWL Fujitsu (n.d.), Kawasaki *et al* developed a Cyber Physical System that collects and analyzes sensor data to predict the evolution of the traffic flow. The huge amount of data collected by taxi probe data was leveraged to build a traffic information system on the cloud. This solution supports mobility on demand and multi-modal transportation and its ultimate goal is to ensure high level of safety on road for the commuters regardless of what means of transport is being used. In addition, it uses car sharing and gives a lot of attention to bicycles unlike the previous solution developed by Hitachi. Fujitsu classified S-Mobility into three categories: *"personal mobility", "safe and secure mobility"* and *"pleasant mobility"*.

- *Personal mobility*: it combines individual mobility with public transportation. Therefore, they have developed multiple technologies to support the elderly mobility, indoor mobility, on-demand transport system and investigated the problem of PMVs charging.
- *Safe and secure mobility*: it aims to prevent traffic accidents through collecting images from an event data recorder or smartphones and processing them to detect stress and fatigue experienced by drivers, thus enhancing the driving safety.
- *Pleasant mobility*: offering new telematics services through a developed vehicle navigation system connected to operation center via smartphones, using machine-to-machine (M2M) network, with additional voice interaction.

[27] https://insidegnss.com/qzsss-indoor-messaging-system/

It is worth noting that Fujitsu's solution focused more on elderly, which makes it unsuitable for other users from different age groups.

5.1.3 Traffic Information System (DLR)

The German Aerospace Center (DLR) Suske et al. (2016) proposed a new Traffic Information System (TIS) that uses social media and environmental information as new data sources to support S-Mobility services. To significantly improve traffic fluidity, such TIS requires that people are connected to ensure their free mobility, vehicles and E-cars are also connected to reduce air pollution, in addition to using shared and public transportation. The proposed TIS can provide three categories of data: real time, predictive and historical data. To implement such a TIS in every smart city, Suske *et al.* believe that an environment information system as well as traffic management center are required. Although this developed TIS highlights the experience of DLR in the S-Mobility and represents an example of their supremacy in this field, successfully implementing it in other Smart Cities in different parts of the world might be challenging due to its complexity and the required expertise and time to make it fully operational.

5.1.4 Vehicular Social Networks (VSNs)

Vehicular Social Networks (VSNs), which are social networks integrated with Internet of Vehicles, are characterized by more dynamic, due to vehicles movement, but weaker relationships compared to traditional social networks. VSNs are usually used to support safety-related and entertainment-based applications. In Ning et al. (2017), a VSNs based solution was developed to enable traffic anomaly detection based on bus trajectory data collected through crowd sensing model. This solution functions in two steps: traffic modeling and anomaly detection. In the first step, urban roads are segmented based on bus lanes data. Then, spatial and temporal segments (TS-segments) are extracted using stopping items. Finally, a TS-segment matrix is constructed to describe the real traffic situation around the city. In the second step, Local Outlier Factor (LOF) is computed using the average speed and stop time of each TS-segment, and anomalous regions are identified using the inner-line anomaly detection method.

According to this study, to efficiently support S-Mobility objectives VSNs need to overcome a number of challenges in relation to message dissemination, big trajectory data analysis and trust, as well as security and privacy preservation. Therefore, in spite of its promising features and potential, VSNs technology is still in its infancy and substantial development is still needed to make it credible enabler of S-Mobility.

5.1.5 Analysis and discussion

In Table 3, we compare the aforementioned systems in terms of the set of S-Mobility challenges covered by each of them. We can easily deduce that parking management is neglected by all the proposed systems while they address traffic management and routing issues in addition to minimizing air pollution. Ensuring high level of safety for road users is a paramount objective for S-Mobility but it has not been addressed by the above systems, except Fujitsu system.

In Table 4, we compare the above systems based on their distinguishing features and limitations. The comparison metrics include the level of development of the system in terms of the attained Technology Readiness Levels (TRL). The level of maturity of the proposed solutions by these systems varies from defining a new concept and architecture to the development of a robust model and its implementation in a new platform. Other metrics used are the source of traffic data collected, its type in terms of whether its source is fixed location or mobile, the architecture of the data storage solution (centralized database vs. distributed database) as well as its scalability level. Moreover, ensuring the security and privacy preservation of users (i.e., drivers and passengers) personal or sensitive data (e.g., their location) is fundamental to ensure wide acceptance of such systems by citizens and their voluntary participation in the data collection phase through their smartphones.

In order to validate any proposed solution for S-Mobility, we must test it using real data, testbed or simulation platforms. There is a lack of open data relevant to the transportation field, due to privacy concerns, industry practice and so on Ketabi, Alipour, and Helmy (2017). In next section, we present some data provider platforms that involved online interface for the user.

6 Future directions

The aim of this section is to highlight the limitations of current enabling technological solutions for S-Mobility and shed the light on main prospects for future research directions in this emerging field. The lack of an efficient system or platform that provides solutions to all challenges associated with different aspects of S-Mobility eventually results in several shortcomings that affect Smart Cities citizens' quality of life. The efficient management of traffic flows, achieving optimal multi-modal and multi-criteria routing and significantly reducing air pollution are the most addressed challenges in the developed systems and platforms. The efficient parking management and ensuring road safety, however, have received less attention in these existing systems although they play a major role in the mobility ecosystem. In what follows, we summarise the lessons learned from this survey in relation to each of these challenges and provide our vision on how to address them in the future.

6.1 Parking management

The inefficient management of available parking spots is one of the most influencing factor of the increase in traffic congestion in cities. In this survey, we focused on investigating free parking space detection inaccuracy issues. From the literature review, we found that sensor devices and smartphone-based applications are the most used data sources in this context. Sensors are usually preferred to avoid privacy and security issues related to crowd sensing in addition to the willingness of users to participate in this process. Moreover, free-riders and selfish liars negatively affect the quality of collected data. On the other hand, sensor readings can be affected by environmental conditions in addition to the incurred cost for the installation. Despite its high scalability and reliability, computer vision is still an expensive data source for parking management systems and is not suitable for outdoor parking due to its sensitivity to weather conditions. Recently object detection algorithms are used to identify the availability of parking spaces instead of detecting weather a given place or block of spaces is free or occupied. This solution is affordable, scalable, and simple to implement and update. As any other system, parking management is not just data collection but involves also data processing, data storage (centralized or distributed), data analytics, data dissemination, system deployment (large scale), etc. As a futuristic vision, we believe that parking management issues could be relieved, especially in urban areas, through supplementing the existing car parks capacity and on-street parking spots with private parking spots of local inhabitants who can lease their spots, when they are not used, to reduce the impact of cruising for parking on the congestion level and earn extra income from this service. Realizing this service, however, requires involvement of both start-up companies and city authorities to regulate this service and ensure its success.

6.2 Traffic management

Traffic congestion causes economic and human losses as well as environmental damages. To avoid such negative impact or at least minimize it, traffic management techniques are used, which include, but not limited to, traffic flow estimation and prediction along with traffic light control systems. Methods used to estimate traffic flow are grouped into three classes: microscopic, macroscopic and mesoscopic. The first class is the most widely used due to its accuracy although it is more complicated to implement. Macroscopic models are less popular than the previous class but easier to implement as they provide a general view of the road network traffic instead of studying individual vehicles movement. The last class

Table 3. **S-Mobility challenges covered by the proposed systems**

	Parking management	Traffic management	Traffic routing	Air pollution	Road safety
Hitachi Okuda et al. (2012)		✓	✓	✓	
Fujitsu Kawasaki (2015)		✓	✓	✓	✓
DLR Suske et al. (2016)		✓	✓	✓	
VSN Ning et al. (2017)		✓			

Table 4. **A summary of the main features and limitations of the proposed S-Mobility solutions**

	TRL	Data sources	Fixed location data sources	Central storage	Means of transport	Privacy & security issues	Scalability	License
Hitachi	Concept, Architecture & Solution	Information platform	Yes	UMI	Multi-Modal	No	Yes	proprietary
Fujitsu	Approach & Platform	Smartphone, Taxi probe data	Yes	CPS	Multi-Modal	No	Yes	proprietary
DLR	System & Architecture	Heterogeneous	Yes	TIS	Multi-Modal	No	Yes	proprietary
VSN	Model	Crowd-sensing	No	No	Buses	No	No	—

is mesoscopic, which combines the advantages of both of the above classes.

Predicting the evolution of traffic flow in urban areas is more difficult than freeways due to the complexity of the road layout and traffic pattern variations. As opposed to long-term traffic prediction, short-term traffic prediction is more accurate since the used data are updated more frequently at the expense of the required large storage and fast processing. Achieving fast and accurate short-term traffic prediction is a necessity as it enables faster and more efficient response to potential bottlenecks. We foresee that Intel's Myriad X Vision Processing Unit (VPU)- the first of its class to feature the Neural Compute Engine – providing a dedicated hardware accelerator for deep neural network inferences will enable the development of new highly accurate deep neural network based traffic prediction models. Such models are expected to meet the above speed and accuracy requirements. Responding efficiently to predicted deterioration of traffic conditions may involve alteration of default driving policies or traffic signalling systems through smart and adaptive traffic light control systems, such as the schemes developed in S. D. et al. (2020) and ALEKO and Djahel (2020), or virtually inflating road network capacity through granting selected set of vehicles temporary access to under-utilized reserved lanes S. D. et al. (2018). We believe that the future of traffic management system is VANET-based. Due to their rapid reactions, self-driving cars would significantly reduce traffic congestion and accidents. However, with VANETs in particular and IoT-based systems in general, privacy, security, and authentication difficulties become crucial challenges.

6.3 Traffic routing and air pollution reduction

Promoting the use of multi-model transportation by citizens can significantly alleviate several traffic related issues and make commuters travel more comfortable. Integrating Electric Vehicles (EVs) and flying taxis in multi-model transportation systems will be beneficial in many ways, such as reducing air pollution and efficiently offloading ground transportation system in highly congested urban areas. Such system requires optimal and accurate complex planning of departure and arrival times of different transportation means to satisfy commuters constraints and ensure efficient use of the whole system capacity with minimum running cost. In any transportation system, achieving optimal or near optimal routing based on single or multiple best route selection criteria is necessary. Achieving this in S-Mobility is, however, more challenging as additional constraints need to be considered. For example, an optimal route for an EV journey should account for the number and location of charging stations, the expected waiting time at stations if a recharge is needed during the vehicle journey, its remaining battery on-board and its battery capacity A. M. et al. (2017).

Based on the findings of this survey, we believe that AI enabled routing techniques, such as J. Q. J. et al. (2019), supported by multi-agent systems embedded in the smart road infrastructure (e.g., run by Intelligent Traffic Light Control Systems (ITLCS)) to quickly and efficiently adapt the route to avoid unpredictable events and their associated delay S. W. et al. (2016). Optimal battery recharge scheduling Rottondi and Verticale (2016) is another issue that is yet to be tackled efficiently, solving it for both EVs and drones used for traffic monitoring will significantly improve the quality of routes suggested to drivers and make the overall transportation system run more efficiently with less emissions. Moreover, although it requires substantial investment in upgrading current road infrastructure if the technology being developed is adopted and widely implemented, wireless charging for EVs will significantly increase the acceptance of EVs by the public I. H. et al. (2018). Such technology allows EVs to recharge their battery wirelessly on the move using dedicated road lanes equipped with such capability. Qualcomm Halo is an example of wireless car charging system currently used by Formula E electric race series to keep the batteries of the BMW i3 medical cars and i8 safety car recharged during each race weekend.

The above technology will certainly leads to an increase of the EVs penetration rate and supports the future vision of transport electrification (i.e., electric vehicles, buses and bikes etc.) to tackle climate change issues and air pollution. The implementation of this approach is facing multiple issues related to battery charging speed, communication protocols and security issues (vulnerability, privacy, etc.). Using EVs as shared cars, known as electric vehicle-sharing, is very promising solution as it reduces the fleet of cars on the road and lower the emissions. Furthermore, if EVs are recharged from solar power system, this can further reduce greenhouse gas emissions in the city. Finally, we believe that Mobility as a Service (MaaS) combined with transport electrification could be an efficient solution that significantly reduces the fleet of vehicles on the road while maintaining clean air in the city and providing mobility service that meets the commuters requirements.

6.4 Road safety

Road accidents are usually caused by drivers' dangerous manoeuvres, the deteriorated state of both road infrastructure and vehicles, especially in developing countries where the fleet of old vehicles is significant. In order to make commuters travel safer and protect vulnerable pedestrians from accidents adequate measures should be taken. Such measures include developing pedestrian-oriented alert systems that alert pedestrians distracted by the extensive use of their smartphones to the immediate danger of approaching vehicles Liu et al. (2015). Likewise, the era of autonomous vehicles opens up opportunities for enhancing the drivers and pedestrians safety through connecting wearable sensors, worn by the driver to monitor his sleep signs and predict sudden health problems, to the vehicle to switch the control to autonomous driving when needed to avoid accidents.

Enhancing the smartness of the new constructed roads and upgrading the existing infrastructure to make it more interactive with autonomous vehicles, for example, will certainly play a major role in reducing causalities on the roads. Such smart roads will be a source of a wealth of traffic data that can be of utmost importance to autonomous vehicles as well as traffic authorities to help them make optimal decisions to enhance the road safety. However, the vulnerability of autonomous vehicles to cyber attacks B. S. et al. (2019) will constantly threaten the road safety if sophisticated countermeasures are not in place. Indeed, a hacker who succeeds to remotely control an autonomous vehicle can cause serious disruption to the traffic flow with high risks of human lives loss. Therefore, car manufacturers and cyber security researches and SMEs are invited to join their efforts to be ahead of the hackers by constantly thinking of new attack scenarios and developing solutions to face them. C-V2X (Cellular Vehicle-to-Everything) communication technologies refer to a system, where "everything" (i.e., the X) may be a different car, a person walking, a piece of road infrastructure, or a network server. This new emerging technology can enhance data collection and processing which will improve the decision making.

6.5 Mobility as a Service – MaaS

We believe that the emerging concept of MaaS Goodall, Dovey, Bornstein, and Bonthron (2017) Y. Li and Voege (2017) could be an efficient solution to the above discussed challenges. MaaS aims to make the mobility as another consumer service that citizens use and pay for based on their needs. It promises to ensure affordable, fast, secure and clean mobility anywhere, anytime and anyhow. MaaS will require the development of a unified and integrated mobility system, high penetration rate of connected and autonomous vehicles, multi-model transport system, coordination between ground and air transport means for enhanced sustainability, in addition to well defined regulation for the use of both autonomous vehicles and Taxi-Drone.

A unified mobility system that integrates the traffic management system, parking management system and traffic routing system could yield substantial benefits in terms of the ability of controlling the traffic flow and mitigating the creation of bottlenecks in specific locations. This can be achieved through a well defined coordination among these three systems, for example knowing in real-time the occupancy level of different car parks in city center enables the routing system to route the vehicles in a way that minimizes their cruising time to select or reserve a parking spot. Likewise, the prediction information provided by traffic management system helps the parking and routing management systems to coordinate their decisions so that any predicted congestion could be avoided or at least alleviated Djahel et al. (2015).

7 Conclusion

This survey provided a comprehensive analysis of the most important emerging challenges that need to be overcome to successfully realize the Smart Mobility (S-Mobility) dream. The addressed challenges covered the main aspects of S-Mobility ranging from parking management to ensuring road safety and lowering air pollution. We also discussed a number of recent technological advances aiming to provide the required systems, platforms and data to underpin the services to be offered by S-Mobility providers to their users. A summary of major limitations impacting the efficiency of existing technological advances supporting different aspects of S-Mobility are also highlighted and future research directions are discussed. Lessons learned from this survey suggest that the integration of different aspects of S-Mobility and the adoption of MaaS framework, underpinned by advanced AI techniques, will shape the future of S-Mobility and determines its successful implementation in Smart Cities.

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