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Modeling Transportation Systems involving Autonomous Vehicles: A State of the Art

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Abstract

Autonomous Vehicles (AVs) promise many benefits for future mobility. Several modeling studies investigated their potential impacts with special focus on spatial and/or socio-economic features. Spatial modeling represents (i) in detail the technical specifications of the novel mode, and ii) the spatial features of the area in which the system is implemented. Most of these models are agent-based. Socio-economic modeling addresses the conditions of market penetration and diffusion using mathematical methods with commercial or social orientation. Furthermore, it investigates investment and operating costs.
This paper summarizes the main modeling works on transportation systems involving AVs that were published in the academic literature up to end 2016. In addition, we provide some examples of applications and address their respective outreach and limitations. We present recommendations for future developments.
This way, the paper takes part to a research project of which the ultimate goal is to build a predictive model that can be used by operators and policy-makers in order to test AVs scenarios.

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Keywords: Autonomous vehicles, mobility services, spatial modelling, economic modelling

1. Introduction

Since the beginning of prosperity of the automotive era, the automation of car-driving has attracted specific studies: let us quote the car-to-car communication system using radio waves in Milwaukee during the 1920s (The Milwaukee Sentinel, 1926), the electromagnetic guidance of vehicles in the 1930s and 1940s, or the testing of smart highways by adding magnets to vehicles during the 1950s and 1960s (The Victoria Advocate, 1957). In 1980, Mercedes-Benz and Bundeswehr University Munich created the first autonomous car in the world, enabling to start thinking about legislation adaptation (Davidson, et al., 2015). Since then, many companies launched themselves in the quest for the perfect car or autonomous system, including Mercedes-Benz, General Motors, Google, Continental Automotive Systems, Inc. Autoliv, Bosch, Nissan, Toyota (Google Car), Audi, Oxford University, among others. Addition impetus was provided by the DARPA Grand Challenges I (2004), II (2005) and III (2007). In 2016, five US states (California, Florida, Michigan, Nevada, Tennessee and the District of Columbia) allowed to test autonomous vehicles, while 16 other states are considering taking legislative bills about automated driving (Weiner, et al., 2016). The experiments on autonomous vehicles show promising results. Such in-field experiments are mainly intended to test self-

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driving technology and possibly also the attitudes, use gestures and behaviours of potential users. Yet, up to now there has been no large scale implementation of AV fleet in a given territory. Prior to that, it is obviously important to deliver safe and reliable technology and to settle a suitable regulatory framework. Even more important, though less obvious, is the requirement to ensure commercial success, i.e. the purchase of hiring of AVs by individual customers of firms, which requires in turn convincing evidence of AV-based services attractiveness within the range of travel solutions that compete to serve mobility purposes. This is why a number of researchers have modelled AV-based services as mobility solutions under particular territorial conditions.

This paper reviews the models developed so far, with the aim to summarize their findings and to assess their outreach and limitations. As it turns out, the reviewed models fall into two broad categories depending on their main orientation that can be geographic or socio-economic. Geographic or spatial models focus on technical conditions concerning service performance, operations and availability in relation to users' needs and alternative solutions. The choice from among alternative solutions indeed leads to economic issues. Models belonging to the socio-economic category put the emphasis on the temporal conditions of AV development: this involves issues of technology readiness, legal framework, demand inclination and adoption, in relation to the production costs of self-driving cars.

The rest of the paper is organized in four parts. Section 2 reviews models that emphasize spatial conditions: they can be further divided according to whether they are rooted in travel demand needs and choices, or in the dynamic performance of a technical system that links the supply and demand sides. Then, Section 3 addresses socio-economic models, from market penetration to production costs passing by customership issues. Next, Section 4 reports on the evaluation of potential impacts that range from traffic volumes and parking demand to environmental impacts, passing by safety. Lastly, Section 5 discusses the outreach and limitations of the reviewed models and their applications, before proposing some directions for further research.

2. Spatial Models of AV-based Services

2.1. Models rooted in Travel Demand

Levin et al. (2015a) propose a four-step model dividing demand into classes by value of time and AV ownership. AVs are considered as private vehicles. Mode choice is between parking, repositioning, and transit based on a nested logit model. Static traffic assignment uses a generalized cost function of time, fuel, and tolls. Levin (2015b) incorporates dynamic traffic assignment (DTA) with endogenous departure time choices. Thus, the model considers more realistic flow propagation and intersection control options. In addition, it has only studied the case of full autonomous vehicles.

Results of static and dynamic assigment prove that using autonomous vehicles improves the capacity of the intersections, but does not reduce significantly the congestion.

Auld et al. (2017) used a simulation model (POLARIS) which includes an activity-based model (ADAPTS) and a traffic simulation model. Market penetration is controlled on a regional scale by adjusting road capacity. Results show that capacity and value of time affect significantly vehicle-kilometres travelled (VKT).

Kloostra et al. (2017) assumed that autonomous vehicles will change road capacity thanks to ACC technology. Then, they modified road links capacities to simulate theoretical increase in throughput enabled by AV driving behaviour. They distinguished two types of road links: freeways and arterial streets. A static assignment in Emme 4 is realised. In addition, they analysed the impacts on parking operations.

2.2. Agent-based models

Agent-based models are an effective tool for the study of innovative urban services, as agents act and react according to the information received in real time. On the other hand, activity models offer improved reproduction of the demand and allow a more realistic analysis of users' mobility. Thus, agent-based models are highly used in literature to describe and analyse operations of AV.

In 2013, Burns et al. estimate the utility of shared autonomous vehicles (SAV) for users (waiting time) and operators (cost of production). They consider as variables local specifications, trip length, speed, fleet size and vehicle's cost parameters (Burns, et al., 2013). The model assumes that the vehicle speed is constant and origin-destination trips are uniformly distributed over the study area. In addition, an application on three US cities of different sizes Ann Arbor, Babcock Ranch (Florida) and Manhattan (New-York) confirms the economic potential of AV.

The study realized by ITF (2015) simulates the shared mobility in the real network of Lisbon using agent-based models. Mode choice process is based on a rule-based approach. The demand is generated based on the Lisbon Travel Survey. The user groups, especially for new services, are not considered. A trip is generated when a user send a request. Route choice minimizes travel time by integrating the average speed per section per hour. Sixty stations are spread in the city and three types of vehicles' are considered in the model of two-, five- and eight-passenger cars.

One of the most relevant studies is that developed by Fagnant and Kockelman (2014). They simulate SAVs in Austin (Texas) using an agent-based model (MATSim). SAVs are used by 2% of the total demand. The city is composed into traffic zones. Each traffic zone is characterized by an factor of attractiveness. All the trips are generated every 5 minutes a day using Poisson distributions. The model is then structured by following four major steps: (1) *SAV location and trip assignment*, which determines which available SAVs are closest to waiting travellers (prioritizing those who have been waiting longest), and then assigning available SAVs to those trips. The assignment is done according to a First-Come First Served (FCFS) order. A vehicle shall be assigned to a customer in an interval of 5mn; otherwise the user is put in the waiting list and is considered as a priority in the next simulation. (2) *SAV fleet generation*, which defines the fleet size. In particular, the fleet size is determined by running a SAV "seed" simulation run, in which new SAVs are generated when any traveler has waited for 10 minutes and is still unable to locate an available SAV is 10 minutes away or less. (3) *SAV Movement* is characterized by a vehicle speed equal in a normal hour to 3 times the number of areas. Passengers boarding and alighting last 1mn. The calculation of the vehicle position is registered every 5 minutes. (4) *SAV relocation*, aims to balance the vehicles distribution ahead of the demand. Four strategies are proposed. The objective is to ensure that - for each grid cell - the difference between available vehicles and vehicles required is minimal in absolute terms (less than a defined threshold). Zhu et al. (2017) propose two reactionary local repositioning strategies and evaluate their effects in terms of empty vehicle miles travelled and level-of-service provided.

In 2015, Fagnant and Kockelman explored the potential of electric vehicles. They found that the average distance travelled per day is greater than that allowed by vehicle range (Fagnant, et al., 2015b). Chen et al. (2016) develop this model with considering moreover charging stations. The stations are generated in order to allow vehicles to reach the user's origin or destination. The model is simulated for a medium-sized city, for a range of vehicles of 130km and normal charging stations (4 hour charge).

In addition, Zhang et al. (2015a; 2015b) reproduce the model of Fagnant with considering users' incomes and dynamic ridesharing (DRS). Vehicles and routes assignment reduce the total cost shared. In 2017, they implement a parking module in a discrete event simulation (Zhang, et al., 2017) with various pricing strategies.

Fagnant et al. (2016) found that DRS would reduce the vehicle-kilometres travelled by 7% and the waiting time by 25%. The DRS as defined by Fagnant is applied only if induced extra-time for current riders and new travellers can be tolerated.

Boesch et al. (2016) use agent-based model to evaluate required AV fleet sizes to serve different levels of demand. The agent-based model largely adopts the assumptions of the model of Fagnant (2014) with excluding the relocation policies of the AV. The study shows that the relationship between the demand and fleet size is non-linear and the ratio increases as the demand increases.

Levin et al. (2016) develop an event-based framework for SAV. Then, the framework was implemented on a cell transmission model-based traffic simulator considering that all vehicles are SAVs. Parking has limitless capacity. Vehicles assignment obeys to first-come first-served policy. Algorithms typically consist on three steps, performed iteratively, to find a dynamic user equilibrium assignment. Shortest paths are found for all origin-destination pairs.

Vakayil et al. (2017) propose a spatially hub-based SAV network model that analyses transfers between AVs and mass transit. The model considers transit frequency, transfer costs and two rebalancing strategies. It proves that an integration between AV and mass transit services leads to reduction in congestion and vehicular emissions.

Yu et al. (2017) assessed the potential of using on-demand SAV as the alternative to the low-demand buses to improve the first/last-mile connectivity in a study area in Singapore. The agent-based model is tested for a bus-only scenario and a series of scenarios integrating AV with various fleet sizes. Criteria are defined for each actor. For users, the out-of-vehicle time is evaluated. For transportation services, it is the impact on road traffic. From AV operators' perspective, the profitability is considered. Results are positive if all users accept to share the vehicle.

An application in Singapore is based on SimMobility. It is an integrated agent-based demand and supply model. It comprises three simulation levels: (i) a long-term level that captures land use and economic activity, with special emphasis on accessibility, (ii) a mid-term level that handles agents' activities and travel patterns, and (iii) a short-term level, that simulates movement of agents, operational systems and decisions at a microscopic granularity. Further details could be available in (Spieser, et al., 2014; Lima Azevedo, et al., 2015; Azevedo, et al., 2016). The application considers that the vehicle could anticipate the demand to reduce waiting times and to ensure a balance between required vehicles and available vehicles in each area. All existing competing modes (taxis, trains, buses ...) are considered. The cost of service is assumed about 40% less than the regular taxi service. The study distinguishes between internal trips, external trips and transits. The results highlight that for 2400 vehicles and 10 stations, the waiting time is 5 minutes and the number of trips per vehicle is 16 (Azevedo, et al., 2016).

3. Socio-economic models of AV development

3.1. Market penetration

Several automakers predict the integration of fully self- driving vehicles in the market by 4 to 10 years: Audi suggests 2017, Ford 2020, Nissan 2020, Google 2018 and Tesla 2023 (Davidson, et al., 2015). In 2012, the IEEE predicts that 75% of the fleet will be autonomous in 2040 (IEEE, 2012). According to (Litman, 2015), this rate will be achieved in 2060 only. More recently, the French government studied two entry scenarios: a trend-based scenario, in which the deployment is very gradual from 2040; and a breaking scenario where, by 2025, cars can be automated (Janin, et al., 2016).

In addition, surveys in Austin show that 40% (Bansal, et al., 2016) to 50% (Zmud , et al., 2016) of US respondents want to use private AVs for everyday use. Lavasani et al. in (2016) proposed a market penetration model for AV by using a generalized Bass model. Assuming that AVs will become available in 2025, the market of new car sales may reach about 8 million annually in 10 years, and saturation may occur in 35 years assuming a 75% market size. The sensitivity analysis concluded that the market size strongly impacts adoption rate, while the price of the technology does not seem influencing the diffusion process.

3.2. Potential customers

In recent years, various surveys investigated the general acceptance of AVs. In terms of age, some studies suggest that the service offered by the SAV will have a strong potential to capture the elderly and those with reduced mobility (Rödel, et al., 2014; Schoettle, et al., 2014; Schoettle, et al., 2015; Fagnant, et al., 2015a). Other studies come to the conclusion that younger people are more open towards the introduction of AVs (KPMG, et al., 2012; Power, 2012; Krueger, et al., 2016; Abraham, et al., 2017). In terms of the gender, men are more likely to use AV (Piao, et al., 2005; Rödel, et al., 2014; Schoettle, et al., 2015; Abraham, et al., 2017), but less likely to pay (Lavasani, et al., 2017). Anderson et al. (2014) suggest that non-motorized people would rather be captured by the service, while Krueger et al. (2016) find that motorization or preferences for public transport do not highly affect the attractiveness of AVs. In addition, Krueger et al. (2016) show that current carsharing and multiple mode users have a higher probability of choosing SAVs with DRS. Power et al. (2012) and Bansal et al. (2016) notice that residents of urban areas and people with higher income are more inclined to use AV. Lavasani et al. (2017) find that willingness to pay is affected by travel frequency, commuting distance, demand for parking and perception of AV benefits.

3.3. Production costs

Costs of AVs depend on the learning rate. Bansal et al. (2016) suggest a price of $23,950 in 2025, while Boston Consulting Group (2015) predicts that in 2025AV will cost $9,800.
Burns et al. (2013) studied the production costs of AVs spread in three different cities. They estimate capital costs (depreciation, finance, registration and insurance) and operating costs (energy, maintenance and repair, and other costs) and found that SAVs would costs to customer $0.25/km (or $0.10/km for electric and small vehicle) instead of $1/km (for taxis).
Spieser et al. (2014) analyse the impacts of a total substitution of private cars by SAVs in Singapore. Lifespan of SAVs is assumed over 2.5yrs, which could be reduced to 1.5yrs if ridesharing is considered (Zhang, et al., 2015a). The purchase costs are about $15,000. Thus, SAV costs on average $9,728/year instead of $11,315/year for cars. By integrating the value of time for an average SAVs waiting time of 5,5mn, the costs gap is even more significant ($5,527/year for the AV and $18,295/year for cars).
Fagnant et al. (2016) consider a penetration rate of 1.3%. The purchase costs are about $70,000 per AV and the average lifespan 400.000km (or 7 years). The American Automobile Association (AAA) estimate operating costs around of $0.3/km. As a result, the SAV costs for user about $0.625/km, which is 3 times less than the taxi fare. For operator, the rate of annual return on investment is around 13% for a total fleet of 2118 AVs.
Considering that vehicles are electric (SAEV), operating costs vary from $0.41 to $0.47 per occupied mile travelled. SAEVs are price competitive with SAVs when gasoline reaches $4.35 to $5.70 per gallon (Chen, et al., 2016).

4. Impacts of autonomous vehicles

4.1. Impacts on mobility

Fagnant et al. (2014; 2015b) prove that one SAV would replace 9 to 11 conventional vehicles while inducing 10% more VKT. The ITF (2015) emphasizes that the substitution of conventional cars by SAV would reduce the total fleet by 90%. In addition, the vehicles are more used (70% of the day against the current 5%). The ITF also shows that the deployment of AV would increase the VKT for different rates of market penetration. Spieser in (2014) indicates that a total replacement of cars by SAVs in Singapore would reduce by 2/3 the total fleet of vehicles on roads. The application of the Levin model in Austin (2016) proves that the replacement of cars by the private AVs will greatly increase congestion and travel time. The anticipated relocation makes the situation more critical. The DRS reduces the fleet size by 5.3% and empty VKT by 4.8% (Zhang, et al., 2015a). Boesch et al. (2016) found that the total vehicle fleet could be significantly reduced (by 90%) if ridesharing is allowed and waiting time is over 10mn. According to Chen et al. in (2016), the use of electric vehicles would pass the ratio to only 3.7 of replaced conventional vehicles, with an increase in VKT from 7 to 14%. Gucwa (2014) used an activity-based model to investigate the relationships of not shared AVs and road capacity, time value and vehicles operating costs. The study shows that VKT could increases by between 8% and 24%. Similar studies find that VKT could increase by 3% to 30% (Childress, et al., 2015) and around 20% (Zhao, et al., 2017).

4.2. Impacts on urban parking

For a market penetration of 2%, the demand for parking is reduced by about 90% (Zhang, et al., 2015b). The ITF (2015) found that for the case of 100% AV, space savings are around 85% to 95%. However, for the case of 50% of AV, the rate of space savings is insignificant. Fagnant et al. (2015b) suggest that the total parking demand will fall by around 8 vehicle spaces per SAV. In addition, moving the parking from downtown to less dense outlying areas allows for significant savings (Litman, 2012; Fagnant, et al., 2015a). Zhang et al. (2017) suggest that SAV system can reduce parking land by 4.5% in Atlanta at a 5% market penetration level.

4.3. Impacts on accidents

Li et al. (2016) found that AV can save Americans $76 billion each year. The Highway Traffic Safety Administration (NHTSA) found that 94% (±2.2%) of crashes between 2005 and 2007 were caused by the driver (NHTSA, 2008) while over 40% of fatal crashes involve driver alcohol or drug use, driver distraction and/or fatigue (NHTSA, 2012). The French Interdepartmental Observatory of Road Safety (ONISR, 2016) found that over 90% of crashes were human caused in France. Therefore, if autonomous vehicles could eliminate human causes of accidents, the number of crashes could extremely decrease and motor-vehicle deaths could be greatly reduced.

4.4. Environmental impacts: energy consumption and pollutant emissions

The environmental impact is estimated on the basis of a Life-Cycle Analysis, which includes the vehicle operations (movement, cold start ...), but also cars' manufacturing and the construction of related infrastructure (parking, stations, maintenance depots...). Since deployment of SAVs reduces the total vehicle fleet (as cited above), using them implies significant costs savings. The high use of AV shortens their life span to 1.5-2.5 years (Zhang, et al., 2015a; Spieser, et al., 2014), which helps improve the fleet performances. Currently, the AV technology reduces from 4% to 10% of energy consumed in acceleration and deceleration (Anderson, et al., 2014). Also, the use of AV reduces by 85% (Fagnant, et al., 2015b) to 95% (Zhang, et al., 2015a) emissions induced by cold starts. In addition, sharing vehicles could save more than 4.7% of energy, greenhouse gas and pollutants emissions (Zhang, et al., 2015a).
However, the use of electric vehicles would generate a significant demand for electricity during the peak charging period of the day (53% of the fleet concurrently charging). Fast charging, although inducing 15% more in cost, is very effective at demand spreading, with only 8% of the fleet charging during the peak charging period.

5. Conclusion: Outreach, limitations and some recommendations

This brief state of art in modelling transportation systems involving AVs is summarized in Figure 1. We observe that major models focus on the supply operations and set-ups without detailing the demand side beyond statistical and spatial description in the form of an origin-destination matrix of trip-flows.
On the supply side, agent-based approaches allow to assess AV fleet size required while optimizing the waiting time and empty VKT. Furthermore, these models permit to reproduce in a realistic, detailed and robust way movements of vehicles considering several strategies. However, studies considering the real network are very scarce (ITF, 2015; Adnan, et al., 2016; Anderson, et al., 2014; Azevedo, et al., 2016). Further, urban constraints which determine the locations of stations and their capacities are not considered at all, even in the case of electric vehicles. Similar to car sharing, two service configurations are possible: station-based and free-floating. The free-floating configuration is employed for a broader variety of uses than the station-based one (Bereck, et al., 2016). The combination of fixed stations and free-floating (while respecting the conditions of accessibility (Ciari, et al., 2015)) could reduce waiting time and locating stations in low dense areas (which is also economically attractive). Using dynamic parking cost (relevant to area's configuration and state of congestion) could be explored as well.
Assignment strategies of vehicles to customers should be optimized as well. Indeed, almost all studies are based on a FCFS strategy; a strategy that could be optimized using heuristic insertion or simulated annealing (Jung, et al., 2013). In addition, all aforementioned models are applied on urban centres of cities. It would be interesting to explore the service potentialities in suburban zones, freeways and around major train stations.
On the demand side, almost all of the studies estimate the AV demand based on market penetration. Studies using real inputs are those exploring full replacement of cars by AVs. In addition, the AVs are not integrated in a multimodal chain. A detailed study of the users' utility of SAV will enable capturing individual preferences while distinguishing between (i) utility of acquiring and/or maintaining and (ii) utility of using AVs. This study is essential since it enables confirming service potential and defining pricing strategies. Its results are used as inputs of economic models and modal choice models. Further, taking into account day-to-day traffic for the year should be explored using activity-based models, while distinguishing between typical weekday, weekend day, holiday or special day events.
On the other hand, to assure AVs sustainability and its dissemination, it is necessary to develop an in-depth knowledge of production costs and demand evolutions in order to promote informed and rational choices. Production costs concern all components involved in transit system operations (track and station elements, vehicles, and staff) that have to be acquired or hired and maintained at acceptable operating conditions. The models of new taxi apps present useful business insights. The yield management used by UBER, LYFT, GrabTaxi… permits to smooth the demand over time.
Moreover, further studies of the acceptability of AVs with the various stakeholders are necessary: mainly users, transport authorities, transit operators, insurance companies and car manufacturers.
Finally, let us outline that these works would highly benefit from detailed data on production costs, as well as on commercial revenue and individual utility of the user and environmental impacts. For an innovative service, some data cannot be observed but must be inferred from comparison bases, and simulated by means of an ad hoc model.

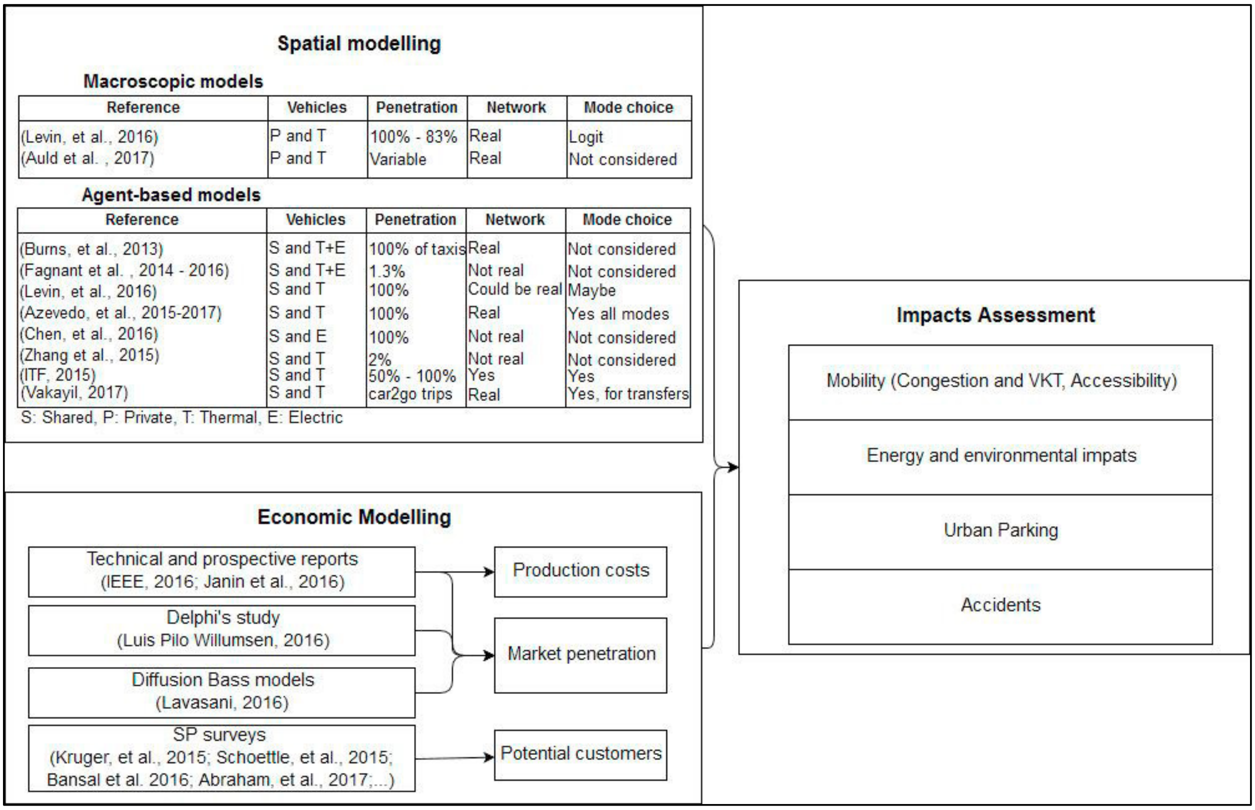

Figure 1: Synthesis of literature review.

References

Abraham, Hillary, et al. 2017. Autonomous vehicles and alternatives to driving: trust, preferences, and effects of age. *Transportation Research Board 96th Annual Meeting.* 2017.

Adnan, Muhammad, et al. 2016. SimMobility: A Multi-Scale Integrated Agent-based Simulation Platform. 2016.

Anderson, James, et al. 2014. *Autonomous Vehicle Technology: A Guide for Policymakers.* s.l. : RAND Corporation, 2014.

Auld, Joshua, Sokolov, Vadim et Stephens, Thomas. 2017. Analysis of the impacts of CAV technologies on travel demand. *Transportation Research Board 96th Annual Meeting.* 2017.

Azevedo, Lima Carlos Miguel, et al. 2016. Microsimulation of Demand and Supply of Autonomous Mobility On-Demand. *Proceeding of the 95th annual meeting of Transportation Research Board*. 2016.

Bansal, Prateek, Kockelman, Kara et Singh, Amit. 2016. Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies.* 2016, Vol. 67, pp. 1-14.

Bereck, Henrik, Ciari, Francesco et Axhausen, Kay. 2016. Comparing Car-Sharing Schemes in Switzerland: User Groups and Usage Patterns. 2016.

Boesch, Patrick, Ciari, Francesco et Axhausen, Kay. 2016. Required Autonomous Vehicle Fleet Sizes to Serve Different Levels of Demand. *Proceeding of the 95th annual meeting of Transportation Research Board*. 2016.

Boston Consulting Group. 2015. Revolution in the driver's seat, The road to autonomous vehicles. [En ligne] 2015. https://www.bcgperspectives.com/content/articles/automotive-12 consumer-insight-revolution-drivers-seat-road-autonomous-vehicles/.

Burns, Lawrence, Jordan, William et Scarborough, Bonnie. 2013. *Transforming Personal Mobility.* New York, United States : The Earth Institute, Columbia University, 2013.

Chen, Donna, Kockelman, Kara et Hanna, Josiah. 2016. Operations of a shared, autonomous, electric vehicle fleet: implications of vehicle & charging infrastructure decisions. *Proceeding of the 95th annual meeting of Transportation Research Board.* 2016.

Childress, Suzanne, et al. 2015. Using an Activity-Based Model to explore possible impacts of Automated Vehicles. *Proceedings of 94th Annual Meeting of the Transportation Research Board.* 2015.

Ciari, Francesco, Weis, Claude et Balac, Milos. 2015. Evaluating the influence of carsharing stations' location on potential membership: a Swiss case study. *Euro Journal on Transportation and Logistics.* 17 Mars 2015, pp. 1-25.

Davidson, Peter et Spinoulas, Anabelle. 2015. Autonomous Vehicles - What Could This Mean For the Future Of Transport? Sydney : s.n., 2015.

Fagnant, Daniel et Kockelman, Kara. 2016. Dynamic Ride-Sharing and Optimal Fleet Sizing for a System of Shared Autonomous Vehicles. *Proceeding of the 95th annual meeting of Transportation Research Board*. 2016.

Fagnant, Daniel et Kockelman, Kara. 2015a. Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations. *Transportation Research Part A*. 2015a, Vol. 77, pp. 167-181.

Fagnant, Daniel et Kockelman, Kara. 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies.* March 2014, Vol. 40, pp. 1-13.

Fagnant, Daniel, Kockelman, Kara et Bansal, Prateek. 2015b. Operations of a shared autonomous vehicle fleet for the Austin, Texas Market. *Proceeding of the 94th annual meeting of Transportation Research Board.* 2015b.

Gucwa , Michael. 2014. *Mobility and Energy Impacts of Automated Cars.* s.l. : Stanford University, 2014. Dissertation.

IEEE. 2012. Look Ma, No Hands! [En ligne] 5 Septembre 2012. http://www.ieee.org/about/news/2012/5september_2_2012.html.

ITF. 2015. *Urban Mobility System Upgrade: How shared self-driving cars could change city traffic.* Paris : OECD, 2015.
Janin, Lionel, Nemri, Mehdi et Raynard, Christine. 2016. *La voiture sans chauffeur, bientôt une réalité.* Paris : France Stratégie, 2016.
Jung, Jaeyoung, Jayakrishman, R. et Park, Ji Young. 2013. Design and modeling of real-time shared-taxi dispatch algorithms. 2013.
Kloostra, Bradley et Roorda, Mattew J. 2017. Fully Autonomous Vehicles: Analyzing transportation network performance and operating scenarios in the Geater Toronto Area. *Transportation Research Board 96th Annual Meeting.* 2017.
KPMG et CAR. 2012. *Self-Driving Cars: The Next Revolution.* Ann Arbor : s.n., 2012.
Krueger, Rico, Rashidi, Taha et Rose, John. 2016. Adoption of Shared Autonomous Vehicles - A Hybrid Choice Modeling Approach based on a Stated Choice Survey. *Transportation Reearch Board 95th Annual Meeting.* 2016.
Lavasani, Mohammad, et al. 2017. Investigating the Willingness to Pay for Autonomous Vehicles and the Likelihood of Residential Relocation. *Transportation Research Board 96th Annual Meeting*. 2017.
Lavasani, Mohammad, Jin, Xia et Du, Yiman. 2016. Market Penetration Model for Autonomous Vehicles Based on Previous Technology Adoption Experiences. *Proceeding of the 95th annual meeting of Transportation Research Board*. 2016.
Levin, Michael W. et Boyles, Stephen D. 2015a. Effects of autonomous vehicle ownership on trips, mode and route choice. *Proceeding of the 94th annual meeting of the Transportation research board*. 2015a.
Levin, Michael William. 2015b. *Integrating Autonomous Vehicle Behavior into Planning Models.* Austin : The University of Texas, 2015b. Thesis.
Levin, Michael, et al. 2016. A general framework for modeling shared autonomous vehicles. *Proceeding of the 95th annual meeting of Transportation Research Board*. 2016.
Li , Tianxin et Kockelman, Kara. 2016. Valuing the Safety Benefits of Connected and Automated Vehicle Technologies. *Transportation Research Board TRB 95th Annual Meeting.* 2016.
Lima Azevedo, Carlos, et al. 2015. Microsimulation of Demand and Supply Autonomous Mobility On-Demand. *Proceeding of the 94th annual meeting of Transportation Research Board.* 2015.
Litman, Todd. 2015. *Autonomous Vehicle Implementation Predictions: Implications for Transport Planning.* s.l. : Victoria Transport Policy Institute, 2015.
Litman, Todd. 2012. *Parking Management: Strategies, Evaluation and Planning*. Victoria : Victoria Transport Policy Institute, 2012.
NHTSA. 2012. *Fatal Analysis Reporting System.* Washington D.C : U.S. Department of Transportation, 2012.
NHTSA. 2008. *National Motor Vehicle Crash Causation Survey.* s.l. : U.S. Department of Transportation, 2008.
ONISR. 2016. *Bilan définitif de l'accidentalité routière 2015.* 2016.
Piao, J. et McDonald, M. 2005. An assessment of user acceptance of intelligent speed adaptation systems. *Proc. Intelligent Transportation Systems.* 2005.
Power, J.D. 2012. *Vehicle Owners Show Willingness to Spend on Automotive Infotainment Features.* Westlake Village : s.n., 2012. Technical Report.
Rödel, Christina, et al. 2014. Towards Autonomous Cars: The Effect of Autonomy Levels on Acceptance and User Experience. *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications.* AutomotiveUI '14, 2014, Vol. 11.
Schoettle, Brandon et Sivak, Michael. 2014. *A survey of public opinion about autonomous and self-driving vehicles in the U.S., the U.K., and Australia.* s.l. : The University of Michigan Transportation Research Institute, 2014. Technical Report.
Schoettle, Brandon et Sivak, Michael. 2015. *Motorists' preferences for different levels of vehicle automation.* s.l. : The University of Michigan Transportation Research Institute, 2015. Technical Report.
Spieser, Kevin, et al. 2014. Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore. [éd.] Springer. *Road Vehicle Automation.* Septembre 2014.
The Milwaukee Sentinel. 1926. Phantom Auto' will tour city. [En ligne] 8 Decembre 1926. [Citation : 23 Juillet 2013.] https://news.google.com/newspapers?id=unBQAAAAIBAJ&sjid=QQ8EAAAAIBAJ&pg=7304,3766749&hl=fr.
The Victoria Advocate. 1957. Power companies build for your new electric living. [En ligne] 24 Mars 1957. https://news.google.com/newspapers?nid=861&dat=19570324&id=qtFHAAAAIBAJ&sjid=nn8MAAAAIBAJ&pg=1952,2616834&hl=fr.
Vakayil, Akhil et Samaranayake, Samitha. 2017. Innovative Applications and Evaluations of Ridesharing and Ridesourcing Services. *Transportation Research Board TRB 96th Annual Meeting.* 2017.
Weiner, Gabriel et Walker, Smith. 2016. Automated Driving: Legislative and Regulatory Action. [En ligne] 2016. cyberlaw.stanford.edu/wiki/index.php/Automated_Driving:_Legislative_and_Regulatory_Action.
Yu, Shen, Zhang, Hongmou et Jinhua, Zhao. 2017. Embedding Autonomous Vehicle Sharing in a Public Transit System: Example of Last-Mile Problem. *Transportation Research Board TRB 96th Annual Meeting*. 2017.
Zhang, Wenwen et Guhathakurta, Subhrajit. 2017. Parking Spaces in the Age of Shared Autonomous Vehicles: How Much Parking Will We Need and Where? *Transportation Research Board TRB 96th Annual Meeting*. 2017.
Zhang, Wenwen, et al. 2015b. Exploring the Impact of Shared Autonomous Vehicles on Urban Parking Demand: An Agent-Based Simulation Approach. Cambridge, Massachusetts, United States : s.n., 2015b.
Zhang, Wenwen, et al. 2015a. The performance and benefits of a shared autonomous vehicles based dynamic ridesharing system: an agent. Washington DC, United States : s.n., 2015a.
Zhao, Yong et Kockelman, Kara. 2017. Anticipating The Regional Impacts of Connected and Automated Vehicle Travel in Austin, Texas. *Proceedings of the 96th annual meeting of Transportation Research Board*. 2017.
Zhu, Shirley et Kornhauser, Alain. 2017. The interplay between fleet size, level-of-service and empty vehicle repositioning strategies in large-scale, shared-ride autonomous taxi mobility-on-demand scenarios. *Transportation Research Board 96th Annual Meeting.* 2017.
Zmud , Johanna, Sener, Ipek et Wagner, Jason. 2016. *Consumer Acceptance and Travel Behavior - Impacts of Automated Vehicles.* s.l. : Texas A&M Transportation Institute, 2016. Technical Report.