EMBRY-RIDDLE Aeronautical University
SCHOLARLY COMMONS

Journal of Aviation/Aerospace Education & Research

Volume 30
Number 1 *JAAER 2021*

Article 1

2021

Testing and Validation Framework for Autonomous Aerial Vehicles

Mustafa I. Akbas
Embry-Riddle Aeronautical University, akbasm@erau.edu

Introduction

Autonomous aerial vehicles are positioned to have a significant impact on various industries. This potential has already been observed by authorities, regulators, and industry. For instance, the United States Air Force (USAF) has called for increased level of autonomy (Endsley, 2015). NASA and Uber have been exploring the autonomous vertical takeoff and landing (VTOL) aircrafts in their Urban Air Mobility (UAM) studies (Hackenberg, 2018; Holden & Goel, 2016). Another field with a similarly fast, if not faster, progress is the self-driving or autonomous ground vehicle technology. The industry investment and the advances in Advanced Driver-Assistance Systems (ADAS) have increased the expectations from the public and various sectors. While the first objective of the ADAS is to improve safety, improved autonomy and particularly the full autonomy brings additional opportunities. Some technologies form the driving force of the autonomous systems. There has been an increasingly growing progress in the Artificial Intelligence (AI) engines, data analytics tools, complex and non-deterministic system components, which are at the core of the autonomous platforms.

Both the autonomous ground and aerial vehicles will cause market disruptions with their pervasive deployment (Straubinger et al., 2020; Goyal, 2018; Meyer & Shaheen, 2017; Bansal & Kockelman, 2017). A "smart city" is an urban area, where a variety of electronic methods and sensors are used to collect data (Su, Li, & Fu, 2011). The advances in smart city and Internet of Things (IoT) technologies will multiply the impact of autonomous vehicles as they enable the integration of cyber-physical systems (CPS) with various technologies such as the cloud services (Ang, Seng, Zungeru, & Ijemaru, 2017). The autonomous vehicle technology is expected to change the concept of vehicle ownership as the Mobility as a Service (MaaS) and air taxis become commonplace. These changes will have natural consequences on various fields, such as insurance, maintenance, parking, and towing. The access to transportation will be 24/7, which will allow optimization of the transportation infrastructure and services. The continuous access to transportation system is shown to have significant impact on freight industry and traffic management (Heard, Taiebat, Xu, & Miller, 2018; Das et al., 2017). The people with limited access to mobility, such as disabled and elderly people, will have options and different forms of services available to them. There are already pilot applications of ground and aerial delivery applications with autonomous robots, cars, and drones.

Table 1 demonstrates the potential impact of the autonomous vehicles in four sample fields: public transportation, planned communities, logistics, and agriculture. The "Impact" column shows the projected impact of the autonomous technologies for that field in the long term with large-scale deployment. However, short term or current applications are possible in all of these fields with several adjustments. Therefore, the last column in the table gives the possible simplification of the application for a near-term implementation of the autonomous technology in the corresponding field.

Table 1

Examples for the Impact of Autonomous CPS

Field	**Impact**	**Near Term Adjustment**
Public Transportation	24x7 Access Infrastructure Utilization On-call Access	Limited Routes Managed Urban Areas Lower Speeds
Planned Communities	Driverless communities Improved Safety Efficient Architecture	Controlled Environments Controlled Interaction Lower Speeds
Logistics	Warehouse Operations Outdoor Logistics Operations Long Haul and Last Mile	Controlled Environments Remote Control
Agriculture	24x7 Operation Improved Robotic Capability Fine Grained Data	Lower Speed Controlled Interaction

The potential of the autonomous vehicles can be achieved only if their safety and reliability are validated. To achieve highly or fully autonomous capabilities, a significant leap forward in testing and validation is required. The technology core of the vehicles changed as they became autonomous. The traditional vehicles operated by people are replaced by software-defined and networked computers operated by intelligent agents. The fundamental technology in this system is a traditional networked sensor and signal processing chain with a decision support system (Razdan et al., 2019). Hence, the traditional testing and validation methods fall short of satisfying the requirement of testing such complex systems. The manual testing is inefficient, costly, and dangerous. This inefficiency results in bug detection latency, which causes numerous recalls and makes it harder to comply with the safety standards. Therefore, the automated tests must cover the majority of testing while manual testing is used for focused test efforts to catch bugs that automated testing may miss.

In this paper, we present a validation framework and testing regime that uses modeling and simulation (M&S) and separation of concerns for solving the issues in the validation of autonomous CPS with a focus on aerial vehicles. We use an abstraction stack to separate the tests for different systems that make up the autonomous vehicle. This stack is integrated with constrained pseudo-random test generation and functional assertions to identify errors. The overall system aims to create an evolving safety measure for the AI-based aerial systems.

Background and Related Work

Despite the advances in autonomous systems and technology, autopilot functions have been limited for a variety of reasons such as keeping the operator engaged or possible bugs in the decision-making process. Autonomous functions need to be standardized to ensure autonomous vehicles don't make maneuvers that would result in collisions. Hence, validation of these features is an important component of the development and regulation of aerial vehicles. In this section, we give an overview of the validation efforts for autonomous aerial vehicles. A more general view of the validation efforts in all autonomous systems will be given in the following section along with the challenges.

The formal methods and model-based techniques have been utilized in avionics (Bienmüller et al., 1999; Souyris, Wiels, Delmas, & Delseny, 2009). The model-based techniques improve the efficiency of the simulation-based methods as they work on abstract models (En-Nouaary, Dssouli, & Khendek, 2002). However, the AI components and the diversity of hardware used in recent autonomous aerial vehicles makes it challenging to apply traditional methods, and researchers use different methods for validation. Patelli and Mottola (2016) apply model-based, real-time testing to a well-known autopilot. The approach creates an abstract model of the autopilot functionality for testing and demonstrates several issues in the operation of the autopilot. McAree, Aitken, and Veres (2016) use a model-based design for the semi-autonomous control system for an inspection drone. The scope of the study is limited as it only targets maintaining a distance from the target and keeping a relative pose. However, the implementation is versatile as the developed model can be used for multiple types of simulation testing and also for final deployment. Mason, Nigam, Talcott, and Brito (2017) integrate model-based techniques with simulation and statistical methods. Even though their main focus is not verification, it aims to improve the reliability of the vehicle and mission specifications using these methods.

Desai, Dreossi, and Seshia (2017) combine model checking and runtime verification for the robot design. The approach includes an implementation language and an online monitoring system. The group also propose a similar approach for ground autonomous vehicles, where they propose a toolkit for the verification, a high-level language and a practical test example (Dreossi et al., 2019, Fremont et al., 2019; Fremont et al., 2020). Another method proposed for the validation and testing of autonomous systems is the metamorphic model-based testing, which has been employed in various domains (Segura, Fraser, Sanchez, & Ruiz-Cortes, 2016). Lindvall, Porter, Magnusson, and Schulze (2017) proposed a framework to validate the simulated drone's behavior based on metamorphic testing. The approach uses several core scenarios and generate variations of them according to the distances and obstacles in the scenario. Then, other factors such as the illumination are varied in the generated scenarios to find the causes of errors.

The simulation has been an important tool for studying CPS (Akbas, Solmaz, & Turgut, 2016; Medrano-Berumen, Malayjerdi, Akbas, Sell, & Razdan, 2020; Rentrope & Akbas, 2017). Simulators used for autonomous vehicle testing vary by great degree in what their approach and focus are. The simulators create a virtual test environment that simulates the environment and actors to varying degrees of fidelity. The test focus varies from vehicle dynamics to the traffic networks and city layouts.

Methodology

Autonomous vehicles will be a critical component of technological transformation in cities with the smart city technologies and IoT applications (McKinsey Digital, 2015). Hence, their safety and reliability are extremely important. Even though the challenges and objectives mentioned in this paper can be generalized to all of these systems, our initial focus will be on the aerial autonomous vehicles and the ground autonomous vehicles. In this section, we first lay out the challenges of autonomous vehicle validation. Then we give our research goal and describe the current efforts.

Research Goal

Our research goal is focused on building a framework for the testing and validation of autonomous aerial vehicles. We aim for tackling the challenge of autonomous CPS validation with an initial focus on aerial autonomous vehicles. The key insights that are used as a guide towards solving this problem will be the extensive research in the fields of validation and verification for semiconductor chips, embedded software, and real-time systems. These fields have developed methodologies relying on the use of cascading mathematical abstractions in combination with scientifically driving the test generation and coverage analysis process to achieve products with significantly low error ratio.

Challenges and Current Efforts

The challenges. The idea of autonomous ground vehicles has been around for a longer time than we imagine. In 1960, the Radio Corporation of America and General Motors were advertising the future of transport as the cars that can drive themselves (Ackerman, 2016). The goal of the campaign was deploying autonomous vehicles in major highway systems as early as 1975. Autonomous aerial vehicles are not a new idea, either. The first autopilot was invented in 1912 to keep a plane flying straight and level (Stevens & Lewis, 1992).

There are several groups that estimate the market in the U.S. to reach over $100 billion annually when these vehicles have a large share of the automotive sector (Clements & Kockelman, 2017). The market estimates for autonomous aerial vehicles are no different (Roth & Sims, 2019; Morgan Stanley, 2018) and there are already numerous urban air mobility vehicle manufacturers aiming to achieve certification. Despite these high expectations, today the gating factor towards the active deployment of autonomous vehicles is the open research issue surrounding the validation and verification. Without the resolution of this issue, a clear measurable paradigm for autonomous vehicle safety cannot be built and broad-based deployment is not possible.

The autonomous vehicle functionality can be broadly split into three layers. The bottom layer is the mechanical system of the vehicle. The next layer consists of the perceptual system which monitors the environment and builds an internal model of the surroundings. The top layer is the decision-making system which uses the results of perception and the mission plans to decide on next steps for the vehicle. This is the layer with high-risk probability. The validation and verification efforts must provide a measurable coverage analysis for the testing state space, which will make it possible to develop adequate standardization.

The testing of mechanical systems has been performed very well by the manufacturers for a long time. On the other hand, the testing and validation of the perception and decision-making layers is currently an open problem. There is a variety of ad-hoc methods, ranging from shadow driving to randomization in simulation to attack this problem. However, all of these techniques lack scientific rigor and a framework for validation leading towards convergence of the safety task. Unless a safety framework is developed, regulators have no way to provide a scheme for validation, and, therefore, it is impossible to reach the expected potential of the market.

Current efforts. The field of validation and verification has been increasingly active for autonomous vehicles. The most common testing environments used in validation are given in Table 2 with the identified issues with them.

Table 2

Common Testing Environments and the Issues with Them

Test Type	Issues
Real-World Testing	Low probability tests are difficult to produce Extremely slow and costly (Kalra & Paddock, 2016)
Controlled Environment	Recreates predefined situations Not sufficient for scenario analysis (Razdan et al., 2019)
Image Based Testing	Slow and costly Limited to available datasets
Simulation	Current solutions are not progressive

The current efforts have problems in efficiency, cost, coverage, and progression as presented in Table 2. These issues are shown to be significant obstacles for the progress in autonomous vehicle technology (Razdan et al., 2019). One of the important issues is the lack of capability to separate the testing of different subsystems. For instance, consider a real-life testing of an autonomous drone. When there is an error during the flight operation, how does the tester know where the problem originates? Is it the reasoning system or the perception system? Is it possible to test these separately first? Another critical problem is the lack of a test regime, which systematically generates and tests scenarios with well-defined goals. The M&S present important opportunities as it allows fast execution of various scenarios. However, the simulation cannot be efficient without a well-planned test regime, which would help the tester understand the completeness of the tests. There must be a conceptual model for the decision-making system and the perception system to create a testing regime and formally validate the vehicle's actions.

There are end-to-end approaches for validation of autonomous ground vehicles (Alnaser, Akbas, Sargolzaei, & Razdan, 2019; Medrano-Berumen & Akbas, 2020; Medrano-Berumen, Malayjerdi et al., 2020; Winner, Lemmer, Form, & Mazzega, 2019). We employ some of the principles of these approaches in our framework, such as the utilization of M&S in combination with the real-life tests (Medrano-Berumen & Akbas, 2020). However, we define a new concept of separation of concerns and focus our efforts on the aerial vehicles. Even though a universal verification framework can be created for all autonomous systems, it is important to note the differences for these domains. Autonomous technology is applicable in both domains with similar challenges and different constraints.

The autonomous ground vehicles operate in a restricted three-dimensional domain. The movement perpendicular to the ground is unexpected and illegal in most situations. The transportation system physically restricts the operation corridors of the vehicles and there are well-established regulations in this system. Since the transportation system has been established and used for a long time, it is also a congested operation domain that is more prescriptive (roads, lanes, signs, etc.) compared to aerial transportation. On the other hand, the autonomous aerial vehicles operate in a mostly unrestricted three-dimensional environment. The takeoff and landing have been traditionally challenges for the aircrafts and the last 10 feet delivery is a serious challenge as the aerial delivery is one of the first expected applications for the autonomous drones. Compared to ground vehicles, aerial vehicles generally operate in an environment with smaller number and variety of actors. However, they mostly operate in higher speeds and varying atmospheric conditions. Ground vehicles typically have limited planar scope, while air vehicles have to check a complete 360-degree sphere of potential actors and actions continuously. Ground vehicles have the option to stop for decision making, which is not always the case for air vehicles. While the ground vehicles operate in more crowded environments with more actors, objects, and pedestrians, it is more difficult for aerial vehicles to predict where the other actors would come from. Another important challenge to consider for the aerial vehicles is the existence of adversarial actors. The unmanned aerial vehicles have been traditionally used in operational domains with higher number of adversarial actors compared to the ground vehicles.

Testing and Validation Framework

Our approach in this paper aims to create a framework for the testing and validation of autonomous CPS with an initial focus on aerial vehicles. The overview of the envisioned end-to-end testing and validation strategy is demonstrated in Figure 1. The autonomous vehicles are composed of complex components, which go through numerous scenarios in real-life. Therefore, we divide the strategy in Figure 1 into several stages.

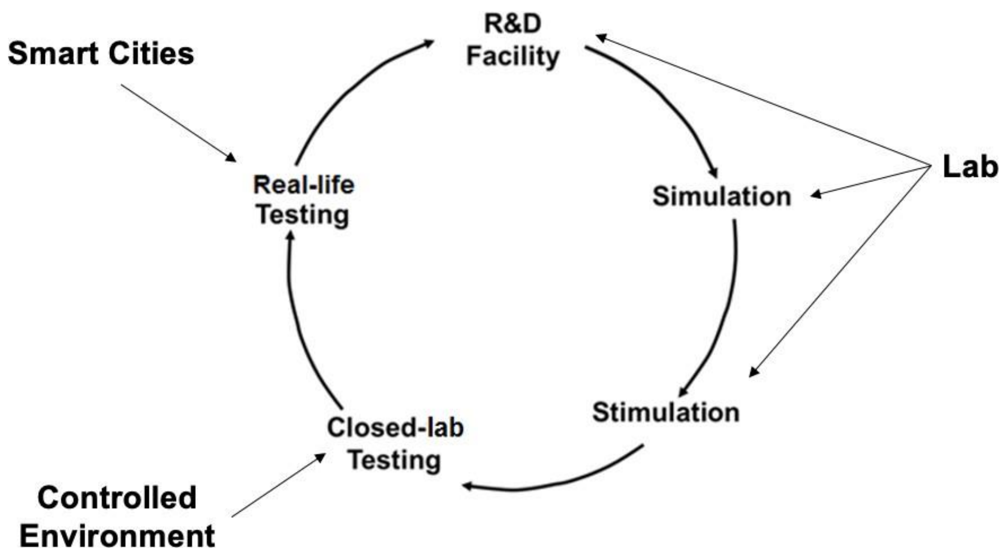

Figure 1. End-to-end testing and validation plan for autonomous vehicles.

The first phase in the strategy is the test design and analysis, which is one of the most critical components. The designed tests will guide the simulation effort. Considering the vast size of the possible scenario set, a major part of the validation will be performed using simulation. The simulation platform and the fidelity level will be chosen according to the characteristics of the scenarios. Then, a portion of the selected scenarios will feed the test scenarios in hardware-in-the-loop testing, which is also called "Stimulation". The last phases of the testing procedure will use the aerial vehicle under test and test it in first a controlled lab environment, then in selected real-life scenarios. It is important to note the following advantages of this strategy:

- The validation effort is divided according to the focus areas.
- Resources are used efficiently as they are chosen and used based on the requirements of specific testing strategy.
- The testing of separate components, such as sensors, is performed separately.
- The focused testing of the decision-making system contributes in the "explainable AI".

DOI: https://doi.org/10.15394/jaaer.2021.1849

In the testing and analysis phase, we abstract the vehicle functionality in multiple layers. We first separate the perception and decision-making functionalities, each of which can be further separated into multiple layers of abstraction for testing purposes. The differentiating factors of our approach are given in Figure 2. The 'Separation of Concerns' principle is used to decompose the problem. Then the decomposed problems are formulated by using several abstraction levels. For instance, the overall hardware and communication system of the vehicle can be abstracted in multiple levels, such as the processor components, processors, sub-systems, system architecture, and network. Similarly, the perception system can have the levels of signals, objects, objects with content and the scene. Further examples can be given for the abstraction levels. However, it is important to note the critical contribution of this methodology, which is the testing strategy focusing on a particular layer and the cascaded analysis of these layers for the overall validation.

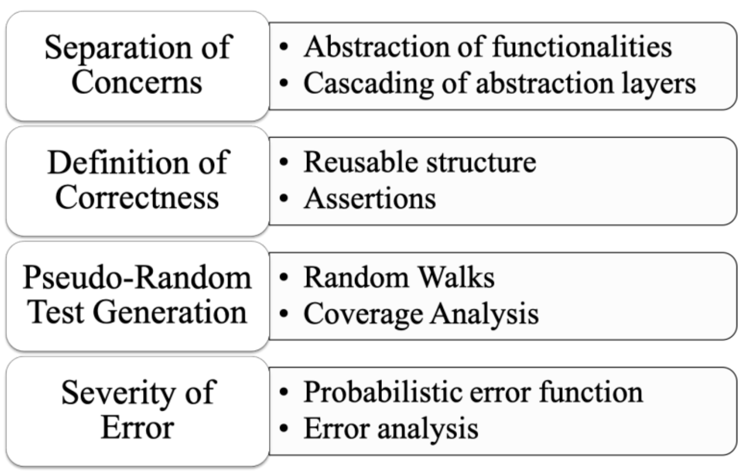

Figure 2. Main components of the verification scheme.

The second component in Figure 2 is the 'Definition of Correctness.' When we use the separation of concerns, the scenarios are going to be defined in a scenario description language. This method creates a structure, which can be reused and applied in different domains. Even though our initial focus is aerial vehicles, the strategy can be applied to other autonomous systems. These systems have constraints of their functionalities and operation environments. For instance, the directional movements of an aerial vehicle may be limited by its specifications based on its type. There are also temporal limitations, which dictate the continuity of the scenarios. For instance, a vehicle cannot fly a certain distance instantly to escape from a difficult scenario. These constraints shape the scenario description language and limit the testing space. Then, the rules for the vehicle are defined within the domain of the abstraction layer. These are implemented in the methodology as assertions, which enables the definition of correctness for the behavior. The assertion functionality provides the concepts of positive or negative behavior and the test success.

The top two components in Figure 2 create the domain that allows using test generation and formal verification techniques for validation. We use constrained-random test generation to create scenarios. This method is accompanied with random walks as the complexity of the state space and the underlying AI make it difficult to identify corner cases. The random walks will be used to expose the worst-case conditions. The random walks in this stage must be directed with a coverage goal of covering the verification space in the most efficient way.

The test generation is supported by real-world test injection. The existing accident databases and the data records from test tracks can be used to create abstract test scenarios. There are several examples of this method for ground autonomous vehicles (Stark, Medrano-Berumen, & Akbas, 2020). The scenarios generated at the decision-making level serve as the core abstract scenarios and the variations of these are used for testing other sources of error such as environmental conditions or sensor failures as the corresponding tests are generated.

Another important component given in Figure 2 is the ‘Severity of Error.’ We define a probabilistic error function to describe the severity level of the error. The definition of severity is strongly tied with the assertions. Depending on how strict an assertion is, the error function probabilities are going to be arranged accordingly. It is important to note that the validation of the behavior is complex and would be unsuccessful if it is tried to be confined into a set of specific rules. For instance, would it be acceptable to violate your allowed flying corridor to avoid a crash that can potentially have health and cost consequences? The assertions are defined with multiple levels and guide error functions with these levels in such situations.

Conclusion and Future Work

The autonomous vehicles are expected to play an important role in our daily lives. As the enabling technologies have been developed, autonomous systems are finding their ways in the near-term plans of various sectors. However, these systems can be realized and deployed only when their safety is tested and verified. Hence, testing and validation is the gating factor for the next step in the development of these technologies. In this paper, we lay out a framework for the testing and validation of autonomous CPS with a particular focus on aerial autonomous vehicles. The framework has a novel definition of separation of concerns and presents an end-to-end testing and validation plan.

The future work includes the finalization of the development for abstraction layers and the testing of already developed methodologies on aerial vehicles. Applicable solutions for the autonomous system validation problem will have wide implications throughout academia, government, and industry. There is an apparent need for the transition of the whole community in understanding the safety for autonomous vehicles. Therefore, the framework is also planned to be used for the creation of educational material.

References

Ackerman, E. (2016). Leave the driving to us. *IEEE Spectrum, 53*(9), 64. https://doi.org/10.1109/MSPEC.2016.7551361

Akbas, M. I., Solmaz, G., & Turgut, D. (2016). Molecular geometry inspired positioning for aerial networks. *Computer Networks, 98*, 72-88. https://doi.org/10.1016/j.comnet.2016.02.001

Alnaser, A., Akbas, M. I., Sargolzaei, A., & Razdan, R. (2019, December). Autonomous vehicles scenario testing framework and model of computation. *SAE (Society of Automotive Engineers) International Journal of Connected and Automated Vehicles, 2*(4), 205-218. https://doi.org/10.4271/12-02-04-0015

Ang, L.-M., Seng, K. P., Zungeru, A. M., & Ijemaru, G. K. (2017). Big sensor data systems for smart cities. *IEEE Internet of Things Journal, 4*(5), 1259-1271. https://doi.org/10.1109/JIOT.2017.2695535

Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice, 95,* 49-63. https://doi.org/10.1016/j.tra.2016.10.013

Bienmüller, T., Brockmeyer, U., Damm, W., Döhmen, G., Eßmann, C., Holberg, H.-J. . . . Sefton, E. (1999). Formal verification of an avionics application using abstraction and symbolic model checking. *Towards System Safety*, 150-173. https://doi.org/10.1007/978-1-4471-0823-8_10

Clements, L. M., & Kockelman, K. M. (2017). Economic effects of automated vehicles. *Transportation Research Record: Journal of the Transportation Research Board, 2606*(1), 106-114. https://doi.org/10.3141/2606-14

Das, S., Sekar, A., Chen, R., Kim, H. C., Wallington, T. J., & Williams, E. (2017). Impacts of autonomous vehicles on consumers time-use patterns. *Challenges, 8*(2), 32. https://doi.org/10.3390/challe8020032

Desai, A., Dreossi, T., & Seshia, S. (2017). Combining model checking and runtime verification for safe robotics. *Paper presented at the 17th International Conference on Runtime Verification, Seattle, WA,* (pp. 172-189). https://doi.org/10.1007/978-3-319-67531-2_11

Dreossi, T., Fremont, D., Ghosh, S., Kim, E., Ravanbakhsh, H., Vazquez-Chanlatte, M., & Seshia, S. (2019, July). VerifAI: A toolkit for the formal design and analysis of artificial intelligence-based systems. *Conference on Computer Aided Verification, New York, NY*, (pp. 432-442). https://doi.org/10.1007/978-3-030-25540-4_25

Endsley, M. R. (2015). *Autonomous Horizons: System Autonomy in the Air Force—A Path to the Future.* United States Air Force, Office of the Chief Scientist. AF/ST TR.

En-Nouaary, A., Dssouli, R., & Khendek, F. (2002). Timed Wp-method: Testing real-time systems. *IEEE Transactions on Software Engineering, 28*(11), 1023-1038. https://doi.org/10.1109/TSE.2002.1049402

Fremont, D., Dreossi, T., Ghosh, S., Yue, X., Sangiovanni-Vincentelli, A., & Seshia, S. (2019). Scenic: A language for scenario specification and scene generation. *Proceedings of the 40th ACM SIGPLAN Conference on Programming Language Design and Implementation, Phoenix, AZ* (pp. 63-78). https://doi.org/10.1145/3314221.3314633

Fremont, D., Kim, E., Pant, Y., Seshia, S., Acharya, A., Bruso, X., . . . Mehta, S. (2020, September). *Formal scenario-based testing of Autonomous Vehicles: From simulation to the real world.* In 23rd IEEE International Conference on Intelligent Transportation Systems (ITSC), Rhodes, Greece (pp. 1-8). https://doi.org/10.1109/ITSC45102.2020.9294368

Goyal, R. (2018). Urban air mobility (UAM) market study. NASA Technical Report, Report Number: HQ-E-DAA-TN65181.

Hackenberg, D. L. (2018). NASA Aeronautics Research Mission Directorate (ARMD) Urban Air Mobility (UAM) Grand Challenge Industry Day.

Heard, B. R., Taiebat, M., Xu, M., & Miller, S. A. (2018). Sustainability implications of connected and autonomous vehicles for the food supply chain. *Resources, Conservation and Recycling, 128,* 22-24. https://doi.org/10.1016/j.resconrec.2017.09.021

Holden, J., & Goel, N. (2016). Uber elevate: Fast-forwarding to a future of on-demand urban air transportation. San Francisco, CA: Uber Inc.

Kalra, N., & Paddock, S. (2016). Driving to safety: How many miles of driving would it take to demonstrate autonomous vehicle reliability? *Transportation Research Part A: Policy and Practice, 94*, 182-193. https://doi.org/10.1016/j.tra.2016.09.010

Lindvall, M., Porter, A., Magnusson, G., & Schulze, C. (2017, May). Metamorphic model-based testing of autonomous systems. *2017 IEEE/ACM 2nd International Workshop on Metamorphic Testing (MET), Buenos Aires, Argentina* (pp. 35-41). https://doi.org/10.1109/MET.2017.6

Mason, I. A., Nigam, V., Talcott, C., & Brito, A. (2017, September). A framework for analyzing adaptive autonomous aerial vehicles. *International Conference on Software Engineering and Formal Methods, Trento, Italy*, (pp. 406–422). https://doi.org/10.1007/978-3-319-74781-1_28

McAree, O., Aitken, J., & Veres, S. (2016, August). A model based design framework for safety verification of a semi-autonomous inspection drone. *2016 United Kingdom Automatic Control Council* (*UKACC) Conference on Control*, (pp. 1-6), Belfast, UK. https://doi.org/10.1109/CONTROL.2016.7737551

DOI: https://doi.org/10.15394/jaaer.2021.1849

McKinsey Digital. (2015). *Industry 4.0 - How to navigate digitization of the manufacturing sector.* New York, NY: McKinsey & Company.

Medrano-Berumen, C., & Akbas, M. I. (2020). Scenario generation for validating artificial intelligence based autonomous vehicles. *Intelligent information and database systems* (pp. 481-492). Springer Nature International Publishing. https://doi.org/10.1007/978-3-030-42058-1_40

Medrano-Berumen, C., Malayjerdi, M., Akbas, M. I., Sell, R., & Razdan, R. (2020). Development of a validation regime for an autonomous campus shuttle. *IEEE SoutheastCon, Raleigh, NC* (pp 1-8). https://doi.org/10.1109/SoutheastCon44009.2020.9249692

Meyer, G., & Shaheen, S. (2017). Disrupting mobility – Impacts of sharing economy and innovative transportation on cities. *Lecture notes in mobility.* Springer International Publishing. https://doi.org/10.1007/978-3-319-51602-8

Morgan Stanley. (2018). *Urban AirMobility Flying Cars: Investment Implications of Autonomous Urban AirMobility.*

Patelli, A., & Mottola, L. (2016). Model-based real-time testing of drone autopilots. *Proceedings of the 2nd Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use*, (pp. 11-16). https://doi.org/10.1145/2935620.2935630

Razdan, R., Akbas, M. I., Sargolzaei, A., Alnaser, A. J., Sahawneh, S., Alsweiss, S., & Vargas, J. (2019, June). Unsettled technology areas in autonomous vehicle test and validation. *SAE (Society of Automotive Engineers) EDGE™ Research Report EPR2019001*. https://doi.org/10.4271/EPR2019001

Rentrope, J., & Akbas, M. I. (2017). Spatially adaptive positioning for molecular geometry inspired aerial networks. *Proceedings of the 6th ACM Symposium on Development and Analysis of Intelligent Vehicular Networks and Applications, Miami, FL*, (pp. 1-8). https://doi.org/10.1145/3132340.3132348

Roth, M., & Sims, R. (2019). Autonomous vehicles and drones. In D. Staat (Ed.), *A baseline of development: Higher education and technology* (pp. 45-66). Lanham, MD: Rowman & Littlefield.

Segura, S., Fraser, G., Sanchez, A. B., & Ruiz-Cortes, A. (2016). A survey on metamorphic testing. *IEEE Transactions on Software Engineering, 42*(9), 805-824. https://doi.org/10.1109/TSE.2016.2532875

Souyris, J., Wiels, V., Delmas, D., & Delseny, H. (2009). Formal verification of avionics software products. *FM 2009: Proceedings of the 2nd World Congress on Formal Methods*, (pp. 532–546). Berlin, Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-642-05089-3_34

Stark, C., Medrano-Berumen, C., & Akbas, M. I. (2020). Generation of autonomous vehicle validation scenarios using crash data. *IEEE SoutheastCon, Raleigh, NC.* https://doi.org/10.1109/SoutheastCon44009.2020.9249662

Stevens, B. L., & Lewis, F. L. (1992). Aircraft control and simulation (2nd ed.). Hoboken, NJ: Wiley & Sons.

Straubinger, A., Rothfeld, R., Shamiyeh, M., Büchter, K.-D., Kaiser, J., & Plötner, K. O. (2020). An overview of current research and developments in urban air mobility—Setting the scene for UAM introduction. *Journal of Air Transport Management, 87,* 101852. https://doi.org/10.1016/j.jairtraman.2020.101852

Su, K., Li, J., & Fu, H. (2011, September). Smart city and the applications. *In 2011 International Conference on Electronics, Communications and Control (ICECC), Ningbo, China* (pp. 1028-1031). https://doi.org/10.1109/ICECC.2011.6066743

Winner, H., Lemmer, K., Form, T., & Mazzega, J. (2019). PEGASUS—First steps for the safe introduction of automated driving. *Road Vehicle Automation, 5*, 185-195. https://doi.org/10.1007/978-3-319-94896-6_16