Proceedings of Automotive Science and Technology 1(1): 55-66 (2025)

ISASTECH2025

Implementability of Artificial Intelligence and Machine Learning Approaches to Vehicle Homologation Tests

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Abstract

Regulations governing the homologation process for regular and/or public transport vehicles require numerous tests to be carried out during the production phase, and it is extremely important that these tests are evaluated accurately, quickly, and at low cost. This article explores the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques to the regulatory testing processes of MAN Türkiye A.Ş., a manufacturer of public transportation vehicles, within the context of current literature, with the aim of improving the speed and cost-effectiveness of these tests. The research examines the most prominent current applications related to the homologation process and includes approaches utilizing AI/ML approaches as well as numerical/statistical analysis for relevant regulations. A key challenge in current homologation processes is integrating information-based system components into traditionally rigid automotive verification systems. In other words, bridging the gaps between Information and Communication Technologies (ICT) and AI/ML in homologation processes. The merging of AI and ML techniques into the current homologation and self-assessment processes applied to passenger vehicles will undoubtedly increase the accuracy and speed of these processes. The information obtained showed that integrating AI/ML approaches with database-supported engineering field applications, especially those with testing and ICT infrastructure in which MAN Türkiye A.Ş. is strong, will provide benefits in validation processes.

Keywords: Artificial intelligence; Machine learning; Numerical/statistical analysis; Vehicle homologation.

http://dx.doi.org/10.29228/pastech.89083

1. Introduction

Traditional homologation processes, which refer to the type approval of vehicles, aim to ensure the safety of manufactured vehicles on public roads. For a vehicle to reach the commercial stage, the manufacturer must officially meet and approve all regulatory standards related to the vehicle. In order to make vehicles reliable for traffic and more environmentally friendly, an independent framework (WP.29) for harmonized regulations on vehicles at a global level was established in 1958 with the participation of international vehicle manufacturing countries worldwide [1]. WP.29 is also the name of the 'World Forum for Harmonization of Vehicle Regulations' working group of the United Nations Economic Commission for Europe (UNECE) Sustainable Transport Division. While UNECE conducts independent third-party homologation process approval, it also incorporates an OEM-declared self-certification approach. As a vehicle manufacturer, an OEM declares that it has passed the approval process of independent organizations such as TÜV, DEKRA, etc., and that it complies with the regulations on the specified list, thereby ensuring the traffic safety of the vehicle on public roads. In contrast, self-certification is a certification approach whereby the manufacturer guarantees that the product meets all relevant standards. Methods based on officially demonstrating that a vehicle meets regulatory standards and specifications are outlined in Table 1.

Table 1. Methods demonstrating that vehicles meet regulatory standards [2]

Method name	Certifying/Approving Body	Country
Type Approval / Homologation	Government	EU, China, India
Self-certification	Manufacturer	USA, Canada
Combined Self-Certification and Type Approval	Combined	Brazil

Public transport vehicles are of great importance due to the services they provide. This article evaluates the applicability of Artificial Intelligence (AI) and Machine Learning (ML) techniques to the homologation process tests required by UNECE regulations governing the production of public transport vehicles by MAN Türkiye A.Ş., with the aim of enhancing the speed and cost-effectiveness of these tests, based on the current literature. The scope includes only applications related to the homologation process; alongside studies based on AI/ML approaches, those proposing numerical/statistical analysis methods for the relevant regulations have also been evaluated.

The rest of the paper is organized as follows. Section 2 investigates the most current and prominent research that use AI/ML in homologation process. Section 3 analysed the foremost applications covering the use of ICT in homologation process. Section 4 explores the current researches where Numeric/Statistical Analysis employed in homologation process. The research studies examined in the all three sections are compared in terms of application fields, techniques preferred and the improvements obtained in the form of tables within each section. Finally, Section 5 summarizes and concludes the paper.

2. Use of AI/ML in Homologation Process

It is important for vehicle manufacturers to keep and reduce the traffic noise emitted by motor vehicles during acceleration within the limits specified in the UNECE R51 standard. Tan et al. [3] developed a machine learning model using a Back Propagation Neural Network in MATLAB software to determine the noise limits during the acceleration of a vehicle. Using their model, they predicted noise limits for evaluation in future revisions of UNECE R51 regulations, based on historical regulatory noise limit data. The noise limits in the regulations were considered as a function of time to explain their changes, and the revised new limits were predicted based on previously known limits. The prediction results of the obtained model were found to be very close to the noise limits defined in the current regulations. Negative error rates were significantly reduced compared to those obtained from the regression model.

Nguyen et al. [4], based on the problems in ensuring the optimal design of a bus body structure that meets safety standards, designed a bus body and analysed it using finite elements. The simulation of the designed bus structure was performed using the Orthogonal Design Method, in which steel pipes of different wall thicknesses were placed on the chassis to meet the UNECE R66 standard. Functions were created using the Response Surface Method and regression analysis. The design variables were optimized using Particle Swarm Optimization (PSO) in the MATLAB environment. With the optimized design variables, a 16.9% improvement in the total weight of the bus's monocoque structure was achieved, and a structure meeting the survival space conditions specified in the ECE R66 standard rollover test scenario (Figure 1) was created. The survival space is defined as the area that will be separated in the event of a rollover accident to provide passengers, crew, and drivers with a better chance of survival in their respective compartments.

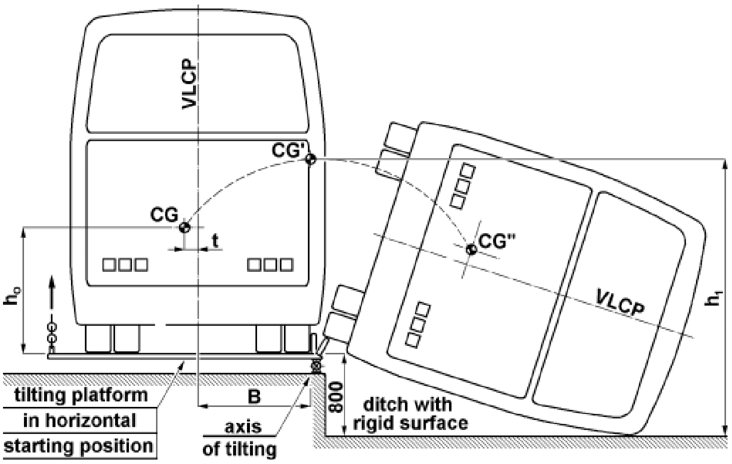


Figure 1. UNECE R66 rollover test configuration

Achariyaviriya et al. [5] examined the energy consumption of electric vehicles (EVs) under real-world driving conditions and compared the results with those of internal combustion engine vehicles (ICEVs) tested under similar driving conditions. To measure the carbon emissions of EVs and ICEVs, they created an energy-centred life cycle to assess the environmental impact of the transition to electric transport, using on-board diagnostic (OBD) systems and GPS for route tracking. Data obtained from the experiments was used to estimate energy consumption using ML techniques and to explain the key factors affecting consumption. It was noted that findings could influence policymakers regarding transport certification and improving energy efficiency. The results emphasized the critical importance of facilitating the transition to electric transport.

Jui et al. [6] analysed the differences between series, parallel and power-split configurations of hybrid electric vehicles (HEVs) (see Figure 2), before analysing existing energy management strategies (rule-based, optimal control theory and supervised learning-based). They emphasized the shift towards integrating ML and AI in the development of energy management strategies. Leveraging advancements in ML and AI, they explored innovative approaches to optimize the performance and fuel economy of HEVs. They identified that the challenges in enhancing HEV energy management strategies with ML algorithms stem from data availability, model complexity, and computational resources.

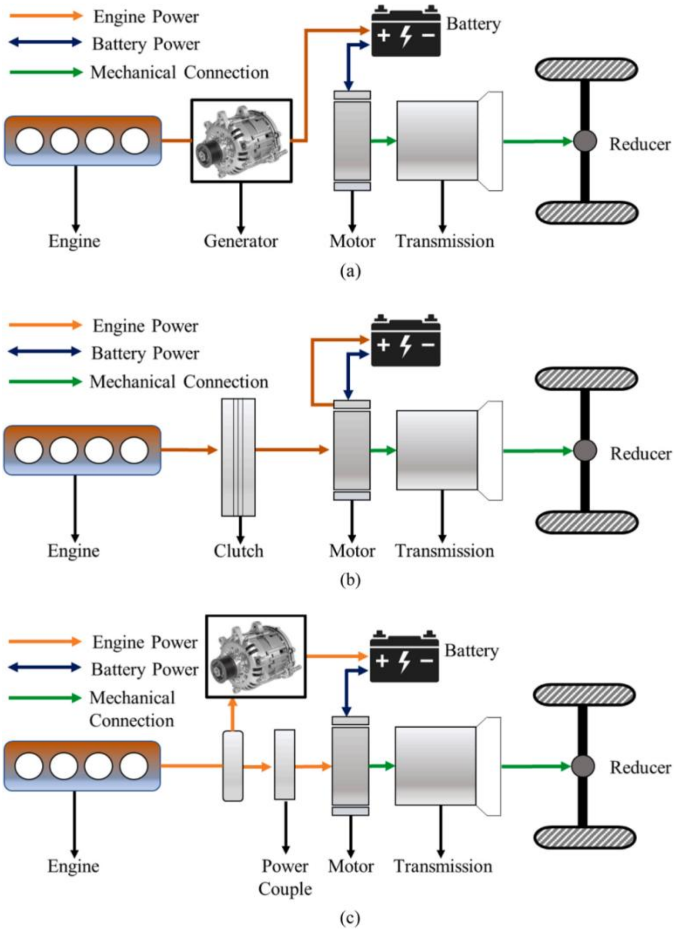


Figure 2. HEV configurations: serial a), parallel b), and power-split [6]

Saito et al. [7] investigated the problem of damage to vehicle compressors and surrounding equipment caused by oscillations and vibrations generated by pressure fluctuations in vehicle turbochargers. A neural network approach was developed to predict the geometric parameters of the operating points where fluctuations occur and the flow velocities at duration of fluctuation. The estimation of fluctuation points, which could be obtained through experiments and computationally intensive CFD analyses, was achieved quickly and cost-effectively using the ML algorithm. The low estimation accuracy obtained for some turbocharger geometries and operating conditions was attributed to the small amount of data in the training set.

Burton et al. [8] presented a chassis safety approach based on a prediction model utilizing sound patterns obtained from the road surface for vehicles. They utilized vehicle sensors to classify road conditions as dry or wet. They used the information obtained to adapt chassis control functions to road surface traction. They noted that incorrect classification of the road surface by the ML could lead to dangerous control actions. They emphasized that, despite the existence of ISO 26262, which analyses traditional software and hardware failures alongside the functional safety of vehicles, and ISO/PAS 21448 standards, which define inadequacies and potential exploits for traditional software and ML, there is no general strategy or approach in the relevant standards suitable for safety verification for non-traditional software. To address these identified shortcomings, they presented an approach based on an argument pattern that examines the collected data in a case study (Figure 3).

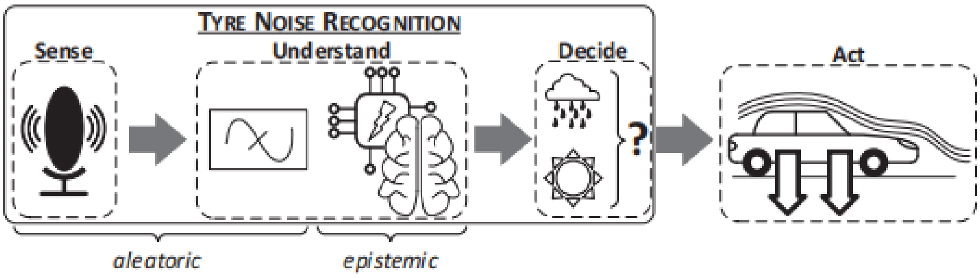


Figure 3. System modelling [8]

Manuguerra et al. [9] proposed a prediction method that combines the fundamentals of Life Cycle Analysis (LCA) and ML to support the design of electric vehicles with early warnings. The methodology of the method is shown in Figure 4. ML techniques were utilized to develop models for a generic electric vehicle, covering design characteristics such as weight and travel distance, addressed in six stages (problem definition, data collection, data preparation, modelling, model evaluation, model interpretation). Unlike existing environmental analyses, all stages of the product life cycle were evaluated as a dataset to provide quantitative results. The estimated model obtained from ML enables the analysis of the environmental impact of electric vehicles in the early design phase, and product engineers utilize this model in LCA. The environmental impact calculated at the end of a case study design differed by 17% from the ML model results.

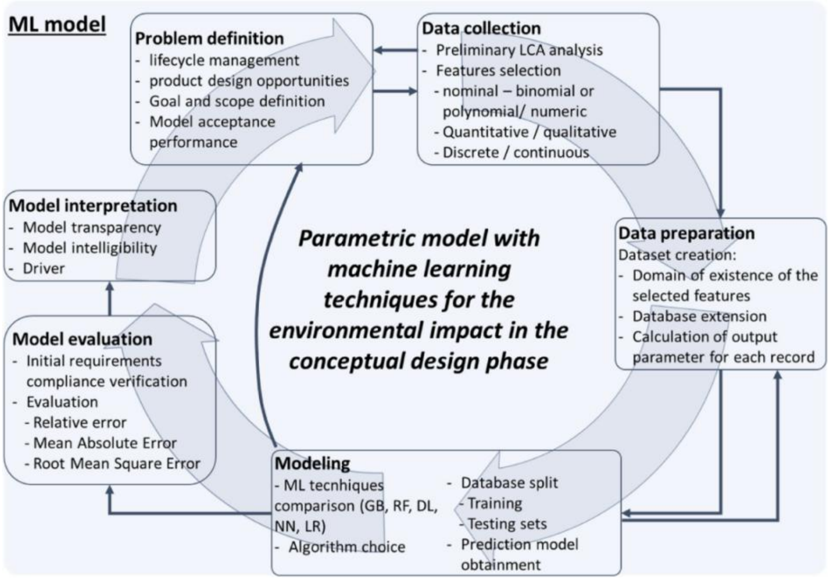


Figure 4. Parametric environmental impact model developed for EV design using ML techniques [9]

Rivera-Campoverde et al. [10] identified the vehicle's driving variables—throttle position, manifold absolute pressure, vehicle and engine speed from on-board diagnostics (OBD), gear, and sea level altitude from GPS—as input data to estimate exhaust emissions from internal combustion vehicles using ML clustering techniques. It was stated that the model they developed, using data obtained from real driving emissions (RDE), yielded similar results to the international vehicle emission (IVE) model. It was stated that the model could be used to estimate emission factors with potential applications in vehicle homologation processes and vehicle emission inventories through short-term real driving tests. Furthermore, it was emphasized that the model could prevent the prolonged operation of portable emission measurement systems (PEMS).

Udoh et al. [11] utilized the ML model for training using a dataset from the United Kingdom Vehicle Certification Agency (VCA), which was shaped by the global standard WLTP (Worldwide Harmonized Light Vehicle Test Procedure) [12] (UNECE) for testing vehicle emissions and fuel consumption. The model, which estimates CO^2 emissions from light-duty passenger vehicles, has been deployed on a web application where users can enter values and select variables to obtain emission estimates (Figure 5). The authors note that the cost-effective model could be useful for vehicle manufacturers, organizations, government agencies, and individuals.

Li et al. [13] conducted an optimization study on the fundamental parameters of the vehicle body structure to improve the in-vehicle NVH (Noise-Vibration-Harshness) performance. A small passenger vehicle under study was modelled using the finite element method, and an acoustic cavity model was created. All panels surrounding the acoustic cavity in the vehicle (B-pillar inner panel, side wall, roof, and other panels) were considered as design variables, and the aim was to select an optimal combination of variables that met the specified conditions. To this end, a multidisciplinary optimization design method based on the Elman neural network algorithm was employed to comprehensively address the vehicle's NVH and crash safety. The results showed that reducing the maximum sound pressure level at the target point of the vehicle led to a significant improvement in the side impact performance of the vehicle body.

Huang et al. [14] conducted road tests with four compact vehicles to predict vehicle interior noise quality. Background noises were removed from the obtained interior noise signals, which were then subjected to an Anchor Semantic Differences (ASD) test to eliminate the effect of individual bias. A regression-based deep belief network was utilized to predict vehicle interior noise quality. They stated that the proposed approach could be extended in the future to address other vehicle noises.

Summary information on the foremost studies based on AI and ML methods in the process of vehicle compliance with regulations is presented in Table 2. According to the table, detection and improvements were achieved using ML techniques, taking into account regulatory limit values in various application areas for different vehicles. These outputs and improvements will only be possible through the systematic integration of data into the test environment.

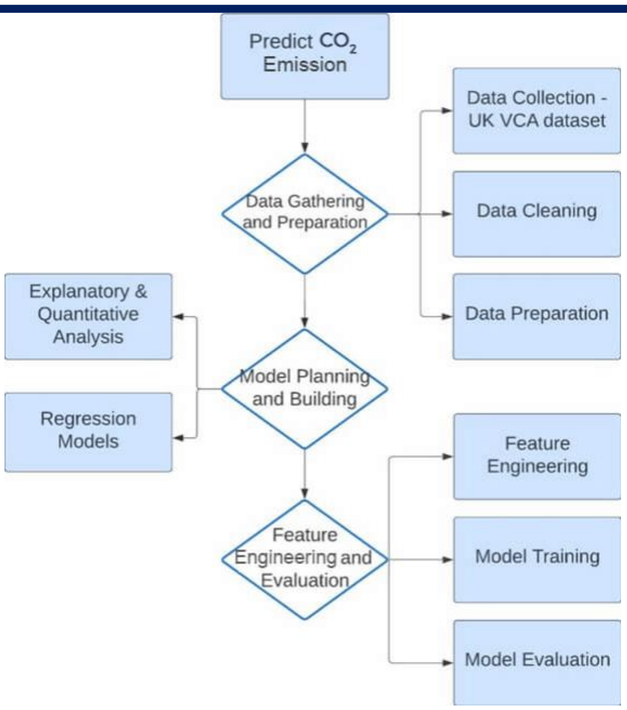


Figure 5. Flow diagram of the prediction analysis model [11]

Table 2. AI/ML-based comprehensive research in the process of vehicle compliance with regulations

Vehicle Type	Application Field/ Components	Standards	Techniques Used	Developments Achieved	References
M1, M2, M3, N1, N2, N3	Noise limit estimation	UNECE R51	Machine learning (SVM, GPR, ET, RT), Backpropagation Neural Network	Traffic noise detection during acceleration	[3]
Coach	Body structure design	UNECE R66	Vertical Design Method, Response Surface Method, Regression Analysis, Particle Swarm Optimization	16.9% reduction in total weight	[4]
Battery electric vehicle (BEV), Hybrid electric vehicle (HEV), Internal combustion engine vehicle (ICEV)	Power transmission unit efficiency	-	Machine learning (XGBoost, Random Forest, MLP, KRR)	Energy efficiency Environmental impact reduction	[5]
Hybrid electric vehicle (HEV)	Energy management strategies	-	Machine learning	Availability in energy management	[6]
Internal combustion engine vehicles (ICEV)	Turbocharger design	-	Machine Learning	Turbocharger fluctuation prediction	[7]
Different vehicle configurations	Chassis inspection	ISO 26262 ISO/PAS 21448	Machine learning	Chassis safety	[8]
Electric bus (shuttle)	Life Cycle Management	-	Machine Learning, Supervised Learning, Regression Analysis	Life cycle assessment	[9]
Internal combustion engine vehicles (ICEV)	Fuel emission estimation	-	Machine learning (K-means, Random Forest)	Inventory of fuel emission factors	[10]
Internal combustion engine vehicles (ICEV) (light-duty vehicle)	Fuel emission estimation	WLTP (Worldwide Harmonized Light Vehicle Test Procedure)	Machine Learning, Regression Analysis	Fuel emissions	[11]
Internal combustion engine vehicles (ICEV) (mini vehicle)	In-vehicle noise estimation	NVH performance test	Artificial Neural Network	In-vehicle noise reduction	[13]
Compact vehicle	In-vehicle noise quality estimation	NVH performance test	Machine Learning, Deep Belief Network, Regression analysis	In-vehicle noise reduction	[14]

3. Use of Information and Communication Technologies in Homologation Process

Information and entertainment systems, driver assistance systems, and safety features supported by electronic components, which have become a typical part of vehicles with the integration of computers into vehicles, support functional safety. Defined as safety-critical systems, driverless vehicles enable autonomous movement by performing precise detection independent of all potential driving routes, traffic, road quality, visibility or weather conditions, and processing data using techniques such as deep neural networks. Public trust and acceptance of driverless vehicles can be achieved by vehicle manufacturers and suppliers placing a high priority on their work on cyber security [15-16]. One of the many challenges facing autonomous vehicles (AVs) is the legal certification process [17].

The SAE classification of AVs is provided (Figure 6). Over time, concerns about the potential risks posed by AI approaches in vehicles have been reported in writing to the UN [18]. Some of these concerns have been stated as AI systems losing control and acting outside human intent. It has been stated that prominent AI applications in the automotive field, such as infotainment management (entering destinations into navigation systems), vehicle management (developing human-machine interfaces), and improving the performance of autonomous vehicles (AVs), should be evaluated within the scope of WP.29. Currently, an Advanced Driver Assistance System (ADAS) is being developed, which encompasses the principle of Crowd Sourcing, whereby vehicles equipped with cameras collect data on the geometry of the roads they drive on and the fixed locations around them, analyse this data in real time using AI within the vehicle, compress it, and send it to a cloud. AVs detect objects around them using perception technologies, analyse the information, make decisions based on driving policies, and map the experiences gathered through AI, ML and the inputs for desired outputs. The above directly concerns work related to homologation process testing. In addition, there are some prominent studies on the next-generation AVs aimed at solving problems that will arise with the direct implementation of AI/ML approaches in vehicles.

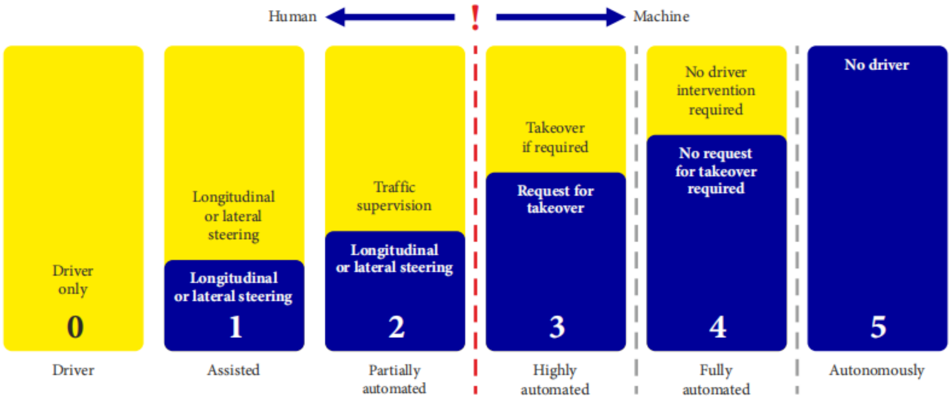


Figure 6. SAE classification of AVs [18]

Anastasi et al. [19] evaluated the effects of embedded AI and ML on machine safety, machine systems, and application development. Within the framework of risk assessment procedures, they emphasized that the EU legislation should be addressed within the scope of the Machinery Directive (2006/42/EC) - Essential Health and Safety Requirements (EHSR). However, they highlighted the limitations of the current scope of legislation within the EU regulatory framework regarding AI and ML, the changing functionality of AI systems, changes in the concept of safety, and the need for improvements in robustness and precision.

Bharilya and Kumar [20] reviewed ML studies on trajectory prediction for autonomous vehicles. They noted that, in addition to AVs travelling on roads commanded by an advanced computer-aided decision-making system instead of a human, it is necessary for them to be able to predict the future behaviour of nearby stakeholders in traffic, just like a human driver. To this end, they comprehensively investigated studies on deep learning and supervised learning methods in AV trajectory prediction. They examined the strengths and weaknesses of the methods, as well as the datasets and evaluation metrics used in trajectory prediction.

Vasudevan et al. [21] conducted a certifiability analysis of ML systems for low-risk automotive software applications. Current automotive system certification methods do not fully certify the safe operation of ML-based components and subsystems. This is because the current safety certification criteria were formulated before the advent of ML. Therefore, they analysed the certifiability of ML approaches used in low-risk automotive applications for the automotive safety standard (ISO 26262).

Wang et al. [22] proposed a reference driver model for scenarios involving merging autonomous vehicles onto motorways (Figure 7). Although UNECE R157 proposes two driver models for comparing the safety assessments of AVs' following behaviours, it does not include non-vehicle following (motorway merging) scenarios. To this end, they proposed a scenario of an attentive and competent driver model incorporating supervised learning-based decision-making and safety-constrained control for motorway merging. The model's safe driving capabilities were compared with those of a human driver, and its attentiveness and competence characteristics were measured.

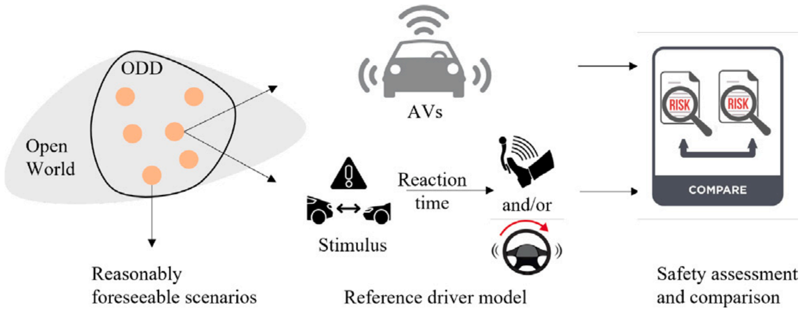


Figure 7. Operational Design Domain (ODD) and AV safety verification model [22]

Benyahya et al. [23] analysed the standards and regulations underlying connected and autonomous vehicles (CAVs). They proposed a Standard Coverage Map (SCM) to protect CAVs, which consist of sensors, AI processors, and external units that guarantee autonomous driving, against cyber-attacks and data leaks (Figure 8). The latest standards and regulations surrounding the entire CAV ecosystem, organizational and technical aspects have been addressed from a cyber perspective.

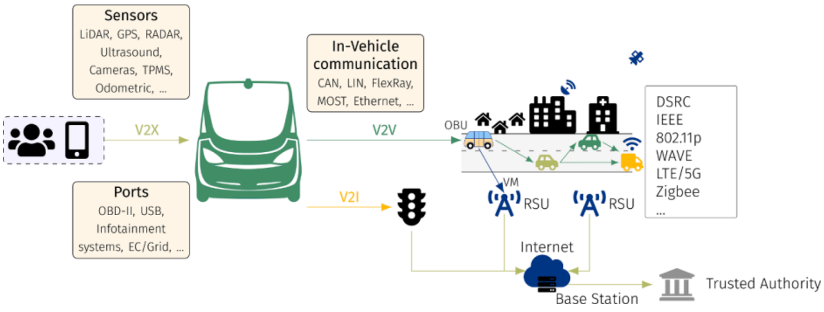


Figure 8. CAV environment and attack surfaces [23]

Summary information on research utilizing AI/ML methods within the scope of ICT for vehicles is provided in Table 3.

Table 3. AI/ML research within the scope of ICT regarding vehicle compliance with regulations

Vehicle Type	Application Field / Components	Techniques / Standards	Developments Achieved	References
General	Machine Safety	Artificial Intelligence, Machine Learning, Machinery Directive (2006/42/EC) - Essential Health and Safety Requirements (EHSR)	Functionality, safety, robustness in AI and ML systems	[19]
Autonomous vehicle (AV)	Orbital tracking	Machine Learning, Deep Learning, Supervised Learning	Trajectory prediction	[20]
General	Software Certifiability Analysis	Artificial Intelligence, Machine Learning, ISO 26262	Security and safety measures	[21]
Autonomous vehicle (AV)	Vehicle safety	Supervised learning, UNECE R157	Safe driving model	[22]
Connected and Autonomous Vehicles (CAV)	Cyberattacks and Data Breaches	ISO/SAE 21434, UNECE R155, UNECE R156, ISO/PAS 5112	Standard Scope Map	[23]

4. Use of Numeric/Statistical Analysis in Homologation Process

The design of damage (deformation) zones in cars is not included in the designs of many bus body designers. UNECE R29 or, more commonly, the NCAP car crash test is preferred to assess the structure's resistance to impact loads. Holenko et al. [24] verified the front impact resistance simulation for a low-entry bus in accordance with UNECE R29 requirements. The main objective of the study was stated as developing an applicable methodology for the front impact simulation of a city bus. The research findings indicated that, unlike suburban and intercity buses, city buses exhibit lower stiffness during frontal collisions. Consequently, it was noted that creating a damage zone, which is absent in most existing city buses, is a requirement in the development of new models.

Lopes et al. [25] aimed to develop technologies incorporating new passive safety solutions for head-on collisions in buses under the UNECE R29 regulation. Current safety standards for the certification of large vehicles require a separate driver's cab, but do not specify a requirement for buses. Within the scope of the research, a test set was created for the frontal collision test, exposing the structure to the impact required by R29. In addition to the recorded test data, the dynamic structural response of the model created in the computer environment using the finite element method (Figure 9) was simulated. The evaluations of strains, accelerations, and displacements were compared with the test results. It was stated that the results obtained could be used to determine whether the proposed models meet the safety criteria or whether further development of the solution is necessary.

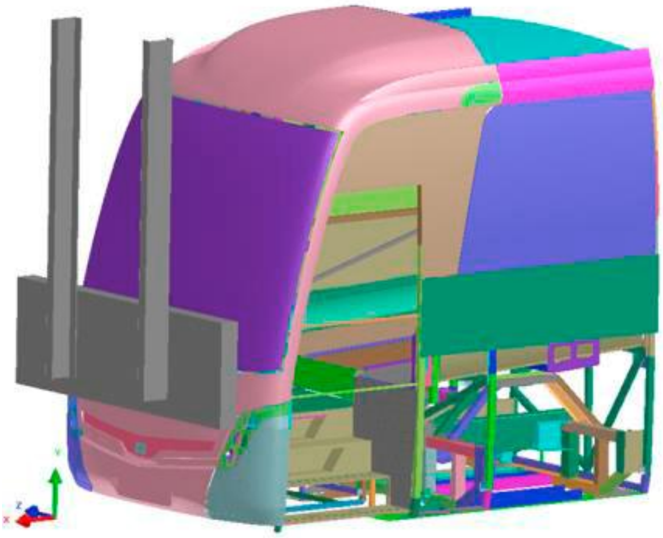


Figure 9. 3D model considered in the finite element analysis [25]

Lopes et al. [26] applied a pseudo-dynamic procedure to evaluate the damage (deformation) energy stored in a bus door structure subjected to a virtual impact from a swinging striker. Currently, passenger vehicles are tested to determine their resilience based on the impact applied to the front surface of the vehicle by a physical impactor swinging at a specified speed. It has been stated that it is possible to evaluate the behaviour of the structure exposed to a virtual dynamic impact using the relevant procedure.

Güler et al. [27] investigated the energy absorption capacity of the front structure of a bus during a frontal collision according to the requirements of the UNECE R29 regulation. For the collision analysis, basic bus structures were analysed in the LS-Dyna non-linear open finite element code environment without any prior development. Weak parts in the front skeleton of the bus body were examined, and the finite element model was validated with experimental studies. The bus structure, whose front structure was reinforced and redesigned, was tested according to UNECE R29 requirements, and its energy absorption capacity was increased with additional energy absorbers. Subsequently, the energy absorption characteristics of the steering armature, which comes into contact with a deformable dummy during impact, were obtained experimentally and numerically. The pre- and post-impact appearances of the bus structure are shown in Figure 10. To determine the effect on the energy absorption characteristics of the two contacting parts, the impact position on the armature, the direction of the armature, and the changes in the dummy were evaluated.

Afripin et al. [28] applied finite element simulation, considering the two prominent pre-collision impact regulations UNECE R29 and NCAP, to determine whether bus structures have sufficient resistance to the load produced by impact. The simulation setups for the regulations are shown in Figure 11. First part was shown as frontal impact according to UNECE R29 and second part was the setup for NCAP. Both simulation models were compared in terms of the energy produced, the deformation of the structure, the maximum stress, and the resulting plastic strain values. The results showed that, although the energy generated in the UNECE R29 simulation was lower than in the NCAP simulation, it underwent greater deformation. In contrast, the NCAP simulation revealed that the structures remained intact and that the steering structure did not come into contact with the driver's body.

Kongwat et al. [29] worked on the design of lightweight frame plans and element sections with the aim of improving energy consumption and operating costs and increasing passenger safety in lightweight buses in the event of an accident. The bending resistance, torsional resistance, and rollover safety of the bus superstructure were examined in accordance with UNECE R66 requirements. The finite element bus structure configuration was subjected to iterative topology optimization of an objective function that considered structural weight and compliance based on maximum displacement constraints for each load condition. The roof structure was identified as the most important design parameter for rollover safety.

Kriston et al. [30] analysed the safety performance under realistic conditions for front impact tests (UNECE R129) for vehicles equipped with only seat belts, only belt guides, and raised seats (Figure 12). In this context, injury risks were calculated by analysing the kinematics of the dummy at the moment of collision. This was compared with a meta-analysis of previously published collision analyses supported by the latest accident data from the EU CARE database. The results determined that, although the seat belt guide and the seat belt alone were statistically equivalent, the seat belt guide in a raised seat could potentially increase the number of injured children.

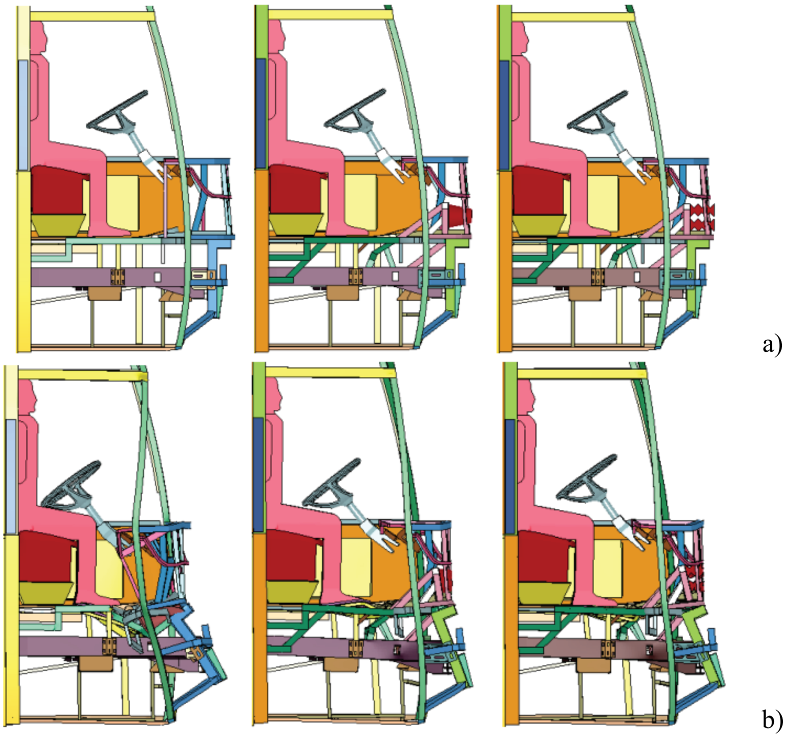
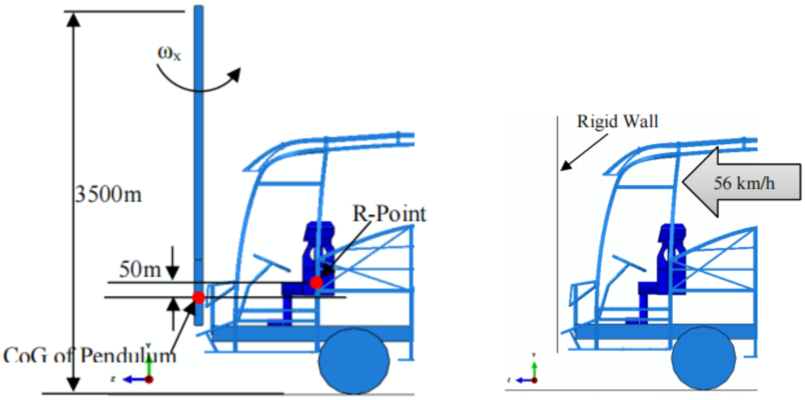
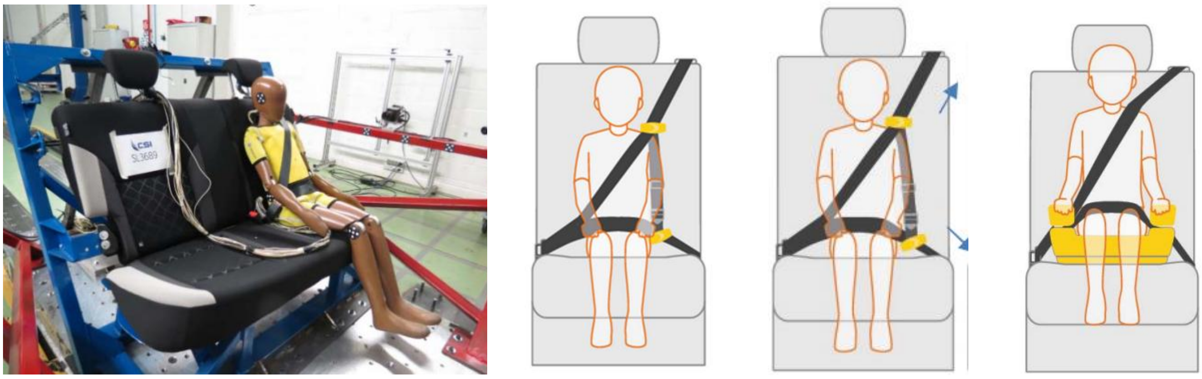


Figure 10. Appearance of the bus structure before a) and after b) the impact [27]



a) b)

Figure 11. Simulation setups for UNECE R29 a) and NCAP b) regulations [28]



a) b) c) d)

Figure 12. Experimental setup a), seat belt b), belt guide c) and raised seat d) [30]

Clar-Garcia et al. [31] demonstrated that the main source of noise emissions from vehicles travelling at speeds above 30 km/h in traffic is tyre-road interaction. Until recently, the methods used to measure noise emissions (CB, CPX, SPB, CPB) have been replaced by UNECE R117, which certifies the rolling noise emissions of tyres. All traditional methods had many drawbacks, such as the difficulty of reproducibility arising from the test track or the vehicle on which the test is performed, the influence of environmental factors, or differing results. To overcome these limitations, they have proposed a new methodology based on drum tests in a laboratory environment and ISO 3744:1994. They have stated that the major advantage of the proposed method is the sound power level parameter, which is not affected by external factors, by explaining the positioning of the microphones, the calculation of the verification factors, the background noise generated by the drum, and the sound power level of the tyre rotating against the drum [32]. Figure 13 shows the experimental setup.

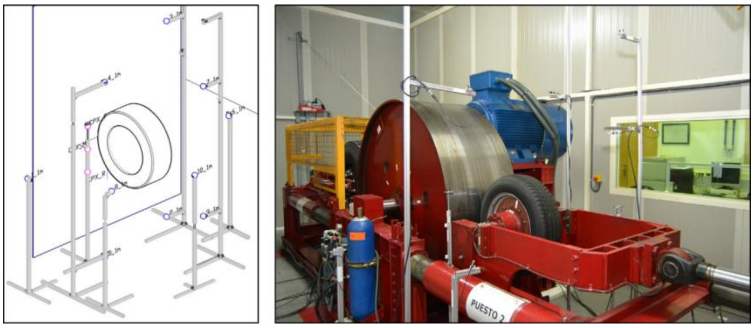


Figure 13. Positioning of microphone arrays around the tyre and the designed experimental setup [32]

Summary information on research that preferred numerical/statistical analysis in the process of vehicle compliance with regulations is presented in Table 4. The studies were generally conducted within the framework of passenger and vehicle safety, and finite element method-based analyses were applied.

Table 4. Research based on numerical/statistical analysis in the process of vehicle compliance with regulations

Vehicle Type	Application Field / Components	Standards / Regulations	Techniques Used	Developments Achieved	References
Low-floor bus	Frontal impact test	UNECE R29 NCAP	Finite Element Method (ANSYS, LS-Dyna)	Frontal impact improvement	[24]
Coach (M3 Class III)	Frontal impact test	UNECE R29	Finite Element Method (ANSYS), Structural optimization	Frontal impact improvement	[25]
Coach (M3 Class III)	Door front impact analysis	UNECE R29	Pseudo-dynamic procedure	Dynamic model approach	[26]
Coach (M3 Class III)	Frontal impact test	UNECE R29	Finite Element Method (ANSYS, LS-Dyna), Structural optimization	Elements that increase energy absorption capacity	[27]
Coach (M3 Class III)	Frontal impact test	UNECE R29 NCAP	Finite Element Method	Energy absorption capacity comparison	[28]
Lightweight bus	Rollover crash resistance	UNECE R66	Finite Element Method, Topology optimization	Rigid design compliant with rollover safety	[29]
General	Child restraint system (CRS)	UNECE R129 EU Directive (91/671/EEC)	ANOVA, Principal Component Analysis	Seat belt configurations and elevated seat analysis	[30]
General	Wheel noise test	UNECE R117 EU Regulation (1222/2009) ISO 3744:1994	Noise power level measurement test	Methodology development and validation for tyre-road noise analysis	[31], [32]

5. Conclusions

This article investigates the applicability of AI and ML techniques to regulatory tests in the homologation processes of MAN Türkiye A.Ş., a manufacturer of public transport vehicles, with the aim of increasing the speed and cost-effectiveness of the tests, within the scope of the current foremost academic literature. Vehicle type approval, homologation, UNECE regulations, NCAP, EU Machinery Directive and EU regulations, and ISO standards were taken into consideration. Within this framework, the research investigated covers a wide range of topics, including vehicle body design, impact/damage, passive safety, engine/component design and propulsion, noise, vibration, energy consumption and emissions, cyber security, ICT security, and product life cycle analysis, all within the scope of relevant standards and regulations.

The studies examined include various current research examples highlighting the effectiveness of AI and ML methods in vehicle homologation processes. These examples clearly indicate the advantages of AI/ML approaches and the improvements achieved in ensuring regulatory compliance according to vehicle type and application area. Furthermore, the concrete benefits of AI/ML techniques integrated with ICT in homologation processes, focusing on safety and performance, have been comprehensively demonstrated through tables.

The findings showed that the challenges in enhancing vehicle performance and safety with AI/ML algorithms stem mainly from data availability, model complexity, and computational resources, which must be taken into account. The availability of data related to real operating conditions of vehicles and use of them in training of AI/ML algorithms have directly effect on the results to be obtained [33-34].

The improvements provided by AI/ML algorithms depend on the regulatory limit values in various application areas for different vehicles being taken into account. The improvements will only be possible through the systematic integration of data into the test environment. The strengths and weaknesses of the methods are changeable based on the datasets and evaluation metrics used.

All traditional vehicle testing methods have many drawbacks, such as the difficulty of reproducibility arising from the test track or the vehicle on which the test is performed, the influence of environmental factors, or differing results. Therefore, the data obtained from testing methods may produce different results on every AI/ML model.

As mentioned earlier, the current automotive system certification methods do not fully certify the safe operation of ML-based components and subsystems. It is stated that it is because of the current safety certification criteria were formulated before the advent of ML. Therefore, the certifiability of ML approaches should be chosen carefully on the basis of the automotive safety standards.

The fundamental challenge in current homologation processes is to integrate information based system components into automotive verification systems, which traditionally have a rigid structure. In other words, it is necessary to bridge the gap between ICT and AI/ML in homologation processes. The integration of AI and ML techniques into the current homologation and self-assessment processes applied to passenger vehicles will undoubtedly increase the accuracy and speed of these processes. The findings obtained shows that integrating AI/ML approaches with database-supported engineering field applications, particularly those with a strong testing and ICT infrastructure such as MAN Türkiye A.Ş., will benefit validation processes.

Acknowledgement

This work was supported by MAN Türkiye A.Ş. The authors would like to thank MAN Türkiye A.Ş.

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