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VIRTUAL PROTOTYPING OF ELECTRIC VEHICLES: AN EXAMINATION OF MODELLING AND SIMULATION TOOLS WITH AN AVL CRUISE CASE STUDY ANALYSIS

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Abstract

The ongoing evolution of alternative drive technologies for vehicles mandates the creation of sophisticated computational tools. Given the intrinsic complexity of these systems, the prototyping phase can be both protracted and costly. Fortunately, computer-aided modelling and simulation environments present a viable alternative. They facilitate the virtual evaluation of innovative drivetrain solutions, thereby eliminating the necessity for physical prototypes. These environments capitalize on extant solutions and readily accessible models of vehicles, drives, and their constituent components, promoting the efficient development of novel concepts and refined drivetrain models. This paper provides a select overview of pertinent vehicle modelling and simulation programs, culminating in the introduction of an electric vehicle model developed using AVL Cruise software. A digital model of the electric vehicle was constructed. This study employed the AVL Cruise software to analyse the energy consumption of an electric vehicle operating under urban driving conditions. This analysis demonstrates the potential of simulation tools for evaluating the performance of electric vehicles in real-world scenarios, offering valuable insights for design optimization. The presented methodology provides a framework for future research on energy efficiency and performance analysis of various alternative drivetrain configurations.

Keywords: energy efficiency; AVL Cruise; vehicle modelling; electric vehicle; simulation

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1. Introduction

The contemporary automotive industry consistently presents engineers and scientists with novel challenges. The imperative to achieve enhanced energy efficiency, minimize exhaust emissions, and ensure optimal occupant comfort and safety necessitates the implementation of increasingly sophisticated technological solutions. In this context, computer programs and environments have become indispensable, assuming a critical role for both automotive enterprises and researchers alike.

The ongoing evolution of electric and hybrid vehicles, driven by advancements in energy storage and electric drive technologies, continuously improves efficiency across varied conditions [1, 2]. However, manufacturer-provided range and energy consumption data often diverge from real-world performance due to usage pattern variability [3, 4]. For users, electric vehicles must offer unwavering reliability and clear range information for effective route planning.

Assessing the impact of driving conditions on an electric vehicle's energy consumption and range traditionally involves extensive real-world testing across diverse terrains, routes, and driving styles [5, 6]. Such tests aim to yield precise, realistic data on range and consumption under typical driving scenarios [7, 8].

Alternatively, simulation studies offer a viable approach. This involves developing a specific mathematical vehicle model [9] or utilizing dedicated vehicle simulation software to manipulate parameters of the vehicle and its drive system [10, 11]. To ensure accuracy, simulations must integrate real-world driving conditions, often using speed profiles (time or distance-based) to represent traffic, along with factors like ambient temperature and road elevation.

The scientific literature extensively covers hybrid and electric vehicle modelling, showcasing diverse tools and models [12–14]. Beyond model descriptions, studies often present simulation results detailing fuel/energy consumption, emissions, and drive system component efficiency across various driving conditions. These simulations are crucial for estimating emissions and pollutants, aiding environmental protection and regulatory compliance.

Modern simulation programs offer functionalities beyond just fuel consumption analysis, enabling comprehensive studies of vehicle operation [15–17]. They allow researchers to identify and mitigate sources of vehicle vibrations and noise [18], and evaluate performance metrics like acceleration, hill-climbing, and maximum speed. Critically, simulations accurately predict fuel consumption under various conditions [19, 20], facilitating the optimization of vehicle and drive system design for improved energy efficiency, ultimately reducing fuel consumption and emissions.

Computer simulations are invaluable for testing and validating vehicle drive systems and components [21, 22], significantly accelerating R&D and reducing testing costs. They enable

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early assessment of new designs, allowing identification and rectification of shortcomings before physical prototyping [23, 24]. While not a complete replacement for empirical research, simulations are crucial tools that reduce research time and expense, and can yield data otherwise difficult or impossible to obtain experimentally.

This paper provides a concise analysis of functionalities within select electric and hybrid vehicle simulation programs. It also presents an AVL Cruise application example for electric vehicle energy consumption analysis. This work aims to inform scientists and engineers in EV/HEV design and development, guiding software selection and inspiring further research. The paper aims to (1) to provide an overview of current simulation tools and methodologies, and (2) to present original research findings from the AVL Cruise case study. The paper furnishes the simulation results, encompassing statistical parameters pertaining to energy consumption, recovered energy, and depth of discharge (DOD). Additionally, it explores the relationships between energy consumption parameters and select route parameters. The concluding portion of the article delves into a discussion of the obtained results and formulating conclusions of the research.

2. Comparative analysis of vehicle simulation software features

2.1. Foundations of electric vehicle modelling: definition and significance

Electric vehicle modelling is the process of mathematically representing their key components and the interactions between them. The goal is to analyse, optimize, and improve the performance of vehicle systems before their physical implementation. Modelling involves creating mathematical representations of real vehicle systems, which allows for simulations of their operation under various operating conditions. The significance of modelling stems from the necessity to expedite the design process, mitigate the costs associated with experimental research, and enhance the safety and reliability of vehicles. In the face of escalating demands for sustainable transportation and energy efficiency, simulations empower engineers to evaluate novel technological solutions, such as advanced battery management systems (BMS) and energy consumption optimization strategies.

The primary objectives of electric vehicle modelling encompass the analysis of energy efficiency, the evaluation of powertrain performance, the design of battery management systems, and the investigation of vehicle dynamics. Energy efficiency analysis facilitates the optimization of energy consumption through the assessment of various powertrain configurations and energy management strategies. The evaluation of electric drive performance enables the determination of operational characteristics for the electric motor, inverter, and transmission system, which is crucial for ensuring the high efficiency of the entire power-

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train. The design of BMS is essential from the perspective of monitoring battery parameters, diagnosing their state, and optimizing charging and discharging processes to extend their lifespan. The investigation of vehicle dynamics encompasses the analysis of vehicle behaviour during acceleration, braking, cornering, and driving under various conditions, thereby enabling control system optimization. Safety simulations are utilized to assess vehicle responses in critical scenarios, including the analysis of trajectory stability and advanced driver-assistance systems (ADAS).

Electric vehicle modelling can be conducted at varying levels of granularity, encompassing component modelling, system-level modelling, and whole-vehicle modelling. Component modelling focuses on the mathematical representation of individual elements, such as the electric motor, battery, or energy management system, thereby enabling their independent analysis and optimization. At the system-level modelling stage, the interaction of key subsystems, such as the powertrain and energy management system, is analysed to optimize their operation within the vehicle. Whole-vehicle modelling integrates all constituent components, enabling comprehensive simulations encompassing mechanical, electrical, and control aspects. This level of modelling facilitates the complete representation of vehicle behaviour under real-world operating conditions, which is crucial for testing control strategies, predicting range, and assessing the impact of various factors on vehicle efficiency

2.2. Methods and approaches in vehicle simulation and modelling

Numerous programs are currently available for vehicle simulation and modelling, each offering diverse functions and capabilities. The selection of appropriate software hinges upon the user's specific requirements, budgetary constraints, and the project's scope. A wide array of mathematical models and simulation programs exist for vehicle research, with each tool providing distinct functionalities, thus making the choice highly dependent on individual user needs. These simulation programs utilize mathematical models to calculate and predict vehicle behaviour, playing a pivotal role in the design, development, and testing of hybrid and electric vehicles. By employing complex mathematical equations, they simulate the intricate interactions between various vehicle components, such as internal combustion engines, electric motors, drivetrain systems, batteries, and control systems. Such simulations enable engineers to assess vehicle performance metrics, forecast energy consumption and emissions levels, and identify potential design flaws before physical prototypes are built. Notable examples include AVL Cruise and Ansys Powertrain, in addition to numerous proprietary simulation tools developed by researchers [25–27].

To achieve detailed simulation, modern vehicle simulation programs utilize a diverse array of mathematical models, each precisely designed to replicate complex vehicle behaviours under various operating conditions. The most appropriate model is chosen based on the specific needs and objectives of the simulation. Linear models operate on the fundamental

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assumption that input and output variables maintain a strictly proportional relationship. This means a change in an input, such as applied force or throttle position, directly results in a proportional change in an output, like vehicle speed or acceleration, by neglecting nonlinear effects. While computationally simple and analytically tractable, making them effective for basic vehicle dynamics (e.g., steady-state speed, constant acceleration, linear braking) [28, 29], their simplification of real-world physics, which often includes nonlinear phenomena such as aerodynamic drag or tire friction, significantly limits their accuracy and applicability in complex driving scenarios. For more intricate problems, nonlinear or hybrid models are indispensable for achieving demonstrably higher accuracy and reliability.

Nonlinear models in simulation programs overcome the limitations of linear models by incorporating complex, non-proportional relationships between input and output variables. This provides a more accurate representation of real-world phenomena, enabling the analysis of interactions among vehicle components like the engine, drivetrain, aerodynamics, and suspension [30–32]. While offering superior fidelity for complex vehicle behaviour, this enhanced accuracy demands increased complexity in development and implementation, requiring deeper expertise in mathematics and modelling techniques. Furthermore, hybrid models combine characteristics from different model types, such as linear and nonlinear approaches, to effectively address complex phenomena requiring consideration of both straightforward and intricate variable relationships.

These models find practical utility in diverse applications, including the assessment of energy expenditure and pollutant emissions across varied operational scenarios [33–35]. Moreover, they are vital for scrutinizing vehicle performance over irregular topographies, precisely modelling the vehicle's environmental interactions. Hybrid models excel in situations requiring a holistic comprehension of system dynamics. They achieve this by strategically integrating the strengths of linear straightforwardness and nonlinear precision, aligning with the simulation's specific aims. This collaborative methodology facilitates a more intricate and veracious depiction of real-world behaviours, distinctly exceeding the capabilities of exclusively linear or nonlinear models used independently.

Vehicle simulations are significantly enhanced by quasistatic models, which assume certain system variables—like engine rotational speed or torque demand—change slowly relative to the simulation timestep. This allows their dynamics to be approximated as instantaneous or steady-state conditions. Mathematically, this means the time derivatives of these variables are negligible over short intervals, enabling the use of algebraic rather, than differential equations. These models are primarily used for analysing energy consumption and exhaust emissions under steady or quasi-steady operating conditions, as exemplified by their implementation in tools like PSAT. Compared to fully dynamic models, which solve time-dependent differential equations, quasistatic models offer significantly faster computational performance due to their reduced complexity. However, quasistatic models are fundamentally limited in capturing transient vehicle dynamics, such as rapid acceleration, cornering,

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or oscillatory responses, because they neglect inertial and higher-order effects. Their applicability is confined to quasi-steady scenarios like constant-speed driving, low-speed operation, or simplified manoeuvres (e.g., linear braking and acceleration along a straight path), where dynamic interactions are minimal [36, 37]. While they can be integrated into broader vehicle dynamics simulations, their use is restricted to cases where transient effects are secondary to steady-state performance metrics.

Dynamic models represent a distinct paradigm from static methods by explicitly detailing a vehicle's temporal evolution, precisely considering changes in applied forces and resultant accelerations. Their core utility resides in examining intricate kinematic behaviours, such as rapid acceleration, deceleration, cornering manoeuvres, and navigation over irregular surfaces [38, 39]. While yielding substantially more comprehensive outcomes than static counterparts, these models necessitate greater processing duration and computational capacity due to their thorough integration of all pertinent parameters and their fluctuating nature. Hence, they are optimally suited for tackling highly complex phenomena, particularly within the field of vehicular motion analysis.

These models are indispensable for simulating vehicle dynamics, accurately portraying a vehicle's deportment throughout its movement. Their applicability extends further, encompassing vehicular static analyses when confronted with elaborate load scenarios. Crucially, dynamic models are pivotal for modelling electric and hybrid automobiles, given their remarkable capacity to depict the multifaceted occurrences inherent in operational conditions. Software such as PSIM and Virtual Test Bed (VTB) exemplify the deployment of dynamic models in this domain [12, 40, 41].

Beyond conventional model-based simulation platforms, data-driven methodologies provide an alternative means for simulating hybrid and electric vehicles. These software applications leverage empirical test data and actual measurements to formulate representations of vehicle performance across varied operational conditions [42–44]. Illustrative examples comprise SimPowerSystem/SimDriveline, ANSYS Simplorer, and PSIM.

Physics-based simulation models, increasingly adopted in vehicle research [28, 29], enhance fidelity by integrating fundamental physical laws (e.g., Nernst equation for batteries, Navier-Stokes for airflow) and empirical data. This contrasts with traditional model-based approaches that often rely on abstracted differential equations or simplified lookup tables. These models excel in complex scenarios, such as transient battery thermal management or tire-road interactions, by resolving nonlinearities and multi-domain effects that traditional methods frequently oversimplify. However, they typically demand more computational resources due to the use of numerical solvers like FEM or CFD. While their implementation requires expertise in physical modelling, their ability to accurately simulate energy consumption or emissions in real-world conditions-validated against measurements-makes them superior to traditional frameworks in high-fidelity applications [45–47].

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Hybrid simulation programs out a niche by offering distinct advantages over purely model-based or physics-based approaches. This strategic marriage of methodologies fosters enhanced simulation accuracy by capitalizing on the strengths of both paradigms. It leverages the theoretical underpinnings embedded within models while simultaneously incorporating practical insights gleaned from empirical test data. Additionally, hybrid programs can potentially achieve faster computational speeds. This efficiency stems from the ability of data to streamline certain calculations that would otherwise be required by complex models. User-friendliness emerges as another benefit, as these programs often don't necessitate profound expertise in intricate mathematical constructs.

Nonetheless, it is crucial to recognize the intrinsic disadvantages linked to hybrid simulation tools. Their implementation complexity poses a substantial challenge, given the demanding requirement for precise amalgamation of theoretical constructs with empirical performance data. Moreover, these approaches can display restricted adaptability. Adjusting simulations to incorporate new scenarios or elements can prove more involved than with exclusively model-driven or physics-based software.

Vehicle simulation software predominantly utilizes three distinct computational paradigms: the forward-facing technique, the backward-facing technique, and a hybrid methodology that integrates aspects of both. The forward-facing method usually starts with driver inputs, such as throttle position, braking, or acceleration demand. These inputs are then translated into power/torque demands for the powertrain components [47, 48]. This method hinges on physical equations and the dynamic interactions between drivetrain components. However, the presence of intricate feedback loops and control algorithms necessitates computationally intensive calculations. Despite this drawback, the forward facing method has proven valuable in developing vehicle models, as evidenced by its application in research studies [49] and programs like PSAT/Autonomie.

The he backward-facing method differs fundamentally from the forward-facing approach by computing power flow in reverse, starting from a predefined driving cycle speed profile (e.g., velocity (v(t)) over time). From this, the required wheel power is calculated and propagated backward through the drivetrain-treated as a series of independent, quasi-static modules—until reaching the energy source (e.g., battery or fuel tank). This method is primarily employed for energy consumption and efficiency estimation, leveraging steady-state assumptions and lookup tables rather than solving time-dependent differential equations, which limits its ability to capture transient dynamic responses like rapid acceleration or inertial effects. By avoiding the computational overhead of dynamic modelling, it achieves significantly faster execution times compared to the forward-facing method, which integrates physical interactions forward from the energy source. Its application is well-documented in energy-focused vehicle simulations, such as those in [50], and implemented in tools like GT-SUITE and SimpleV (Simple Electric Vehicle Simulation), where steady-state performance metrics are prioritized over transient behaviour analysis.

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The mixed procedure combines the advantages of both forward-facing and backward-facing methodologies. It begins with computations performed using the backward-facing technique, enabling the estimation of efficiency parameters and operational boundaries for the model's constituent subsystems. Subsequently, utilizing these established values, the process shifts to the forward-facing method to determine power and energy metrics from the power source to the driven wheels. Nevertheless, the primary disadvantage of this integrated approach is the requirement to maintain two separate models for an identical component [51]. Despite this constraint, the hybrid procedure has been successfully applied in developing vehicle models for software platforms such as AVL Cruise, PSIM, and ADVISOR.

Vehicle modelling and simulation software have emerged as essential instruments in the research and development of electric and hybrid vehicles. Their deployment markedly expedites the innovation pipeline, facilitating the introduction of cutting-edge technologies and, consequently, more efficient and ecologically sound vehicles [52–54]. These computational platforms provide a robust testing milieu, empowering researchers to swiftly and economically assess numerous vehicle configurations across varied operational environments. This virtual proving ground fosters the optimization of vehicle designs, leading to demonstrably enhanced performance metrics. Furthermore, simulation programs possess the remarkable capacity to forecast vehicle behaviour in situations that would be impractical or even hazardous to replicate through physical experimentation.

2.3. Overview of state-of-the-art tools and selected simulation programs for electric vehicle modelling significance

Electric vehicle modelling and simulation constitute critical facets of contemporary automotive engineering, enabling powertrain optimization, driving dynamics analysis, and energy efficiency assessment. Modern simulation tools offer sophisticated capabilities for modelling both individual components and complete systems, accounting for complex mechanical, electrical, and thermal interactions. In previously published works, numerous software platforms have been utilized for the modelling and simulation of entire electric vehicles or their constituent components.

MATLAB/Simulink is among the most frequently utilized tools in the modelling of electric vehicle powertrains, esteemed for its versatility and extensive simulation capabilities. MATLAB, as a programming platform, enables engineers and researchers to analyse and design complex systems, while Simulink, an integrated block diagram environment, facilitates multi-domain modelling without the necessity for code writing. Through libraries such as Simscape and SimPowerSystems, this tool accurately replicates electrical, mechanical, and hydraulic components, including electric motors, batteries, and control systems. The scientific literature underscores its pivotal role in EV research, encompassing both vehicle dynamics and powertrain optimization.

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In the literature, MATLAB/Simulink is extensively employed for the simulation of energy consumption across various driving cycles, such as WLTP and NEDC [55–57], enabling the evaluation of external factors, including ambient temperature and aerodynamics, on energy efficiency [58]. Researchers also utilize it for the design of battery management systems (BMS), analysing the state of charge (SOC) and state of health (SOH) of lithium-ion batteries [59–61]. For instance, in works [62,63] battery performance under variable load conditions was simulated, considering thermal management and cooling strategies, thereby supporting the optimization of battery lifespan and safety.

MATLAB/Simulink also facilitates the simulation of EV drive dynamics, including in-wheel motor configurations, analysing torque and efficiency across various driving scenarios [64–66]. Its advantage lies in the capability to integrate with Hardware-in-the-Loop (HIL) testing, accelerating prototyping and model validation [67–69]. However, limitations include the high computational power required for complex simulations, which can present a barrier for large models, and the significant licensing cost, restricting accessibility for smaller research teams. Nevertheless, due to its flexibility and extensive libraries, MATLAB/Simulink remains an indispensable tool in the advancement of electromobility.

CarSim represents an advanced suite of tools designed for the simulation of vehicle dynamics within a realistic road environment. These programs facilitate the modelling of vehicle behaviour, accounting for diverse road conditions, dynamic loads, and interactions with advanced driver-assistance systems (ADAS). CarSim is recognized as one of the most precise tools for vehicle dynamics simulation, offering accurate physical models that encompass forces acting on the vehicle, rolling resistance, aerodynamics, and the influence of the powertrain on vehicle motion. In the context of electric vehicles, the representation of specific electric drive characteristics, such as instantaneous torque and the impact of energy management on driving performance, is crucial. The high fidelity of physical models and the capability for integration with external control algorithms (e.g., via MATLAB/Simulink) render these tools widely utilized in the automotive industry. However, potential limitations include the relatively protracted configuration time for models and the requirement for specialized knowledge in vehicle dynamics.

The primary application of CarSim is the modelling of electric powertrains and their components, including electric motors, energy transmissions, and control systems. Scientific articles frequently describe the utilization of CarSim for analysing powertrain performance, including dynamic response and energy efficiency. These simulations support the design of more advanced and optimized powertrain components, considering the specific characteristics of electric vehicles, such as high torque availability from zero revolutions per minute.

CarSim is widely utilized in research concerning energy consumption in electric vehicles and the estimation of their range under various operational conditions. The scientific literature indicates the use of this tool for simulating driving cycles (e.g., WLTP, FTP-75) to evaluate

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the impact of external factors, such as ambient temperature, terrain slope, and driving style, on energy efficiency [70, 71]. The results of these analyses are crucial for the refinement of battery management systems (BMS) and charging strategies..

CarSim finds application in the analysis of electric vehicle dynamics, accounting for their unique properties, such as the low centre of gravity resulting from battery placement and the operational characteristics of electric motors. Scientific articles describe simulations concerning vehicle stability during manoeuvres, such as cornering and obstacle avoidance, which facilitates the refinement of traction and stability control systems (e.g., ESP) in EVs. For instance, in paper [72] a model of an in-wheel electric motor was presented and tested under various conditions. The wheel torque, which serves as fundamental information for slip control, such as in VDC, TCS, and ABS systems, was analysed. In paper [73] an analysis of an electronic differential, based on various control theories, was presented. In work [74] an energy-efficient control strategy for electric vehicles with in-wheel motors, based on discrete adaptive sliding mode control (DASMC), was developed.

With the advancement of autonomous driving technologies, CarSim is increasingly utilized to investigate the interaction of electric vehicles with Advanced Driver Assistance Systems (ADAS) and to simulate autonomous control systems. The literature emphasizes its role in testing control algorithms in realistic road scenarios, which is crucial for the safety and reliability of autonomous EVs [75–77].

CarSim is a versatile tool in electric vehicle research, finding applications in powertrain analysis, energy management, regenerative braking, driving dynamics, and integration with autonomous technologies. These areas reflect the priorities of contemporary EV research, such as enhancing efficiency, improving safety, and adapting vehicles to new technological demands. Simulation results obtained from CarSim provide valuable data that support the design of more advanced and sustainable electric vehicles, contributing to the further development of electromobility.

ANSYS and COMSOL Multiphysics are advanced numerical tools utilized for modelling thermal and electromagnetic interactions in electric vehicles. ANSYS offers a broad spectrum of modules, enabling the analysis of fluid mechanics, material strength, and heat transfer, which is crucial for the design of battery cooling systems and the optimization of vehicle aerodynamics. COMSOL Multiphysics, conversely, is valued for its capability to model coupled physical phenomena, such as the influence of electromagnetic fields on thermal losses in electric motors. Both programs are extensively applied in research concerning novel battery technologies and cooling systems for electric drives. However, these tools are limited by their high computational complexity and the necessity for significant computational power to conduct accurate simulations.

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ANSYS is predominantly employed for finite element method (FEM) simulations to assess the structural integrity and durability of electric vehicles. Research focuses on analysing chassis structures, battery enclosures, and their resistance to dynamic loads and collisions [78, 79]. In the literature, it is emphasized that these simulations are pivotal for ensuring passenger safety and protecting heavy components, such as battery packs, in emergency scenarios [80, 81]. Examples include the optimization of lightweight materials to enhance vehicle range without compromising structural integrity [82, 83].

One of the most prevalent applications of ANSYS is the modelling of thermal management in electric vehicles, particularly concerning batteries, electric motors, and power electronics. Heat transfer and computational fluid dynamics (CFD) simulations enable the design of efficient cooling systems, such as liquid or air cooling, which prevent component overheating and extend their lifespan [84–86]. Researchers indicate that these analyses are particularly significant during fast charging of batteries, where substantial amounts of heat are generated.

ANSYS is also utilized for modelling electromagnetic fields in electric motors and power electronic systems. The literature describes how these simulations support the design of more efficient drives, minimizing energy losses and optimizing magnetic field distribution [86–88]. Although ANSYS sometimes falls short of COMSOL in terms of detail in this area, its integration with thermal and mechanical analyses renders it a valuable tool in the design of integrated powertrain systems.

COMSOL Multiphysics distinguishes itself in the literature through its flexibility in multiphysics modelling, which enables precise investigation of interactions between various phenomena in electric vehicles. COMSOL is particularly esteemed for its capability to simulate electrochemical processes in battery cells, such as ion transport, chemical reactions, and material degradation [89–91]. The scientific literature indicates that this tool is utilized to analyse the performance, capacity, and lifespan of lithium-ion batteries, which is crucial for enhancing the range and reliability of electric vehicles [92, 93]. These simulations often incorporate the influence of temperature and charging cycles on internal processes [94, 95].

COMSOL Multiphysics finds extensive application in the modelling of electromagnetic fields in electric motors, enabling the optimization of their design for performance and loss reduction [96, 97]. Additionally, in recent years, an increasing number of articles describe the utilization of COMSOL for the design of wireless (inductive) charging systems, analysing the electromagnetic field distribution between the transmitter and receiver [98, 99]. This area is crucial for the development of modern EV technologies.

In summary, the literature features examples of collaboration between both tools, wherein ANSYS is utilized for the analysis of the overall vehicle structure, while COMSOL is employed for more in-depth modelling of specific components, such as batteries and electric motors.

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AVL Cruise and AVL Cruise M are professional tools designed for powertrain system analysis and performance optimization. AVL Cruise facilitates comprehensive modelling of powertrain configurations, including hybrid and fully electric systems, incorporating detailed technical parameters of components. AVL Cruise M, as a more recent iteration, focuses on system modelling within a multi-domain environment, enabling a more detailed analysis of the impact of control strategies on overall vehicle performance. Both tools offer a high degree of accuracy and the capability for integration with other simulation environments. However, their primary limitations include the high licensing cost and the relatively steep learning curve associated with operational proficiency.

AVL Cruise is an earlier software version, primarily focused on one-dimensional (1D) simulations of vehicle and powertrain dynamics. This program is commonly utilized for simulating energy consumption in electric vehicles across various driving cycles, such as NEDC (New European Driving Cycle) and WLTP (Worldwide Harmonized Light-Duty Vehicles Test Procedure) [100]. Research concentrates on evaluating the impact of vehicle parameters, such as mass, aerodynamic drag, and powertrain efficiency, on range and energy efficiency. For example, these simulations enable the determination of how changes in battery or electric motor design affect powertrain energy performance [101, 102].

The literature describes the utilization of AVL Cruise for the design and optimization of powertrain components, such as electric motors and transmissions. The program enables the selection of appropriate gear ratios and motor power to meet dynamic requirements (e.g., acceleration, maximum speed) while maintaining energy efficiency [103–105]. AVL Cruise finds application in comparative studies between electric vehicles, hybrid electric vehicles (HEVs), and internal combustion engine vehicles. Researchers utilize this tool to evaluate how different powertrain types impact vehicle performance and emissions, which is particularly relevant in the context of designing hybrid powertrains with electrical components [106–108].

AVL Cruise M, as a more advanced version, offers multiphysics simulation capabilities and more detailed component modelling. AVL Cruise M allows for the integration of various physical domains, such as electricity, thermodynamics, and mechanics, within a single model. In the context of EVs, this is particularly advantageous for analysing the interactions between the electric motor, battery, cooling systems, and power electronics. The literature emphasizes that these simulations support the design of integrated powertrains, considering their impact on component performance and durability [109].

One of the most frequently described applications of AVL Cruise M is the detailed modelling of batteries, including electrochemical processes, aging, and thermal management. Research focuses on simulating the impact of charge/discharge cycles on the state of charge (SOC) and state of health (SOH) of batteries, which enables the optimization of energy management strategies in electric vehicles [110]. Thanks to its advanced solver and component libraries,

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AVL Cruise M enables the simulation of vehicle dynamics in complex scenarios, such as rapid acceleration and on-road manoeuvres. Research often combines these simulations with control strategy optimization, for example, using model predictive control (MPC) algorithms, to enhance both driving dynamics and economy [111].

AVL Cruise is more focused on simpler, one-dimensional system analyses, such as overall energy performance, powertrain design, and configuration comparisons. Its advantage lies in its speed and ease of use for less complex models, making it popular in the initial stages of EV design. AVL Cruise M excels in multiphysics simulations and detailed component analyses, such as batteries, hydrogen systems, and thermal interactions. It is preferred in advanced research where precise models and integration with other simulation tools (e.g., MATLAB/Simulink) are crucial.

Table 1 outlines the key features of selected simulation tools—MATLAB/Simulink, CarSim, ANSYS, COMSOL Multiphysics, AVL Cruise, and AVL Cruise M—utilized in electric vehicle modelling. By considering their applications, complexity levels, limitations, and approximate costs, the table enables a rapid assessment of each program's suitability for various research scenarios, ranging from vehicle dynamics analysis and thermal and electrochemical modelling to powertrain optimization. This compilation supports the selection of appropriate software based on simulation objectives, available computational resources, and requirements for precision and integration with experimental data.

Tab. 1. Overview of selected test drive parameters

Program	Applications	Computational complexity level	Limitations	Cost
MATLAB/ Simulink	– Vehicle dynamics modelling – Control system simulation (e.g., BMS) – Energy analysis – Hardware-in-the-Loop (HIL)	Medium to High (model-dependent)	– High computational power for complex simulations – Requires programming knowledge	High (commercial license)
CarSim	– Vehicle dynamics simulation (acceleration, stability) – Energy consumption and range analysis – ADAS and autonomy testing	Medium to High	– Long model configuration time – Requires specialized vehicle dynamics knowledge	High (commercial license)

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Tab. 1. Overview of selected test drive parameters; cont.

Program	Applications	Computational complexity level	Limitations	Cost
ANSYS	– Thermal analysis (e.g., battery cooling) – FEM simulations (crashworthiness) – Electromagnetic modelling of drives	High	– High computational complexity – Requires significant computational power – Complex operation	Very High (commercial license)
COMSOL Multiphysics	– Electrochemical modelling of batteries – Electromagnetic field simulations (motors, wireless charging) – Multiphysics analysis	High	– High computational complexity – Requires advanced physics knowledge – High computational power	Very High (commercial license)
AVL Cruise	– Energy consumption and range simulation – Powertrain optimization – EV, HEV, ICE comparisons	Medium	– Limited to 1D analyses – High license cost – Less detail in dynamics	High (commercial license)
AVL Cruise M	– Multiphysics simulations (powertrains, batteries) – Battery modelling (SOC, SOH) – Control optimization	High	– High license cost – Requires integration with other tools – Complex operation	Very High (commercial license)

In summary, contemporary simulation tools offer a broad spectrum of capabilities in electric vehicle modelling, encompassing both component analyses and whole-system simulations. MATLAB/Simulink predominates as a versatile tool, enabling control system modelling and energy analyses, while CarSim/TruckSim provide realistic vehicle dynamics simulations. PSAT finds application in powertrain efficiency analysis, whereas ANSYS and COMSOL Multiphysics offer advanced capabilities in multiphysics modelling. AVL Cruise and AVL Cruise M, on the other hand, represent professional tools for powertrain performance analysis in a multi-domain environment. The selection of appropriate software depends on the scope of research and the requirements for simulation precision and computational power.

2.4. Model validation and verification

Electric vehicle modelling within computational environments constitutes a crucial element in the design and optimization of contemporary powertrain systems. However, the efficacy of these models hinges on their validation and verification, processes that ensure simulations accurately reflect reality. Model validation involves comparing simulation results with real-world experimental data, thereby assessing how well the model replicates the

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physical behaviour of the electric vehicle. The literature indicates that vehicle dynamics simulations, such as acceleration and cornering stability, are frequently verified through road tests on proving grounds [112]. For instance, data from acceleration and velocity sensors are compared with simulation results of standard driving cycles (e.g., WLTP) to confirm the accuracy of the electric drive model [113]. An example of model validation is the comparison of simulated energy consumption with actual measurements from road tests of hybrid and electric vehicles [114, 115].

Validation of thermal and mechanical models (e.g., battery thermal management or crash-worthiness) relies on data from laboratory tests, such as temperature measurements in battery cells or crash test results. Experimental data from electrochemical battery tests (e.g., discharge curves) are then used to validate simulations of internal cell processes [116, 117].

Error and uncertainty analysis is crucial for understanding the limitations of simulation models. Errors may arise from simplifications within the models, inaccurate input data (e.g., material parameters), or discrepancies between simulation and experimental conditions. The literature emphasizes the application of techniques such as sensitivity analysis to assess how variations in input parameters (e.g., thermal conductivity of materials) affect the results [118, 119]. Error analysis encompasses statistical approaches, such as the Monte Carlo method, to estimate the dispersion of outcomes.

Model accuracy defines how closely simulation results align with experimental data, whereas model credibility pertains to its ability to predict vehicle behaviour across diverse scenarios. Models are considered accurate in driving dynamics simulations (errors below 5% under typical conditions), but their credibility diminishes in extreme situations (e.g., wet surface slippage) if appropriate calibration data are not incorporated [120]. High accuracy in thermal and mechanical analyses is contingent upon the appropriate selection of parameters and computational meshes, as well as the necessity for validation against specific materials used in batteries. Accuracy in electrochemical modelling (e.g., predicting battery capacity with an error <2%) is achievable, but its credibility depends on the quality of input data, such as chemical reaction parameters. In multiphysics simulations, such as wireless charging, results are credible only with rigorous calibration against experimental data.

Validation and verification of electric vehicle models within modelling and simulation software are indispensable for ensuring their utility in EV design. Comparison with experimental data enables model calibration and accuracy assessment, while error and uncertainty analysis reveals simulation limitations. The key to credibility lies in the close correlation of simulations with real-world tests and the continuous refinement of models, thereby facilitating the effective design of modern electric vehicles that meet efficiency, safety, and reliability requirements.

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2.5. Trends and challenges in the modelling and simulation of electric vehicles

Modelling and simulation of electric vehicle powertrains within computational environments are undergoing dynamic evolution, responding to escalating demands in efficiency, safety, and sustainable development. Contemporary trends in this field reflect the advancement of digital technologies and the need for more realistic representations of EV systems, while challenges centre on the complexity of data integration, model accuracy, and optimization of design processes.

Digital twins are emerging as a prominent trend in electric vehicle modelling, enabling the development of real-time virtual replicas of physical systems. In the context of electric vehicles, digital twins integrate simulation data, encompassing vehicle dynamics, battery thermal processes, and electrochemical processes, with operational data. This integration facilitates continuous monitoring and optimization of vehicle operational parameters. For instance, a digital twin of a powertrain can forecast battery energy consumption or motor efficiency based on data derived from real-world operating conditions. However, ensuring adequate model accuracy and real-time data synchronization remains a critical challenge, necessitating the application of advanced computational infrastructure and reliable data sources. An analysis of the relevant literature indicates that digital twins demonstrate potential in reducing costs associated with physical testing [121, 122]. Nevertheless, their full-scale implementation still encounters difficulties arising from input data uncertainties and computational complexity.

The integration of simulation models with sensor data from electric vehicles constitutes another pivotal trend, enhancing simulation realism and enabling their validation under real-world conditions. In tools such as AVL Cruise M, data from temperature, acceleration, and battery state-of-charge sensors are utilized to calibrate multiphysics models, facilitating more accurate predictions of vehicle range and dynamics. For instance, data from road tests of hybrid and electric vehicles can be input into AVL Cruise to verify energy consumption simulations. Challenges in this area include managing large data volumes (big data), ensuring data quality, and developing methods for rapid model updates based on changing operating conditions. This integration is particularly crucial in the context of autonomous systems, where data from LIDAR or radar sensors must be consistent with driving dynamics simulations.

Driver behaviours and driving styles play a significant role in the energy consumption of electric vehicles, constituting a nascent field of research in modelling and simulation. In CarSim and AVL Cruise, vehicle dynamics models incorporate driving styles (e.g., aggressive acceleration or gentle braking) to evaluate their impact on range and energy efficiency. A challenge lies in developing realistic driver profiles that reflect the diversity of driving styles in real-world conditions and integrating them with simulations. For example, overly simplified assumptions regarding regenerative braking can lead to errors in energy recovery prediction,

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thereby reducing model credibility. A solution may involve utilizing telemetry data from real-world vehicles to calibrate these models.

Currently, artificial intelligence (AI) is revolutionizing the modelling and optimization of electric vehicles, offering novel possibilities in data analysis and design. In environments such as ANSYS or COMSOL Multiphysics, machine learning (ML) algorithms are employed to accelerate thermal and electromagnetic simulations, for example, by predicting temperature distributions in batteries based on limited input data. In AVL Cruise M, AI supports the optimization of energy management strategies, utilizing methods such as neural networks to predict battery SOC and SOH. A key trend is also the application of AI in sensitivity analysis and uncertainty reduction, which enables faster estimation of the impact of parameters such as thermal conductivity or transmission losses. However, challenges include the need for large training datasets, potential overfitting of AI models, and the integration of these solutions with traditional simulation solvers. The literature emphasizes that AI can enhance simulation accuracy, but requires rigorous validation with experimental data.

In summary, trends in electric vehicle modelling, such as digital twins, sensor data integration, driver behaviour modelling, and the application of artificial intelligence, are opening new avenues for designing more efficient and reliable EVs. However, each of these areas presents challenges: from ensuring real-time data synchronization, through replicating complex human interactions, to validating AI models. The advancement of these technologies will drive innovation in electromobility, responding to the increasing demand for sustainable transport.

3. Application of AVL Cruise in electric vehicle simulation: A Case Study

This study utilized a vehicle modeling and simulation platform to scrutinize the energy expenditure of an electric vehicle (EV) operating in an urban setting. To accomplish this, an EV model was developed within the AVL Cruise software, into which twenty-one authentic urban driving speed profiles were integrated. The ensuing simulation outcomes facilitated the examination of the following metrics:

- total energy consumption per kilometer (kWh/km),
- recovered energy per kilometer (kWh/km),
- depth of Discharge (DOD) of the battery (%).

Subsequently, the collected data underwent statistical analysis to ascertain the mean values, medians, and distribution characteristics of these critical energy consumption parameters..

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3.1. Model of electric vehicle in AVL Cruise

The AVL Cruise s a robust software solution for simulating and modelling diverse vehicle powertrain architectures. It conceptualizes a vehicle as a network of interdependent subsystems, incorporating both the vehicle chassis and its propulsion elements. This platform furnishes users with broad functionalities, enabling them to:

- accurately forecast energy consumption for vehicles currently in their developmental stages;
- conduct thorough examinations of energy transfer, power allocation, and drivetrain losses from the energy source to the wheels;
- refine propulsion systems to achieve optimal fuel economy, diminished pollutant emissions, and requisite traction characteristics;
- perform in-depth analyses of torsional oscillations within compliant chassis frameworks subjected to varying loads;
- investigate thermal dissipation across various powertrain components.

The software incorporates a comprehensive database of actual vehicle and powertrain constituents, each thoroughly parameterized. Model construction commences with the designation of the vehicle category (e.g., automobile, coach, lorry, motorbike), followed by the selection of the desired propulsion system architecture (e.g., conventional, electric, hybrid). Users can precisely define the operational characteristics of each component and delineate the energy management protocol via a user-friendly environment. AVL Cruise further supports the inclusion of ancillary systems like climate control and electric power steering, alongside environmental variables such as wind resistance, ambient thermal conditions, and road surface properties. Operators can opt for predefined driving profiles, import bespoke cycles, or synthetically generate random cycles representative of diverse operational scenarios.

The simulation leverages a hybrid backward/forward computational methodology to efficiently and accurately evaluate the influence of input parameters on powertrain component efficacy, computing all feasible variable permutations. Post-simulation, AVL Cruise furnishes a full spectrum of outcomes, including fuel consumption rates, emission magnitudes, vehicle performance indicators (e.g., gradient ascension capability, acceleration durations), and graphical representations of powertrain element operation. These findings are presented in accessible visual and tabular formats, enabling insightful comparative assessments of performance, efficiency, and fuel economy across distinct powertrain configurations. This capability is instrumental for critical decision-making during the vehicle development lifecycle.

The electric vehicle selected for this simulation is a front-wheel drive configuration, as schematically represented in Figure 1 within the AVL Cruise program.

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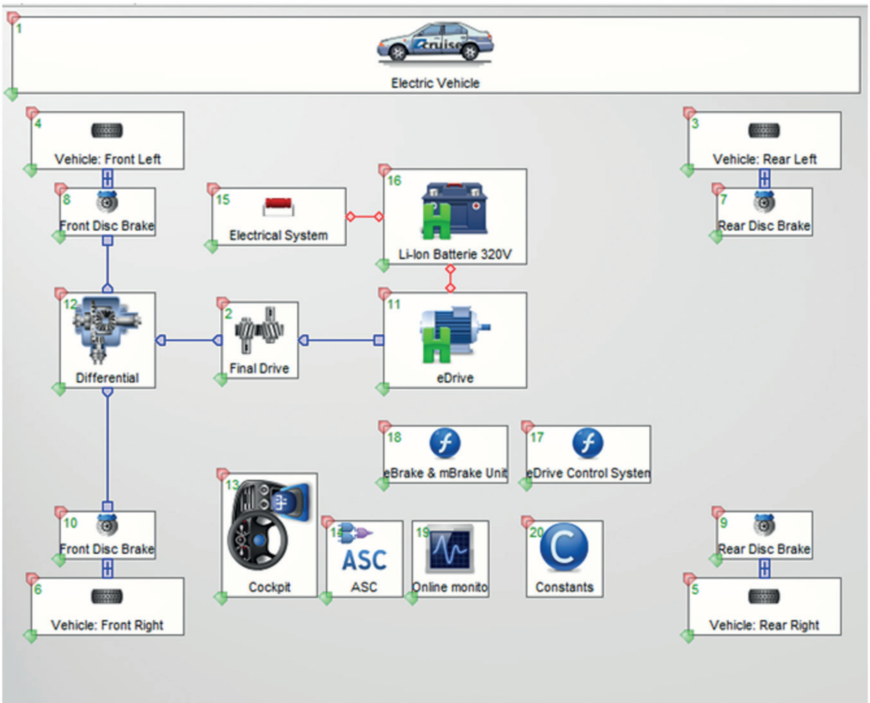

Fig. 1. Schematic diagram of the electric vehicle model in AVL Cruise

This EV model features a wheelbase of 2467 mm and a centre of gravity located at a height of 500 mm. The vehicle's curb weight is 1200 kg, with a maximum gross weight of 1580 kg. Significantly, the vehicle incorporates an energy recuperation system designed to capture energy during braking events. Table 2 provides a comprehensive summary of the electric vehicle's key parameters.

Tab. 2. Electric vehicle specifications

Parameter	Value
Height of centre of gravity [mm]	500
Wheelbase [mm]	2467
Frontal area [m²]	1.97
Mass [kg]	1350
Battery energy capacity [kWh]	40
Battery state of charge [%]	100
Nominal voltage [V]	320

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3.2. Test drives

This research leveraged a GPS device to collect empirical data from 21 separate journeys, each covering 5 kilometres, within the urban core of a medium-sized European metropolis. Driving conditions in such environments are typically marked by recurrent halts, accelerations, brief periods of constant velocity, and deceleration events. Table 3 presents a summary of the statistical attributes of these excursions, which were subsequently incorporated into the simulation.

Analysis of the collected data revealed maximum vehicle speeds ranging from 47.10 km/h to 66.02 km/h, with a median maximum speed of 52.26 km/h. The median average speed across all trips was 21.23 km/h. Furthermore, the maximum recorded vehicle acceleration was 3.63 m/s², while the maximum deceleration reached 8.82 m/s².

Tab. 3. Overview of selected test drive parameters

Parameter	Min	Max	Mean	Median	Coefficient of variation
Test drive duration, [s]	574	1889.91	955.24	853.47	39%
Max velocity, [km/h]	47.1	66.02	53.66	52.26	8%
Average velocity, [km/h]	9.94	30.9	21.07	21.23	29%
Max acceleration, [m/s²]	1.8	3.63	2.65	2.91	16%
Max deceleration, [m/s²]	1.9	8.87	3.56	3.07	45%

3.3. Simulation results

This section presents a detailed analysis of selected energy consumption parameters for an electric vehicle, utilizing the data presented in Table 3. This investigation aims to evaluate and quantify the energy efficiency of the electric vehicle, encompassing total energy consumption and recovered energy.

Tab. 3. Overview of selected energy consumption parameters

Energy efficiency	Min	Mean	Median	Max	Coefficient of variation
Total energy consumption, [kWh/km]	0.13	0.15	0.14	0.2	13%
Energy recovered from braking, [kWh/km]	0.01	0.02	0.02	0.04	33%
DOD, [%]	3.34	3.8	3.67	4.67	10%

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An examination of total energy consumption revealed a range of 0.13 kWh/km to 0.20 kWh/km. The mean energy consumption across all journeys was 0.15 kWh/km, with a median value of 0.14 kWh/km. The standard deviation for this metric was 0.02 kWh/km, yielding a coefficient of variation of 13%. This moderate variability suggests the influence of varied driving conditions on the vehicle's energy efficiency during the analyzed trips. Figure 2 graphically illustrates the correlation between total energy consumption per kilometer and both trip duration and average speed observed during the analyzed trips.

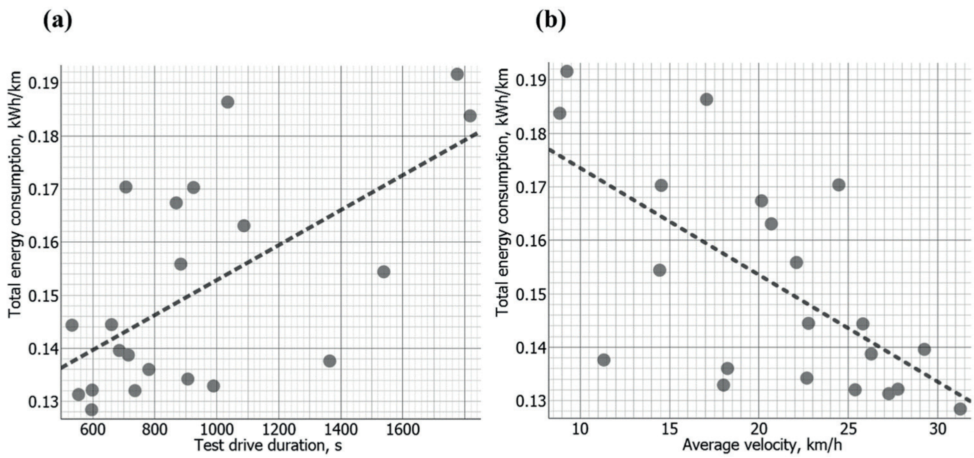

Fig. 2. Total energy consumption in relation to (a) trip duration, (b) average speed

Energy consumption per unit distance directly reflects an electric vehicle's operational efficiency under varying driving circumstances. This research examined how route characteristics influence energy draw via computational modelling. Figure 2a illustrates a direct correlation between journey length and energy utilization, signifying that extended travel periods result in heightened energy expenditure. Conversely, an inverse relationship exists between the average transit velocity and energy consumption per kilometre for the electric vehicle, as presented in Figure 2b. At lower speeds (below 10 km/h), energy consumption exhibits greater fluctuation, with certain readings surpassing 0.60 kWh/km. In distinction, at speeds exceeding 20 km/h, energy consumption appears more stable, generally registering at or below 0.50 kWh/km. This implies that smoother driving, involving fewer interruptions, contributes to diminished energy requirements.

The Depth of Discharge (DOD), which quantifies the proportion of battery capacity expended during use, ranged from 3.34% to 4.67% over the analyzed journeys. The mean DOD registered at 3.80%, while the median stood at 3.67%. A very low standard deviation of 0.39%, resulting in a coefficient of variation of 10%, indicates uniform battery power management approaches throughout the simulations. This consistency positively impacts both the vehicle's energetic

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efficacy and the operational lifespan of the battery. Figure 3 depicts the correlation between DOD, journey duration, and mean velocity during the examined trips.

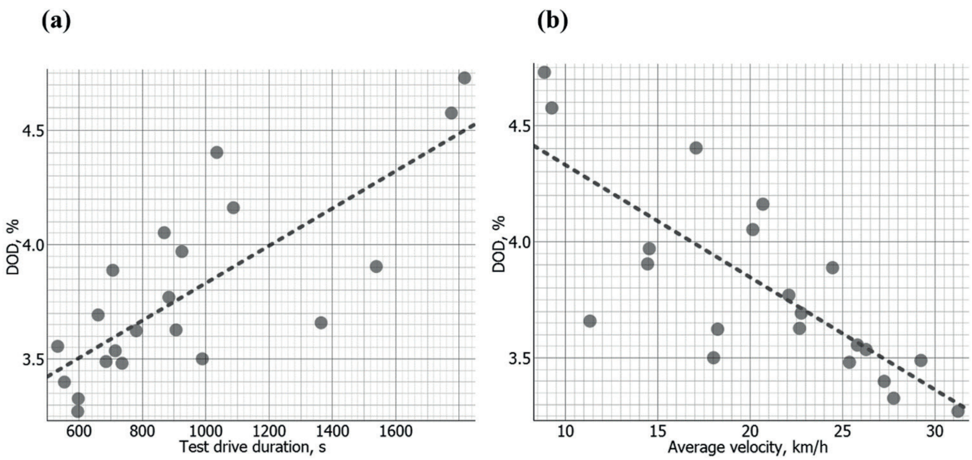

Fig. 3. DOD in relation to (a) trip duration, (b) average speed in the analysed trips

The DOD metric is crucial for evaluating an electric vehicle's battery energy demands. As shown in Figure 3a, a positive correlation exists between trip duration and DOD, which is expected since longer driving periods require more energy and thus a higher DOD. Average vehicle speed also affects DOD; Figure 3b indicates that higher average speeds generally lead to increased energy consumption and, consequently, a greater DOD.

An examination of the analysed journeys indicated that the recuperated energy during propulsion ranged from 0.01 kWh/km to 0.04 kWh/km. Both the mean and median values for this parameter were determined to be 0.02 kWh/km (Table 3). The standard deviation for this metric was 0.01 kWh/km, yielding a coefficient of variation of 33%. This elevated variability, in comparison to other analysed parameters, suggests that the efficiency of the vehicle's energy recovery system is substantially affected by particular operational circumstances, encompassing elements such as vehicular velocity, topographical features, and operator conduct. Figure 4 visually depicts the correlation between recovered energy per kilometre and both journey duration and average speed recorded during the analysed trips. Urban driving contexts, distinguished by frequent deceleration and acceleration cycles, offer optimal conditions for the regenerative braking technology employed in electric vehicles.

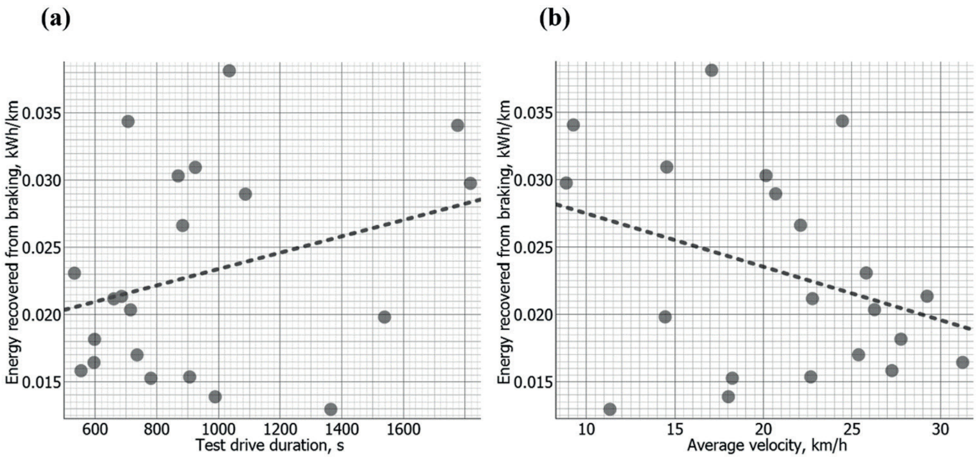

Fig. 4. Energy recovered from braking in relation to (a) trip duration, (b) average speed in the analysed trips

As Figure 4a demonstrates, the simulation outcomes for an electric vehicle traversing diverse urban routes indicate a positive correlation between regenerated energy and extended journey times. This aligns logically with the increased opportunities for braking within longer urban drives. Conversely, an inverse relationship is apparent between the average vehicle velocity and the amount of energy recuperated, as portrayed in Figure 4b. Reduced average speeds generally correspond to greater energy recovery. This pattern likely arises from the more frequent deceleration occurrences and tempered driving behaviours commonly found in urban traffic scenarios.

The collation of energy consumption and recovered energy with driving conditions was analysed for several reasons. Firstly, it enabled the evaluation of the impact of driving dynamics on the vehicle's energy balance. For instance, the positive correlation of energy consumption with trip duration highlights the increased energy demand and reduced regeneration efficiency. Conversely, the inverse relationship between energy consumption and average speed suggests that smoother driving minimizes losses from frequent acceleration and braking phases. Secondly, the amount of energy recovered during a trip can reduce energy consumption, thus confirming the effectiveness of regenerative braking in urban driving conditions. This approach allows for the identification of key driving parameters that can be optimized in EV control strategies, such as the regeneration system.

Despite its advantages, this approach has limitations that require further development in future research. Firstly, there is a lack of validation of the results with real-world measurements (e.g., from road tests). Secondly, the quasi-static nature of the backward-facing method does not account for transient dynamics (e.g., inertial effects), which limits the anal-

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ysis of abrupt manoeuvres. Finally, the influence of external factors (e.g., ambient temperature, road slope) was not considered, even though they can significantly modify energy consumption. Further research should verify the results with road tests and incorporate more comprehensive vehicle and simulation environment data.

4. Discussion and conclusions

This This paper combines a state-of-the-art review of simulation tools for electric and hybrid vehicles with a case study demonstrating the practical application of AVL Cruise for energy consumption analysis. The review highlights a range of modeling approaches, from linear and quasistatic models for rapid energy assessments to dynamic and physics-based models for high-fidelity transient simulations. Tools like MATLAB/Simulink and AVL Cruise excel in powertrain optimization and energy flow analysis, while CarSim and ANSYS/COMSOL provide superior resolution for vehicle dynamics and multiphysics interactions, respectively. The choice of tool depends on the simulation objective, with AVL Cruise proving particularly effective for steady-state energy studies, as shown in the case study.

The case study illustrates the use of AVL Cruise to analyze the energy consumption of a lightweight electric vehicle (1350 kg, 40 kWh battery) under urban driving conditions, based on 21 real-world speed profiles. AVL Cruise's intuitive interface and extensive component libraries enabled rapid model development, allowing specification of vehicle parameters (e.g., mass, frontal area) and integration of driving cycles. The software employs a combined backward- and forward-facing computational approach, calculating energy flow from wheel power demands to the battery, which is ideal for steady-state analyses. Key features include customizable powertrain configurations, real-time energy flow visualization, and graphical outputs (e.g., Fig. 2–4), which facilitated the analysis of energy consumption (13–20 kWh/100 km, mean 15 kWh/100 km), depth of discharge (DOD: 3.34–4.67%, mean 3.80%), and recovered energy (1–4 kWh/100 km, mean 2 kWh/100 km).

The results align with typical urban EV performance (15–20 kWh/100 km for short distances), reflecting the lightweight vehicle and conservative driving cycles. Simulations revealed that longer trip durations and higher maximum decelerations (>3.56 m/s²) increase energy consumption, while smoother driving at higher average speeds (>20 km/h) reduces it. Recovered energy peaked with stronger decelerations, contributing up to 26% of total consumption, highlighting the role of regenerative braking optimization. However, the low absolute values necessitate validation against real-world measurements to quantify errors, as suggested by references [10, 123].

AVL Cruise's strengths include its speed, flexibility, and ability to model complex powertrains without physical prototypes, reducing development costs and time compared to road testing. The methodology involves defining vehicle architecture (e.g., front-wheel drive, battery

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specifications), selecting driving cycles, and analyzing outputs via statistical tools, making it accessible for engineers. However, its reliance on quasistatic assumptions limits its ability to capture transient dynamics, such as rapid acceleration or tire slip, which requires more advanced tools like CarSim for dynamic studies.

By focusing on AVL Cruise's application, this study demonstrates how simulation tools provide insights into energy efficiency, guiding powertrain optimization and sustainable vehicle design. The presented framework supports further research into alternative drivetrain configurations, but its accuracy depends on rigorous validation. Future work should incorporate real-world data comparisons, thermal effects, and driver behavior to enhance model fidelity. Additional avenues include refining battery models and integrating external factors (e.g., ambient temperature, road inclination) to improve predictive capabilities for diverse conditions.

This paper serves as a foundation for researchers and engineers, illustrating the practical use of AVL Cruise in EV development and highlighting its role in analyzing operational aspects like energy consumption, range, and performance. By emphasizing methodology over exhaustive research outcomes, it offers a replicable approach for simulation-based design optimization, paving the way for advancements in electric and hybrid vehicle technologies.

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