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Simulation and Modeling Programs for Electric and Hybrid Vehicles: A Review and Case Study of AVL Cruise for Energy Consumption Analysis

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Abstract Continuous advancements in alternative drive technologies for vehicles necessitate the development of sophisticated computational tools. Due to the inherent complexity of these systems, prototyping can be a time-consuming and expensive endeavour. Fortunately, computer-aided modelling and simulation environments offer a viable alternative by enabling the virtual testing of novel drivetrain solutions without the need for physical prototypes. These environments leverage existing solutions and readily available models of vehicles, drives, and their components, fostering the efficient development of new concepts and optimized drivetrain models. This paper presents a curated overview of select vehicle modelling and simulation programs, followed by the introduction of an electric vehicle model developed within the AVL Cruise software.

Keywords electric vehicle, modelling, simulation, energy efficiency, AVL Cruise

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1. Introduction

This contemporary automotive industry presents engineers and scientists with a continuous stream of novel challenges. The imperative to achieve greater energy efficiency, minimize exhaust emissions, and ensure the comfort and safety of vehicle occupants necessitates the implementation of increasingly sophisticated technological solutions. In this context, computer programs and environments have assumed a critical role, becoming indispensable tools for both automotive enterprises and researchers.

Electric and hybrid vehicles, in particular, undergo continuous advancements. The development of energy storage and electric drive technologies fosters improved efficiency across diverse driving conditions and geographic regions, as evidenced in relevant literature [1,2]. However, manufacturer-provided range and average energy consumption figures may not always translate directly to real-world scenarios. These parameters exhibit variability contingent upon usage patterns, as corroborated by research [3,4]. From a user standpoint, an electric vehicle should exhibit unwavering reliability under all circumstances. Furthermore, range information should be presented with utmost clarity to facilitate effective route planning by drivers.

Evaluating the influence of driving conditions on an electric vehicle's energy consumption and range necessitates the execution of real-world testing procedures. This entails subjecting the vehicle to a battery of tests conducted across diverse terrain types, along varied routes, and incorporating a spectrum of driving styles, as documented in extant research [5-8]. The paramount objective of these tests is to generate significantly more precise data pertaining to the range and energy consumption that can be realistically anticipated under commonplace driving circumstances.

An alternative approach to investigating the influence of driving conditions on energy consumption and range lies in the utilization of simulation studies. This methodology entails the development of a mathematical model specifically tailored to the vehicle under examination [9]. Alternatively, dedicated vehicle simulation software can be employed, enabling the manipulation of vehicle parameters and its drive system [10, 11]. To ensure the veracity of the simulations, it is imperative that they incorporate real-world driving conditions. Many simulation programs utilize speed profiles as a function of time or distance to represent traffic conditions. Additionally, other relevant factors, such as ambient temperature and road elevation, can be integrated into the simulations.

The field of scientific literature dedicated to hybrid and electric vehicle modelling boasts a plethora of publications showcasing diverse tools and the resultant vehicle models [12-14].

Beyond intricate descriptions of the models themselves, numerous studies incorporate simulation results, furnishing comprehensive data on fuel/energy consumption, emissions of harmful exhaust components, and the efficiency of individual drive system components across a spectrum of driving conditions. These computer simulations facilitate the estimation of anticipated exhaust emissions and other pollutants generated by the vehicle, a critical aspect for environmental safeguarding and adherence to emission regulations.

The functionalities provided by contemporary simulation programs transcend the realm of mere fuel consumption analysis. These programs have evolved into formidable instruments that facilitate the execution of holistic simulation studies encompassing a multifaceted spectrum of aspects pertinent to vehicle operation, as documented in the extant research [15-17]. Computer simulations empower researchers to pinpoint the origins of vibrations and noise generated by the vehicle, subsequently enabling the development of design and technological solutions geared towards their mitigation. Additionally, they permit the evaluation of the vehicle's performance in terms of acceleration, hill-climbing capabilities, and the attainment of maximum speed. Simulation studies play a pivotal role in the precise prediction of fuel consumption under a multitude of driving conditions. This, in turn, paves the way for the optimization of both vehicle and drive system design with a focus on energy efficiency, culminating in demonstrably reduced fuel consumption and emissions.

Computer simulations stand as an exceedingly valuable instrument within the process of testing and validating drive system components and other vehicular elements, as corroborated by extant research [21, 22]. Their implementation serves to demonstrably expedite the research and development process while concurrently mitigating testing expenditures. By leveraging simulation programs, researchers are empowered to conduct preliminary assessments and analyses of novel design concepts and technological solutions prior to the commencement of prototyping and physical testing phases. This proactive approach facilitates the identification of potential shortcomings at an early juncture of the project, enabling their rectification and the optimization of the design itself [23, 24].

It is imperative to acknowledge that computer programs and environments do not supplant empirical research entirely. Nevertheless, they constitute exceedingly valuable tools that demonstrably reduce research time and expenditures. Furthermore, they offer the potential to glean information that may be inaccessible or arduous to obtain through laboratory experiments or field tests.

The present paper endeavours to furnish a concise analysis of the functionalities resident within select programs designed for the simulation and modelling of electric and hybrid vehicles. Additionally, it presents an illustrative example of the AVL Cruise program's application in analysing the energy consumption of an electric vehicle. This article serves as a valuable repository of information for scientists and engineers engaged in the design and development of electric and hybrid vehicles. The analysis of the capabilities offered by select simulation and modelling programs can facilitate the judicious selection of appropriate software tailored to specific project requirements. Moreover, the example of utilizing AVL Cruise for electric vehicle energy consumption analysis has the potential to serve as a catalyst for further research in this domain.

The first section of the article embarks upon a discussion of various types of simulation and modelling programs employed for vehicles, delving into their capabilities and the computational procedures they utilize. Subsequently, a particular simulation study of an electric vehicle, realized using the AVL Cruise program, is presented. The following section of 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. Analysis of capabilities of selected programs for vehicle simulation and modeling

Currently, there are numerous programs available for vehicle simulation and modelling, each offering diverse functions and capabilities. The choice of appropriate software depends on the specific needs of the user, budget considerations, and the scope of work. There exists a wide range of mathematical models and simulation programs designed for vehicle research. Each of these tools provides different functionalities and capabilities, making the selection of the right tool dependent on the specific requirements of the user.

Simulation programs leverage mathematical models to calculate and predict vehicle behaviour. These model-based programs play a pivotal role in the design, development, and testing phases of hybrid and electric vehicles. Employing complex mathematical equations, they simulate the intricate interactions between various vehicle components, including internal combustion engines, electric motors, drivetrain systems, batteries, and control systems. These simulations empower engineers to assess vehicle performance metrics, predict energy consumption and emissions levels, and identify potential design flaws before physical prototypes are constructed. Prominent examples of such programs include AVL Cruise and Ansys Powertrain, alongside numerous proprietary simulation tools developed by researchers, as evidenced in [25- 27].

To achieve this level of detail, contemporary vehicle simulation programs draw upon a diverse arsenal of mathematical models, each meticulously crafted to replicate the intricate behaviours of vehicles under various operating conditions. The selection of the most appropriate model hinges on the specific needs and objectives of the simulation being conducted.

Simulation programs that leverage linear models hinge on the fundamental assumption of proportional relationships between input and output variables. In essence, this translates to a change in the value of one variable inducing a directly proportional change in the value of another. While these streamlined models prove to be instrumental in analysing fundamental vehicle behaviours such as speed, acceleration, and braking, their inherent simplification of reality necessitates limitations in their application. They are best suited for straightforward phenomena. When confronted with more intricate problems, the utilization of more sophisticated nonlinear or hybrid models becomes indispensable to achieve results characterized by a demonstrably higher degree of accuracy and reliability.

Simulation programs that using nonlinear models transcend the inherent limitations of their linear counterparts by incorporating intricate, nonlinear relationships between input and output variables. These sophisticated models provide a significantly more nuanced reflection of reality, enabling the analysis of phenomena that are beyond the grasp of linear models alone. By meticulously accounting for the interactions among various vehicle components, such as the engine, drivetrain, aerodynamics, and suspension, nonlinear models facilitate a demonstrably more accurate representation of the object under study.

Consequently, nonlinear models offer superior fidelity in simulating real-world vehicle behaviour, making them the preferred choice for analysing complex phenomena. However, this enhanced accuracy comes at the cost of increased complexity in both development and implementation. Successfully utilizing these models necessitates a more profound expertise in mathematics and modelling techniques.

The realm of simulation programs extends to the utilization of hybrid models, which strategically combine characteristics from distinct model types, such as linear and nonlinear models. These multifaceted models are adept at tackling complex phenomena that necessitate consideration of both straightforward and intricate relationships between variables.

Illustrative examples of their application encompass the analysis of energy consumption and exhaust emissions under a multitude of driving conditions. Additionally, they prove instrumental in analysing vehicle behaviour while traversing uneven terrain, meticulously accounting for the vehicle's interactions with the environment. Hybrid models flourish in scenarios demanding a comprehensive understanding of the system's behaviour. They achieve this by judiciously incorporating the advantages of both linear simplicity and nonlinear fidelity, as dictated by the specific objectives of the simulation. This synergistic approach fosters a more nuanced and accurate representation of real-world dynamics, demonstrably surpassing the capabilities of purely linear or nonlinear models employed in isolation.

The many of vehicle simulation programs is further enriched by the inclusion of quasi-static models. These models hinge on the fundamental assumption that specific variables, such as engine rotational speed, exhibit a gradual rate of change compared to other variables within the system. Their primary application lies in the analysis of energy consumption and exhaust emissions, as exemplified by their implementation in programs like PSAT. While offering demonstrably faster computational speeds relative to dynamic models, quasi-static models are inherently unsuited for the analysis of dynamic vehicle behaviours. Their domain of expertise lies primarily in simulating vehicle statics, encompassing the analysis of vehicle behaviour at rest or under low-speed conditions. They can be incorporated into vehicle dynamics simulations, but their applicability is limited to straightforward manoeuvres such as braking or accelerating along a straight line.

Dynamic models stand in stark contrast to their static counterparts by explicitly describing a vehicle's behaviour as it unfolds over time. This entails meticulously accounting for the variations in forces and accelerations that the vehicle experiences. Their core competency lies in analysing the vehicle's dynamic movements, encompassing manoeuvres such as acceleration, braking, cornering, and traversing uneven terrain. While offering a significantly richer tapestry of results compared to static models, dynamic models necessitate a corresponding increase in both computational time and power. This stems from their comprehensive incorporation of all relevant variables and their dynamic fluctuations. Consequently, they are ideally suited for tackling the most intricate phenomena, such as the realm of vehicle dynamics.

Dynamic models reign supreme in the domain of vehicle dynamics simulation, meticulously capturing the vehicle's behaviour throughout the course of motion. Their applicability extends beyond this domain, and they can also be incorporated into vehicle statics simulations, albeit under circumstances characterized by complex loading conditions. Notably, dynamic models play an indispensable role in simulations of electric and hybrid vehicles. This is due to their remarkable ability to represent the intricate phenomena that manifest during driving conditions. Programs such as PSIM and Virtual Test Bed (VTB) exemplify the utilization of dynamic models in this context.

Beyond the realm of model-based simulation programs, data-driven approaches offer an alternative path for simulating hybrid and electric vehicles. These programs leverage real-world test data and measurements to construct simulations of vehicle behaviour under diverse driving conditions. Illustrative examples of such programs include SimPowerSystem/SimDriveline, ANSYS Simplorer, and PSIM.

The efficacy of this approach is further corroborated by the burgeoning body of research that utilizes physics-based simulation models for vehicles, as evidenced by works documented in [28, 29]. Physics-based simulation programs are rapidly gaining traction within the field of vehicle simulation, presenting several compelling advantages over traditional model-based approaches. These programs leverage real-world data to construct simulations of vehicle behaviour, potentially leading to enhanced accuracy, particularly in intricate scenarios. This is because physics-based simulations directly incorporate the complexities of real-world physics, which may not be fully captured by traditional mathematical models.

Furthermore, physics-based simulations can often achieve faster execution speeds compared to programs that rely on complex mathematical models. This stems from the fact that they bypass the need to solve intricate mathematical equations, streamlining the simulation process. Additionally, their implementation is generally simpler as it avoids the time-consuming development of complex mathematical models.

Hybrid simulation programs carve out a niche by offering distinct advantages over purely model-based or physic-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 the practical insights gleaned from real-world 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 do not necessitate profound expertise in intricate mathematical models.

However, it would be remiss not to acknowledge the inherent drawbacks associated with hybrid programs. Their implementation complexity presents a significant hurdle, as it necessitates the meticulous integration of mathematical models with real-world test data. Furthermore, they may exhibit limitations in flexibility. Modifying simulations to accommodate novel conditions or components can be a more intricate undertaking compared to purely model-based or physic-based programs.

Vehicle simulation programs primarily employ three distinct computational approaches: the forward-facing method, the backward-facing method, and a hybrid method that merges both. The forward-facing method aligns its computations with the direction of power transmission. Initiating with a specified value (often an acceleration signal), it calculates the requisite torque for each drivetrain component, meticulously following the power flow through each subsystem until the desired vehicle speed is attained [30, 31]. 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 [32] and programs like PSAT/Autonomie.

The backward-facing method stands in stark contrast to its forward-facing counterpart. Here, computations progress in the opposite direction of power transmission. This method begins with a specified driving cycle's speed profile. Based on this, the requisite wheel power is estimated and meticulously propagated back through each drivetrain component, ultimately reaching the energy source. Notably, the backward-facing approach treats each drive element as an independent module. This characteristic facilitates rapid calculations for both straightforward and intricate models. Additionally, it allows for the seamless integration of lookup tables or performance maps, circumventing the need to model every physical phenomenon. Consequently, this method yields demonstrably faster results compared to the forward-facing method. The application of the backward-facing method is exemplified by the construction of vehicle models documented in the study [33] and programs like GT SUITE and Simplev (Simple Electric Vehicle Simulation).

The mixed procedure merges the strengths of both the forward-facing and backward-facing methods. It commences with calculations performed using the backward-facing approach. This initial stage facilitates the estimation of efficiency values and operating limits for the model's subsystems. Subsequently, armed with these known values, the procedure transitions to the forward-facing method to compute power and energy values from the energy source all the way to the wheels.

However, the primary drawback associated with the mixed approach lies in the necessity of maintaining two distinct models for the same component [34]. Despite this limitation, the mixed procedure has found application in constructing vehicle models for programs such as AVL Cruise, PSIM, and ADVISOR.

Vehicle modelling and simulation programs have become invaluable tools in the research and development of electric and hybrid vehicles. Their application significantly accelerates the innovation cycle, paving the way for the introduction of novel technologies and, ultimately, more efficient and environmentally responsible vehicles. These computer programs offer a powerful testing environment, enabling researchers to rapidly and cost-effectively evaluate a multitude of vehicle configurations under diverse driving conditions. This virtual testing ground fosters the optimization of vehicle designs, leading to demonstrably improved performance metrics. Furthermore, simulation programs have the remarkable capability to predict vehicle behaviour in scenarios that would be impractical or even unsafe to replicate in real-world testing.

3. Simulation study of an electric vehicle using AVL Cruise software

This investigation aims to leverage a vehicle modelling and simulation program to analyse the energy consumption of an electric vehicle (EV) within an urban driving environment. To achieve this objective, an EV model was constructed within the AVL Cruise software. Subsequently, twenty-one real-world urban driving speed profiles were incorporated into the program.

The simulation results were then employed to analyse the following parameters:

- total energy consumption per kilometre (kJ/km),
- depth of Discharge (DOD) of the battery (%),
- recovered energy per kilometre (kJ/km),

The data underwent a statistical analysis to determine the average values, medians, and distribution patterns of the aforementioned energy consumption parameters.

3.1. AVL Cruise overview

The AVL Cruise program facilitates the modelling and simulation of vehicles equipped with diverse powertrain configurations. Within the program, the vehicle model is represented as a system comprised of interconnected subsystems, encompassing both vehicle and powertrain components. AVL Cruise offers a comprehensive suite of capabilities, enabling users to:

- generate reliable and precise predictions of fuel consumption for vehicles under development;
- conduct a thorough analysis of energy flow, power distribution, and powertrain system losses, tracing the path from the power source to the wheels;
- optimize the powertrain for a balance between fuel efficiency, minimized harmful exhaust emissions, and desired vehicle traction properties;
- perform an in-depth analysis of torsional vibrations within flexible chassis structures under dynamic load conditions;
- investigate the thermal distribution across powertrain components.

The AVL Cruise program empowers users to leverage an extensive library of real-world vehicles and powertrain components during the vehicle modelling process. This library encompasses a comprehensive set of parameters and characteristics for each component.

The model development process commences with the selection of the target vehicle type. AVL Cruise offers a comprehensive selection, including passenger cars, buses, trucks, and motorcycles. Subsequently, the user chooses the appropriate powertrain configuration from a range of options including conventional, electric, series and parallel hybrid, dual-engine systems, and advanced transmission systems.

In the following steps, users can meticulously specify the parameters of each powertrain component and define the energy management strategy. The program facilitates customization through an intuitive interface; users can access and modify individual parameters by clicking on the corresponding blocks within the vehicle model.

The program further extends its functionality by allowing users to incorporate additional devices, such as air conditioning or electric power steering systems, into the vehicle model. This enables the simulation to account for the impact of these auxiliary systems on vehicle performance.

External factors can also be integrated into the simulation process. Users have the option to select from a range of predefined factors, including wind force, ambient temperature, and road surface conditions. Alternatively, users can define their own custom parameters for these factors.

To complete the model setup, the program offers a selection of built-in driving cycles, catering to various driving scenarios. Users can also import custom driving cycles or utilize the program's capability to generate random cycles that represent urban, suburban, or highway driving conditions.

The simulation leverages a combined backward/forward computational approach. This methodology facilitates a more efficient and accurate assessment of how input parameter values influence the performance of powertrain components. The program calculates all possible combinations of these variables.

Upon simulation completion, users are presented with a comprehensive set of results. This includes fuel consumption values, emission levels, vehicle performance metrics, maximum grade climbing capability, and acceleration times. Additionally, the program generates graphs and characteristics that depict the operational behaviour of the powertrain components. The results are presented in a user-friendly format, incorporating both graphs and tables.

By leveraging the simulation results generated by AVL Cruise, users can conduct comparative analyses of performance parameters, powertrain efficiency, and fuel consumption across various powertrain configurations under defined driving conditions. This facilitates informed decision-making during the vehicle development process.

3.2. Electric vehicle model in AVL Cruise

This section details the specifications of the electric vehicle (EV) chosen for the simulation. The EV is a front-wheel drive configuration, as depicted schematically in Figure 1 within the AVL Cruise program.

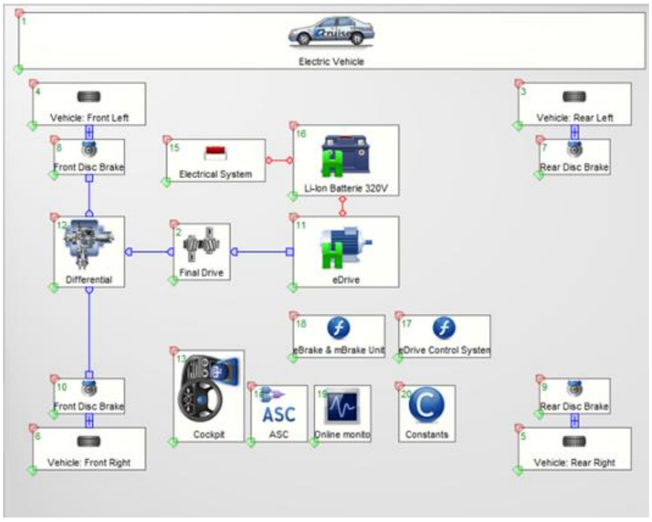

Figure 1. A sample schematic diagram of the electric vehicle model in AVL Cruise

The vehicle possesses a wheelbase of 2467 mm and a centre of gravity positioned at a height of 500 mm. The curb weight of the vehicle is 1200 kg, with a maximum gross weight of 1580 kg. Notably, the vehicle is equipped with an energy recuperation system that captures energy during braking processes.

The braking system comprises disc brakes on all four wheels. The front brake discs possess a larger diameter (1800 mm) compared to the rear discs. The vehicle's frontal area is measured at 1.97 m². A lithium-ion battery with a fully charged energy capacity of 10 Ah is integrated into the vehicle. Both the battery and the electric motor operate at a nominal voltage of 320 V. The minimum and maximum permissible voltage ranges are 220 V and 420 V, respectively. Table 1 summarizes the key parameters of the electric vehicle.

Table 1. 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 [Ah]	10
Battery state of charge [%]	100
Nominal voltage [V]	320

3.3. Test drives

This investigation employed a GPS system to collect data for twenty-one (21) individual trips within the central area of a medium-sized city. Each trip consisted of a 5 km route. Urban driving environments are typically characterized by frequent stopping, accelerating, maintaining constant speeds for short durations, and braking manoeuvres. Table 2 summarizes the statistical parameters of these trips, which were subsequently used in the simulation.

Table 2. Overview of selected test drive parameters

	Duration of the test drive [s]	Maximum speed [km/h]	Average speed [km/h]	Maximum acceleration [m/s²]	Maximumum deceleration [m/s²]
Min	574.00	47.10	9.94	1.80	1.90
Max	1889.91	66.02	30.9	3.63	8.87
Mean	955.24	53.66	21.07	2.65	3.56
Median	853.47	52.26	21.23	2.91	3.07
Standard deviation	371.58	4.34	6.20	0.42	1.62
Coefficient of variation	39%	8%	29%	16%	45%

The analysis of the collected data revealed a range of maximum vehicle speeds across the trips. The highest recorded value was 66.02 km/h, while the lowest was 47.10 km/h. The median maximum speed, which represents the middle value when the data is ordered from lowest to highest, sits at 52.26 km/h. Similarly, the median average speed across the trips was determined to be 21.23 km/h. Notably, the maximum vehicle acceleration experienced during the trips reached 3.63 m/s², while the maximum deceleration event registered 8.82 m/s².

3.4. Simulation results

This chapter delves into a detailed analysis of selected energy consumption parameters for an electric vehicle, drawing upon the data presented in Table 3. The analysis encompasses parameters such as Depth of Discharge (DOD), total energy consumption, and recovered energy. This investigation aims to evaluate and quantify the energy efficiency of the electric vehicle.

Table 3. Overview of selected energy consumption parameters

	DOD [%]	Energy recovered from braking [kJ/km]	Total energy consumption [kJ/km]
Min	3.34	0.47	0.05
Max	4.67	0.70	0.14
Mean	3.80	0.54	0.08
Median	3.67	0.51	0.07
Standard deviation	0.39	0.07	0.03
Coefficient of variation	10%	13%	33%

The analysis of total energy consumption revealed a variability ranging from 0.47 kJ/km to 0.70 kJ/km. The average energy consumption across the trips was determined to be 0.54 kJ/km, while the median value, representing the central point when the data is ordered from lowest to highest, sits at 0.51 kJ/km. The standard deviation for this parameter is 0.07 kJ/km, resulting in a coefficient of variation of 13%. This moderate level of variability suggests the presence of diverse driving conditions during the analysed trips. Potentially, these varying conditions could influence the vehicle's energy efficiency. Figure 2 visually explores the relationship between total energy consumption per kilometre and trip duration, average speed, maximum acceleration, and maximum deceleration experienced during the analysed trips.

Energy consumption per kilometre directly reflects the energy efficiency of the electric vehicle under varying driving conditions. This investigation analysed the influence of route-related parameters on energy consumption through simulation studies. As illustrated in Figure 2a, a positive correlation was observed between trip duration and energy consumption. This suggests that the vehicle's energy expenditure increases with longer travel times.

The relationship between average travel speed and energy consumption per kilometre for the electric vehicle exhibits an inverse trend, as depicted in Figure 2b. At lower speeds (below 10 km/h), energy consumption demonstrates greater

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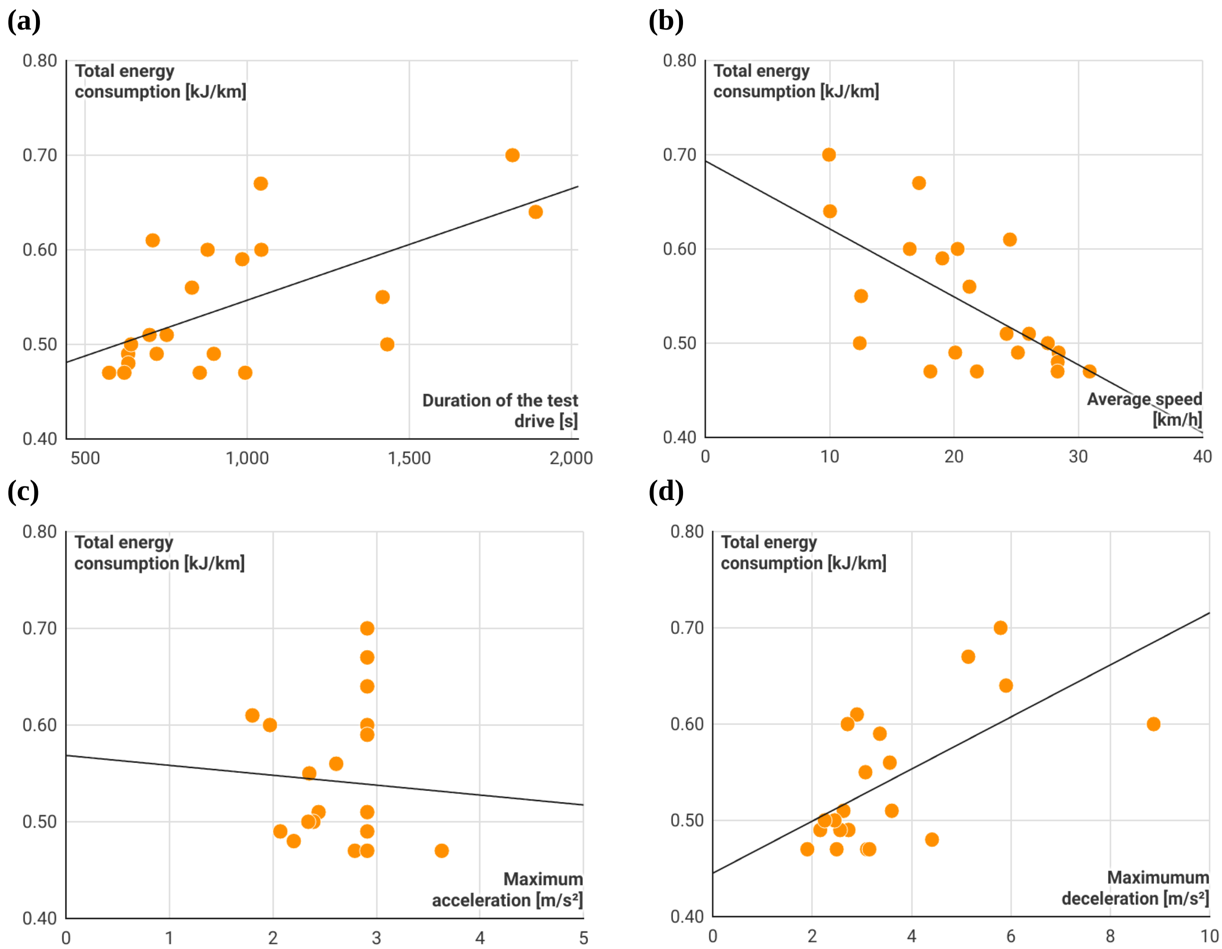

Figure 2. Total energy consumption in relation to (a) trip duration, (b) average speed, (c) maximum acceleration, and (d) maximum deceleration in the analyzed trips

variability, with some data points exceeding 0.60 kJ/km. Conversely, at speeds exceeding 20 km/h, energy consumption appears more consistent, typically reaching values around 0.50 kJ/km or lower. This suggests that smoother travel with fewer stops translates to lower energy consumption.

An examination of the impact of maximum acceleration n energy consumption revealed a relatively scattered distribution of data points around the trend line, as shown in Figure 2c. The most significant dispersion of points occurs within the range of 2 to 3 m/s² for maximum acceleration, where energy consumption exhibits values between 0.50 kJ/km and 0.70 kJ/km. This finding suggests that maximum acceleration has a minimal influence on the overall energy consumption of the electric vehicle.

Conversely, the analysis of the relationship between electric energy consumption and maximum deceleration in the electric vehicle demonstrates a positive correlation, as depicted in Figure 2d. At lower maximum deceleration values, energy consumption remains relatively constant, ranging from 0.47 kJ/km to 0.51 kJ/km. However, with increasing maximum deceleration, energy consumption also begins to rise noticeably, particularly for values exceeding 3.56 m/s². This trend suggests that abrupt braking manoeuvres may lead to higher energy losses due to a potential decrease in the efficiency of the vehicle's energy recuperation system.

The Depth of Discharge (DOD), a parameter that signifies the extent to which the battery's capacity is utilized during operation. The DOD values for the analysed trips range from 3.34% to 4.67%. The average DOD across the trips was determined to be 3.80%, with a median of 3.67%. The standard deviation for this parameter is a mere 0.39%, resulting in a coefficient of variation of 10%. This minimal variability in DOD indicates stable battery energy management strategies employed during the simulations. This stability is advantageous for both the vehicle's energy efficiency and the lifespan of the battery itself. Figure 3 visually depicts the relationship between DOD and trip duration, average speed, maximum acceleration, and maximum deceleration experienced during the analysed trips.

The depth of discharge indicator serves as a valuable metric for assessing the energy demands placed upon an electric vehicle's battery. As illustrated in Figure 3a, a positive correlation exists between trip duration and DOD. This trend is logical, as longer driving times necessitate greater energy consumption, leading to a higher DOD. Average vehicle speed also exerts an influence on DOD. As depicted in Figure

3b, higher average speeds typically translate to increased energy consumption, consequently resulting in a higher DOD.

The impact of maximum acceleration on DOD exhibits some variation, as shown in Figure 3c. The observed scatter in DOD values across different levels of maximum acceleration suggests that the intensity of acceleration plays a role in energy consumption. Lower acceleration values correspond to lower energy consumption and a lower DOD. Conversely, higher acceleration demands more energy, leading to increased energy consumption and a higher DOD. A clear and direct relationship was observed between maximum deceleration and DOD, as shown in Figure 3d. Generally, higher maximum deceleration values tend to coincide with an increase in DOD.

Conventional vehicles dissipate kinetic energy as heat during braking, resulting in an irreversible loss. In contrast, electric and hybrid vehicles possess the ability to recapture a portion of this kinetic energy and utilize it to power the electric motor. This process, known as regenerative braking, significantly contributes to the energy efficiency of electric vehicles.

The analysis of the analysed trips revealed that recovered energy during driving ranged from 0.05 kJ/km to 0.14 kJ/km, with an average of 0.08 kJ/km and a median of 0.07 kJ/km. The standard deviation was calculated to be 0.03 kJ/km, resulting in a coefficient of variation of 33%. This higher level of variability, compared to other analysed parameters, suggests that the effectiveness of the vehicle's energy recovery system is largely influenced by specific driving conditions. These conditions may include factors such as vehicle speed, terrain topography, and driver behaviour.

Figure 4 visually explores the relationship between recovered energy per kilometre and trip duration, average speed, maximum acceleration, and maximum deceleration experienced during the analysed trips.

Urban driving environments, characterized by frequent stops and starts, present ideal conditions for the regenerative braking system employed in electric vehicles. As illustrated in Figure 4a, the analysis of simulation results for an electric vehicle in various urban trips revealed a trend of higher recovered energy with increasing trip duration.

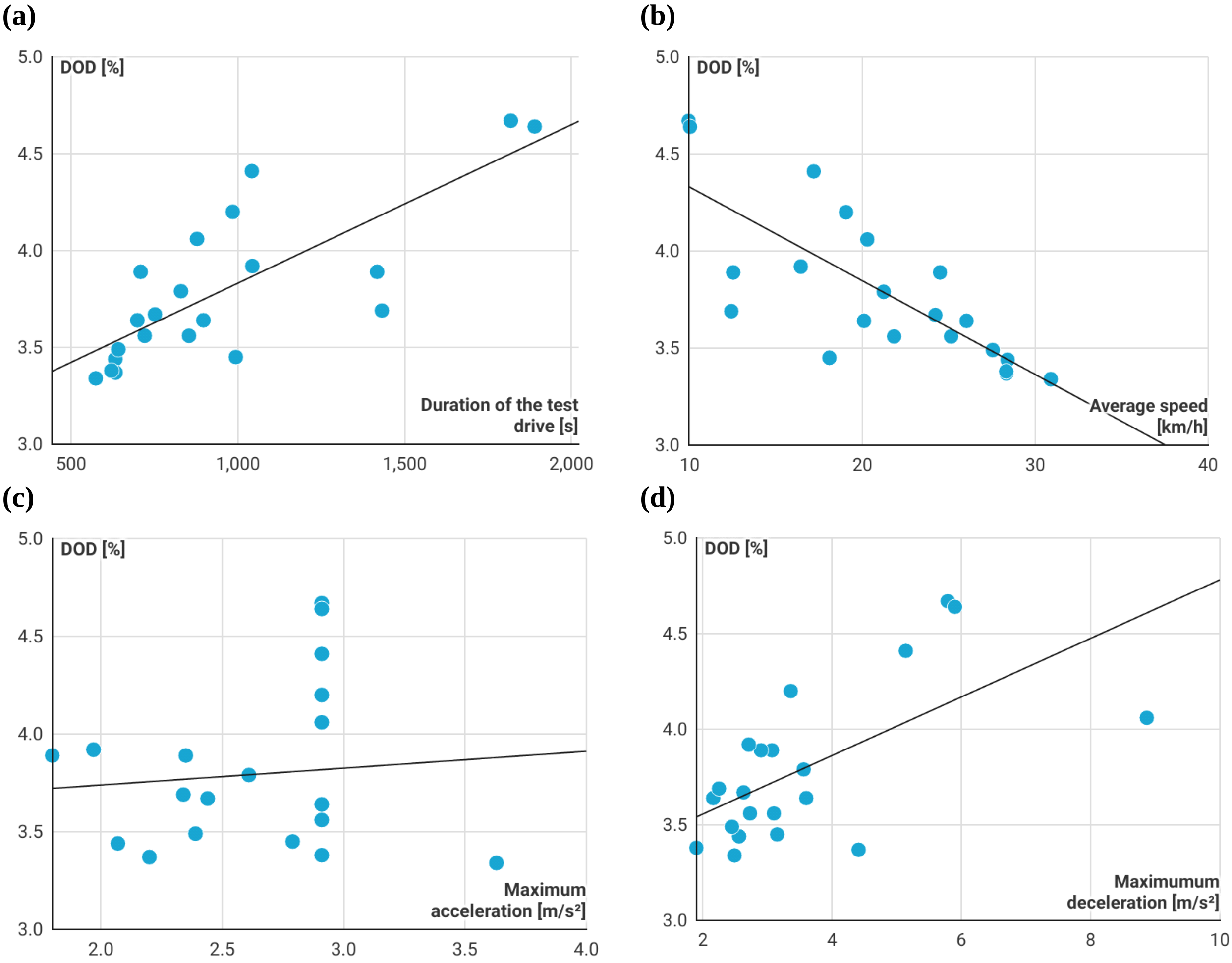

Figure 3. DOD in relation to (a) trip duration, (b) average speed, (c) maximum acceleration, and (d) maximum deceleration in the analyzed trips

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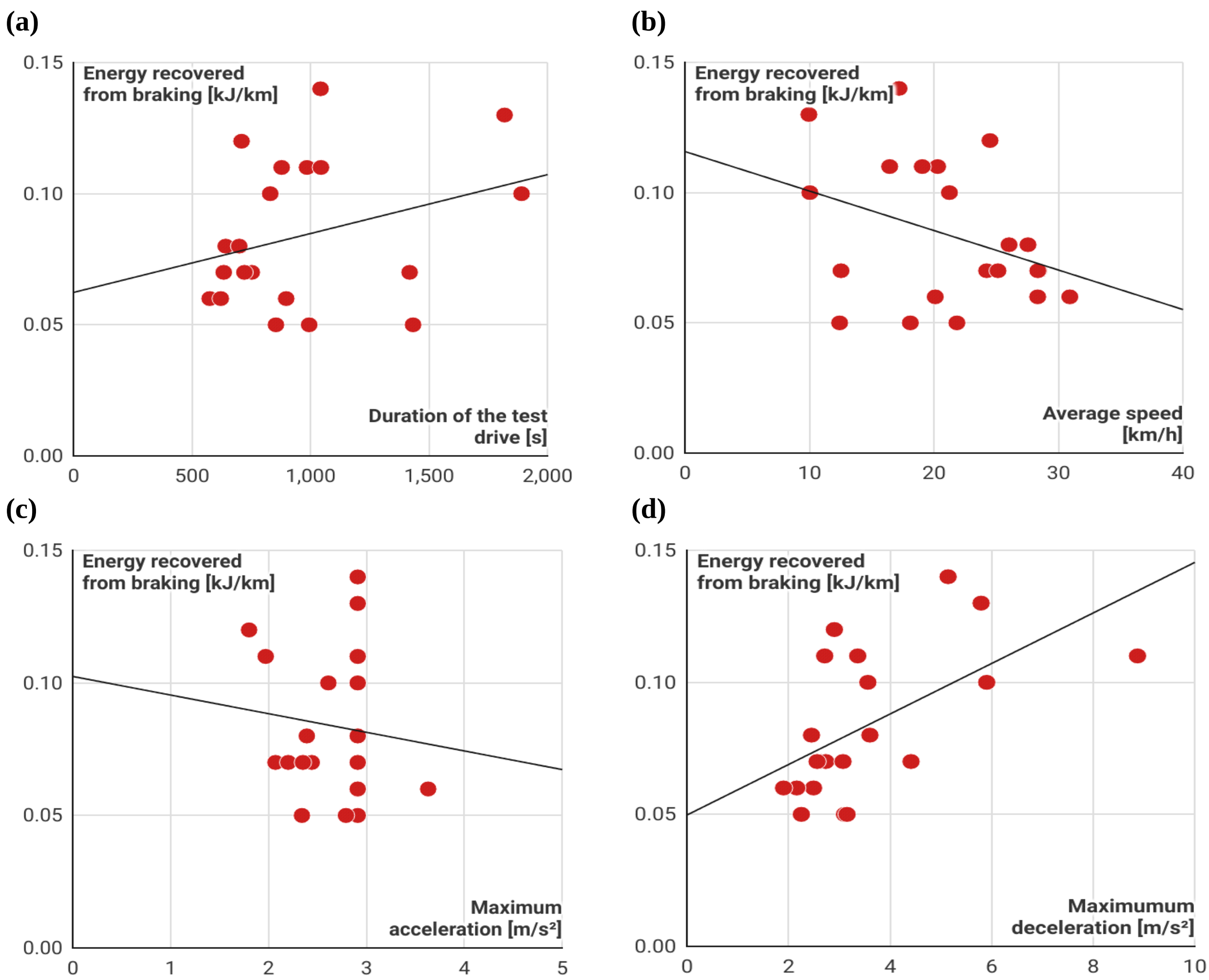

Figure 4. Energy recovered from braking in relation to (a) trip duration, (b) average speed, (c) maximum acceleration, and (d) maximum deceleration in the analyzed trips

This logical observation can be attributed to the increased number of braking opportunities encountered during longer trips within urban settings.

An inverse relationship exists between average vehicle speed and recovered energy, as depicted in Figure 4b. Lower average speeds generally correspond to higher recovered energy values. This trend likely stems from the more frequent braking events and reduced driving dynamics typically associated with urban traffic conditions.

The influence of maximum acceleration on recovered energy exhibited no clear pattern, as shown in Figure 4c. Low recovered energy values (0.05 - 0.07 kJ/km) were observed across a range of acceleration levels, including both low (2.07 m/s^2) and high (3.63 m/s^2) values. Similarly, higher recovered energy values (0.10 - 0.14 kJ/km) did not demonstrate a consistent correlation with maximum acceleration, appearing at various acceleration levels from 1.8 m/s^2 to 2.91 m/s^2.

In contrast, a clear and positive relationship was identified between maximum deceleration experienced during trips and the amount of energy recovered through braking, as shown in Figure 4d. This finding confirms that more intense braking manoeuvres enhance the efficiency of the vehicle's energy recuperation system.

4. Discussion and conclusions

This paper presents a concise analysis of select software programs employed in the simulation and modelling of electric and hybrid vehicles. Additionally, it exemplifies the application of AVL Cruise software in analysing the energy consumption of an electric vehicle.

A multitude of software programs are available for vehicle simulation and modelling, each distinguished by its unique functionalities and capabilities. The selection of the most suitable software hinges upon a careful consideration of user requirements, budgetary constraints, and the specific scope of the project. Broadly categorized, model-based simulation programs leverage mathematical models to predict vehicle behaviour. Conversely, physics-based simulation programs rely on real-world test data and measurements to replicate vehicle performance under diverse driving conditions. Hybrid programs, as their name suggests, integrate elements from both approaches.

The application of vehicle modelling and simulation programs in the development of electric and hybrid vehicles offers significant advantages. These programs can substantially accelerate the development process for new technologies, ultimately leading to more efficient and environmentally friendly vehicles. Additionally, they provide the capability to predict vehicle behaviour under conditions that would be impractical or unsafe to replicate in real-world testing.

This study employed the AVL Cruise software to analyse the energy consumption of an electric vehicle operating under urban driving conditions. A digital model of the electric vehicle was constructed within the AVL Cruise environment. Subsequently, twenty-one speed profiles, collected from real-world urban driving scenarios, were implemented into the program. Leveraging the simulation results, the analysis focused on the total energy consumption, Depth of discharge of the battery, and the recovered energy during operation.

The simulation results revealed a range of values for total energy consumption, from 0.47 kJ/km to 0.70 kJ/km, with an average of 0.54 kJ/km. This translates to an average energy expenditure of 0.54 kJ per kilometre travelled by the vehicle. DOD of the battery also exhibited variability, ranging from 3.34% to 4.67%, with an average of 3.80%. This indicates that, on average, the batteries discharged by 3.80% during the analysed driving scenarios. Recovered energy values also varied, with a range of 0.02 kJ/km to 0.11 kJ/km and an average of 0.06 kJ/km. This signifies that the vehicle recovered an average of 0.06 kJ of energy per kilometre travelled during braking events.

Furthermore, the simulations demonstrated the influence of driving factors on energy consumption, DOD, and recovered energy. These factors include trip duration, average speed, maximum acceleration, and maximum deceleration. Increased trip duration, higher average speeds, and greater maximum acceleration values all contributed to higher energy consumption and DOD of the battery. Conversely, higher maximum deceleration resulted in a dual effect: increased energy consumption and DOD while simultaneously decreasing recovered energy.

The application of AVL Cruise software, as exemplified in the analysis of an electric vehicle's energy consumption, serves as a compelling illustration of how such programs can yield valuable insights that mirror real-world performance. These insights are instrumental in the development of electric vehicles with superior efficiency and reduced environmental impact.

For researchers and engineers engaged in the design and development of electric and hybrid vehicles, simulation and modelling programs represent invaluable tools. These programs enable comprehensive analysis of various operational aspects of electric and hybrid vehicles, encompassing energy consumption, range, performance metrics, and emission levels. By leveraging simulation results, researchers can optimize vehicle designs and achieve improvements in overall efficiency.

This paper serves as a springboard for further exploration within the field of electric and hybrid vehicle simulation and modelling. Numerous avenues warrant further investigation, including the development of more intricate models for vehicle components, the incorporation of external factors that influence energy consumption, and the creation of optimization methods for vehicle designs based on a multitude of criteria. Continued advancements in these areas will undoubtedly contribute to the ongoing evolution and refinement of electric and hybrid vehicle technologies.

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