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Review

Strategies for the Modelisation of Electric Vehicle Energy Consumption: A Review

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Abstract: The continuous technical improvements involving electric motors, battery packs, and general powertrain equipment make it strictly necessary to predict or evaluate the energy consumption of electric vehicles (EVs) with reasonable accuracy. The significant improvements in computing power in the last decades have allowed the implementation of various simulation scenarios and the development of strategies for vehicle modelling, thus estimating energy consumption with higher accuracy. This paper gives a general overview of the strategies adopted to model EVs for evaluating or predicting energy consumption. The need to develop such solutions is due to the basis of each analysis, as well as the type of results that must be produced and delivered. This last point strongly influences the whole set-up process of the analysis, from the available and collected dataset to the choice of the algorithm itself.

Keywords: vehicle model; energy consumption; power-based vehicle model; microsimulation; data-driven analysis model

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1. Introduction

The interest in electric mobility is growing thanks to policies oriented toward the development of sustainable transport. The targeted reduction in greenhouse gas (GHG) emissions is forcing a switch to renew our means of transportation. The immediate changes involve vehicle fleets with internal combustion engines (ICEs) that will be progressively abandoned. The technical developments have led to the improvement of powertrain equipment for electric vehicles (EVs), with an increase in vehicle performance and efficiency [1–3]. This also contributes to a dramatic reduction of pollutants in urban areas. Since the pollution emissions by gas vehicles have reached non-negligible percentages (about 17–30% of the total), improvements in air quality are tangible targets, with less noise produced [4,5]. The high numbers are mainly due to old vehicles still circulating, with a high contribution of about 94% in the EU [6]. Furthermore, the recycling process influences end-of-life vehicles (both ICE-equipped and EVs) on GHG emissions and, therefore, on the environment, must be taken into account. If the former carries out benefits with the removal of GHG sources, i.e., old conventional ICE vehicles, the latter still pertains to a non-negligible amount of GHG emissions related to the recycling processes of EVs, primarily due to the powertrain subsystem. In particular, the issues are mainly caused by the removal of exhaust batteries, which have considerable impacts on environmental pollutants, due to prime materials involved in their construction and manufacturing processes [7–9].

In addition to ICE vehicles, a new way of mobility involves development that is based on alternative energy sources and progressively excludes the use of hydrocarbons. The continuous technical improvements of electric powertrain solutions have led to several EV models on the market [10,11]. Despite these efforts, EV performances are still badly affected by several issues, which can increase energy consumption, such as external environmental temperature or auxiliary power absorption [4,12–19]. Moreover, the existing charging infrastructure is a severe constraint to the expansion and widespread use of EVs and electric mobility [20]. Without the option to safely recharge the battery pack, the risk of the car stopping with no energy is real and contributes to the so-called "range anxiety". The latter reason is what motivates many people to switch from conventional ICE cars to EVs [2,5,21,22].

To assess these solutions, it is important to develop strategies to (correctly and accurately) estimate a priori the behaviour of the vehicle regarding energy consumption. Based on the different aims of the analysis, a different approach can be considered to model the vehicle, obtaining the required tools from distinct scientific disciplines. The advantages offered by IT systems, featured by ever-increasing computational power, allow us to focus also on different aspects related to electric mobility, such as the energy management system (EMS), electric powertrain, or the influences of different driving styles on energy consumption [4,23]. Moreover, vehicular subsystems can be focused on, particularly aimed at improving energy consumption through the reduction of power losses in systems, such as a gearbox or driveline [13,24].

This paper reviews the numerical approaches used to model the vehicle for evaluating energy consumption. A brief overview of the different EVs and the actual strategies for vehicle modelisation are given in Sections 2 and 3, respectively. The main differences between the approaches are illustrated in Sections 4 and 5, with a detailed explanation of each solution adopted according to the main topic of interest, together with the advantages and disadvantages of the chosen method. Finally, Section 6 presents a possible methodology that takes into account the different approaches described in the previous sections, merging the strong points and underlining the weak points that could emerge when adopting the latter strategy.

2. Literature Review

One of the first technical adjustments of the vehicle fleet involved increasing the overall efficiency of ICEs. Significant steps have been taken in this direction, with general improvements in the combustion process (which now requires less fuel). The benefits included reduced fuel consumption and fewer pollutant emissions [8,25].

The electric revolution started with hybrid electric vehicles (HEVs) and their variants in mild- and micro-hybrid electric vehicles (MHEVs, mHEVs). These types of vehicles combine a conventional fuel engine with an electric motor supplied by a battery pack. Batteries can be recharged either during regenerative braking or through ICE itself. Regarding mHEV and MHEV variants, the benefits (e.g., reduced fuel consumption and the general increase in overall efficiency) are huge since less fuel is used. Electric motors replace ICE in particular driving conditions, allowing for braking energy regeneration during the start and stop phases [26]. Moreover, plug-in hybrid electric vehicles (PHEVs) have evolved from HEVs, providing battery charging through standardised electrical plugs. With these types of EVs, their infrastructure interactions are important as they guarantee the electric energy supply. If HEVs and PHEVs are considered "entry level", with the initial integration of electric motors alongside ICE, which produces the vehicle's motion, a change in perspective is provided with extended-range electric vehicles (EREVs). Presently, the electric motor has a primary role in the vehicle's motion, with ICE deployed to charge the battery when travelling. Battery electric vehicles (BEVs) and fuel cell electric vehicles (FCEVs) represent the final steps of this revolution. To be more schematic, all vehicle classes are grouped and described in Table 1 [27]. In addition, references reviewed and considered within this paper are grouped according to the classifications provided in Section 3 and depicted in Figure 1.

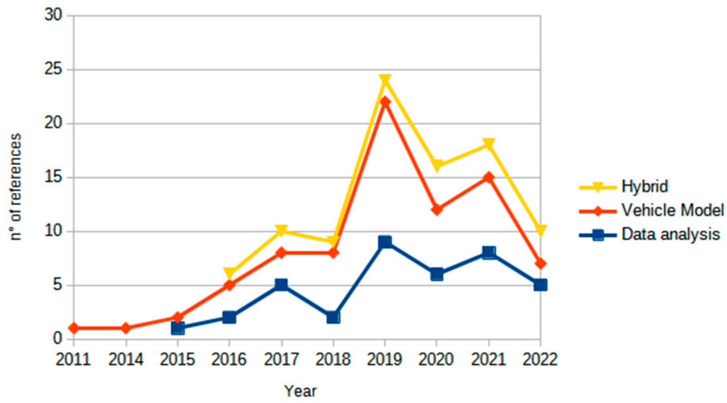


Figure 1. Reviewed references for the content of the paper and chronological trends.

The different types of vehicles include different technical arrangements with respect to powertrain, gearbox, and driveline subsystems, and the definition of a unique and standardised methodology to model the vehicle and evaluate energy consumption is needed. In this way, differences in technical specifications can either be discarded or considered through proper modelisation. The main factors that influence the variations of energy consumption for vehicles are:

- Slope gradients;
- Driving styles;
- Auxiliary systems (e.g., air conditioner, etc.);
- Traffic [14].

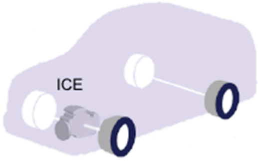
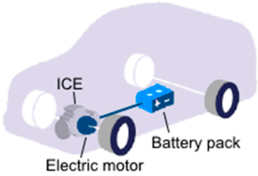
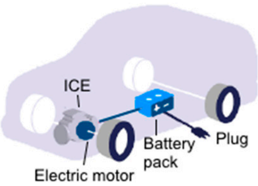
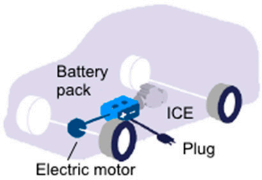
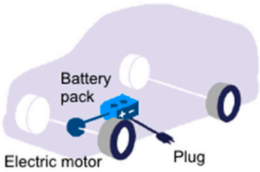
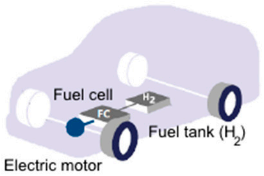
These act differently (whether a conventional ICE-equipped or an EV is considered) [28]. For an ICE vehicle, the following can be observed:

- Slope gradients: the presence of a path with sensible variations of slope angles increases energy consumption.
- Driving styles: the influences on energy consumption depend on the driver's attitude; the differences in the energy demands between driving styles are huge.
- Auxiliary systems (e.g., air conditioner, etc.): the impacts of these subsystems are less direct on ICEs and are hidden because of large tank capacities, but are still considerable.
- Traffic: driving within the city with subsequent stop-and-go dramatically increases energy consumption, with high values of fuel demand from the engine; this is reduced on highways since ICE works at its highest efficiency.

For an EV, the effects are not the same:

- Slope gradients: as previously mentioned for ICE, the effects include increased energy demand and consumption; this condition amplifies the gravity of the issue since (in general) mountainous environments suffer from a lack of charging infrastructure [5].
- Driving styles: as aforementioned, it is up to the driver to adopt a driving style that is less energy-demanding; in this way, energy savings can be considerable, especially on EVs that are featured by medium-low battery capacities [29–32].
- Auxiliary systems (e.g., air conditioner, etc.): the impacts on energy demand and energy consumption are more evident because of reduced battery capacity, estimated at +12% throughout the year [17,33–35].
- Traffic: EVs suffer from the opposite conditions; if driving within the city is beneficial (thanks to regenerated energy during braking, which contributes to recovering and saving energy), problems emerge when driving along the highways (when there are few and less intensive braking opportunities), thus dramatically increasing the energy consumption [36–39].

Table 1. Typologies and characteristics of vehicles.

Type		Powertrain Characteristics	Advantages	Disadvantages
ICE [40]		Fuel engine	Low refuelling time Many refuelling stations	GHG emissions Fossil fuel dependency Low efficiency Noise
HEV, mHEV, MHEV [26]		ICE, electric motor, and battery pack	Higher efficiency Lower emissions Many refuelling stations	GHG emissions Fossil fuel dependency Noise
PHEV [25]		ICE, electric motor, and battery pack	Higher efficiency Home/work recharge Many refuelling stations	Technological complexity
EREV [41]		Electric motor and battery pack, ICE (recharging battery)	Higher efficiency Home/work recharged Many refuelling stations	Technological complexity
BEV [42]		Electric motor and battery pack	Higher efficiency Home/work recharge Low noise No GHG emissions	Fewer recharging stations Long charging time Short driving range
FCEV [43]		Fuel tank, fuel cell, and electric motor	Higher efficiency Low noise No GHG emissions	Lack of refuelling stations Limited commercial availability Technological complexity

3. Materials and Methods

Since electric mobility is a topic that is gaining importance (regarding the practical use of EVs and their implementations, in various contexts), it is essential to consider and analyse the issues related to energy consumption. According to the shape of the problem, this analysis consists of three parts:

1. The available start data;
2. The type (or the aim) of analysis to be set;
3. The type of results to be provided.

This framework describes how to model the problem itself, suggesting which kind of model best fits and should be taken into account [44]. Different approaches define the corresponding strategies to be adopted to model the problems related to electric mobility. Regarding the methods, there are alternative strategies through which energy consumption can be estimated. These strategies can mainly be grouped into two branches:

- Vehicle model-driven approach;

- Data-driven analysis approach.

Since the nature of the problem is different, the strategies will also be different (but with several contact points present between each other).

In particular, for data-driven analysis modelisation, different algorithms can be created for predicting EV energy consumption. This approach makes it possible to perform the design of experiments (DoE) or to set up optimisation problems [45]. Moreover, statistical evaluations can be performed to assess results, catch trends, or evaluate behaviours [4,10]. These quantities are helpful to set evaluations, starting with data patterns from real cases. In particular, the driving range and trips of each vehicle can be considered.

As far as the vehicle model-driven approach, EV models can mainly be grouped into two branches:

- Forward vehicle model (FVM);
- Backward vehicle model (BVM) [25,29].

Through these approaches, vehicle subsystems can be modelled (e.g., the gearbox and the driveline) and their influences can be evaluated on EV performances [24]. Furthermore, the energy management system (EMS) algorithm can be developed and simulated to optimise its behaviour in recovering and managing the energy stored [46].

4. Vehicle Model-Driven Approach

The adoption of a vehicle model-driven approach allows simulation of the behaviour of the whole vehicle, considering partially (or totally) the subsystems of interest, thanks to the vehicle technical specifications that this strategy considers, which are otherwise discarded by the data-driven analysis approach. Moreover, as a result, this method allows for performing a sensitivity analysis, which has a fundamental role as a preliminary assessment of the vehicle performance [5,39,42,47]. Usually, a numerical vehicle model allows for recreating the vehicle itself in a virtual environment. The vehicle model-driven approach is schematised in Figure 2.

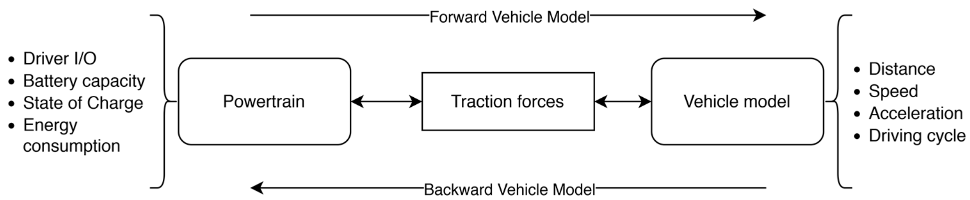


Figure 2. Block diagram of forward and backward vehicle models.

Recalling the aforementioned distinction presented in Figure 2, the threshold is represented by the traction forces and how they are estimated, according to the starting dataset available. In particular, this implies the following distinctions:

- The forward vehicle model (FVM) starts from the already known powertrain characteristics and computes traction forces requested by the driver and generated by the powertrain unit to estimate vehicle kinematics through the vehicle modelisation;
- The backward vehicle model (BVM) starts from already known kinematic quantities and computes traction forces required from the powertrain unit to be generated, estimating the powertrain performance [34].

BVM is mainly used to evaluate the impacts of the virtually-tested vehicle on actual operative conditions, since speed profiles either come from standards (and, therefore, common procedures), or real cases [14]. BVM can be defined as a passive model that processes all kinematic datasets stored from real sampling or standard driving cycles, while FVM is an active model that takes into account the effects of the driver, modelled as a PI controller [34]. The driver–controller commands all acceleration and braking phases; thus, FVM reacts to the inputs generated. Moreover, for FVM, reference speed profiles (or driving cycles) are considered; in this way, the driver chases the speed profile [14,29].

As far as the pure modelisation of the vehicle is concerned, motion resistances are universally considered through analytical formulas. Motion resistance is commonly in a relationship with the vehicle weight; Figure 3 presents the usual scheme. In particular:

- Slope (or gravitational) resistance is defined according to the horizontal component of the weight as depicted in Figure 2 and reported in (1)

$$R_g = mgsin(\theta). \tag{1}$$

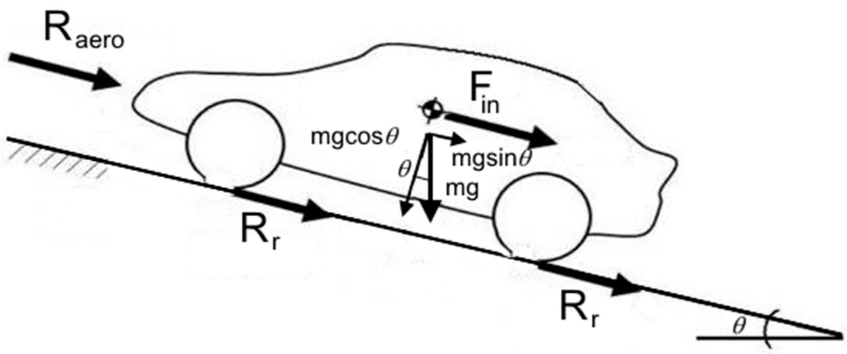


Figure 3. Vehicle model and diagram of motion resistances.

- Rolling resistance is generated by the non-uniform air pressure distribution into the tyre, combined with the elastic tyre deformation during rolling motion. It is modelled according to (2), considering the perpendicular component of the vehicle weight, as already reported in Figure 2. The rolling resistance coefficient shows static and dynamic terms, which depend on v^2, as reported in (3)

$$R_r = k_r mgcos(\theta), \tag{2}$$

$$k_r(v) = f_1 + f_2 v^2. \tag{3}$$

- Inertia resistance (or inertia force) is commonly considered according to the famous Newtonian principle (4):

$$R_{\text{in}} = ma, \tag{4}$$

- Aerodynamic resistance is generated by fluid–dynamic interactions between the vehicle and air in motion. It is basically due to the air–surface friction, high-low pressure differences, and vortex generation in the rear low-pressure zone, where the separation of the boundary layer from the aerodynamic surface is frequent. Aerodynamic resistance is modelled according to the aerodynamic drag Formula (5):

$$R_{aero} = \frac{1}{2}\rho C_D A v^2, \tag{5}$$

where all parameters involved are briefly reported and the meanings are explained in Table 2.

Table 2. Physical quantities involved in the aerodynamic drag resistance formulation.

Parameter	SI Unit	Physical Meaning
ρ	(kg/m^3)	Air density
C_D	(-)	Aerodynamic drag coefficient [1]
A	(m^2)	Vehicle cross-sectional front surface
v	(m/s)	Longitudinal vehicle speed

[1] The value depends on the longitudinal vehicle shape, and it is determined experimentally through wind tunnel experiments with scale models.

The basis of this kind of approach a theoretical relations involve the following: Forward (or backward) vehicle models are validated on standardised driving cycles or procedures, which allow homogeneous evaluations of fuel (or energy) consumption among the different vehicles that can be addressed and tested. For the EU, the New European driving cycle (NEDC) was commonly adopted, which has been dismissed and substituted by the worldwide–harmonized light-duty vehicle test procedure (WLTP) since 2018; for the US, the federal test procedure (FTP) and highway fuel economy test (HWFET) are the most frequently used and widely adopted [24,25,46,48–51].

The computational performances of the model are related to the level of detail considered throughout the modelling process. A lighter vehicle modelisation allows one to quickly estimate the energy consumption with high accuracy and low computational heaviness while penalizing the dynamic simulation; conversely, a detailed vehicle modelisation requires more computational heaviness, refining the quality of results obtained to estimate the vehicle dynamics [1,13]. Among the advantages linked to the adoption of this approach, there is the capability of considering multiple variants, such as the different technical arrangements on the same subsystem. The possibility of fitting the numerical vehicle model (time after time) also allows for virtually testing different technical solutions, with huge money savings (with respect to physical prototyping) [52]. This leads to progressively numerical modelling that is very close to reality, enhancing the development of virtual or augmented realities [53]. Similarly, control algorithms on the vehicle can be implemented, thus modelling both control blocks and strategies for energy consumption optimization [41,48,54,55]. Lastly, different algorithms of the so-called energy management system (EMS) can be virtually tested and their efficiencies on energy storage battery packs can be evaluated [41,46,56]. On the contrary, some limitations are remarkable. If the strong point of the adoption of a vehicle model-driven approach is the focus on the vehicle itself, the immediate weak point is related to the lack of interaction with the external environment. Table 3 reports the so-called SWOT analysis, listing the strengths, weaknesses, opportunities, and threats of the approach considered [57].

Table 3. SWOT analysis for vehicle model-driven approach.

	Strength	**Weaknesses**
Internal elements	Technical specifications considered Vehicle-to-vehicle comparison	Focus on local subsystems
	Opportunities	**Threats**
External elements	Integration with Virtual/Augmented Reality	No interactions with the surrounding environment

4.1. Microsimulation and PVM: Power-Based Vehicle Model

The power-based vehicle model (PVM) is a typical model based on a power balance expression. PVM can be furtherly classified according to the vehicle type considered:

- PFM for a conventional fuel-engine vehicle model;
- PEM for an electric vehicle (EV) model;
- PPM for a plug-in hybrid electric vehicle (PHEV) model.

This type of modelisation can be traced back to a steady-state or quasi-steady time domain computational approach. PVM is a parameterised vehicle model, capable of considering the different technical specifications of the vehicles chosen. PVM is usually implemented as BVM but can also be implemented as a FVM depending on the available starting dataset [37]. The PVM modelisation considers both dissipative and motion power terms, made up of analytical relations previously explained, i.e., in (1) and (5), and reported, i.e., in (6) and (7).

$$P_{wheels} = \left(R_g + R_{aero} + R_r + R_{\text{in}}\right)v \tag{6}$$

$$P_{wheels} = P_{powertrain} \tag{7}$$

The computational performances of this model are related to the level of detail considered throughout the modelling process. Since a lighter vehicle modelisation is accounted for, the energy consumption is estimated quicker with high accuracy and low computational heaviness, with a maximum error of 4% [27]; a detailed vehicle modelisation can be provided referring to the charging operations (through modelling the recharging performances), requiring slightly more computational heaviness but refining the quality of the results obtained [1,13]. The required input data refer to the time domain-acquired vehicle kinematics, i.e., longitudinal speed and acceleration, while the output dataset includes the energy consumption, required power, and battery SOC estimated by the model, as reported in Figure 4. This is the main reason behind the need for starting from standardised driving cycles or a kinematic dataset already acquired [36]. The quality of results also depends on the time-discretization step.

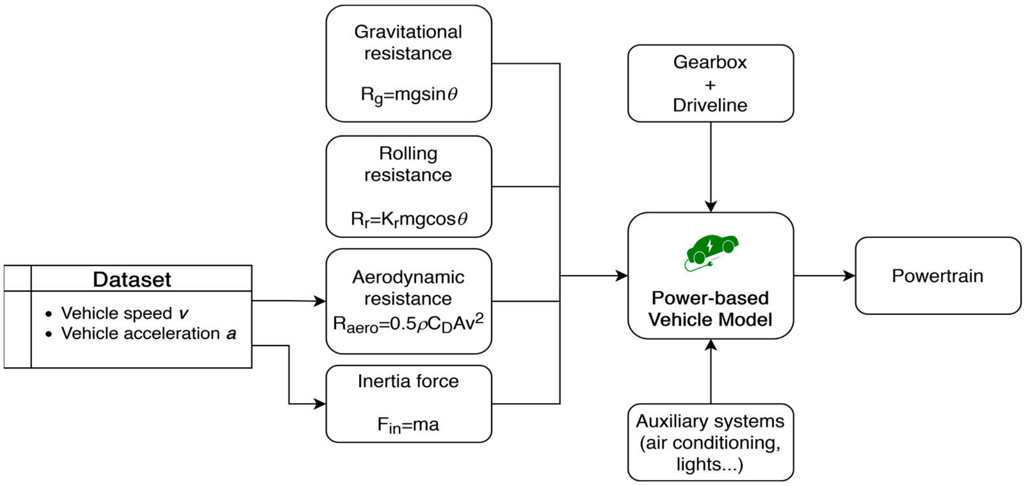


Figure 4. PVM and BVM descriptions through the block diagram.

Moreover, thanks to the light vehicle modelisation, adopting a PVM leads to many advantages, such as the integration of the vehicle model into various systems and scenarios. Microsimulation is a field that exploits this kind of modelisation. Light vehicle modelling can be easily implemented into a broader environment to simulate energy consumption within a congested environment, such as citizen streets, either virtually recreating the traffic flow or considering the kinematic behaviour of the vehicle itself [13,14,27,38,54]. Another advantage of this model is the ease to integrate with GPS data or commercial software through co-simulation [58]. This modelisation is also frequently applied in the presence of a dataset acquired through internal inertial sensors of smartphones or exploiting car sensors through on-board diagnostics (OBD) to act as a "dummy vehicle", which testifies to the great versatility of PVM [1,4,19,30]. Energy consumption can, thus, easily be derived from the starting dataset and obtained via numerical integration of the electric motor power needed.

PVM also underlines the different influences on energy consumption given by on-board subsystems. There are various ways in which the electric motor power can be dissipated by other vehicular subsystems, decreasing the overall efficiency of the powertrain subsystem [48,59]. For example, the cruise control algorithm can be designed and tested through PVM for the purposes of energy saving [37]. Moreover, auxiliary systems (such as air conditioners), gearbox, and driveline can be modelled. and their influences on energy consumption can be evaluated into the PVM [17,24,60,61]. Another valuable example is represented by the modelisation of the heating ventilation and air conditioning (HVAC) system, to estimate its performance in a severe winter season and throughout the year and, hence, to evaluate its weight on the total energy dissipation [17,33]. Different technical solutions can be considered and evaluated among the same starting dataset, such as the HWFET driving cycle, and the most efficient (and less power-absorbing solution) can be assessed and proposed. For practical examples of innovative traction systems that have been designed, virtually assessed, and optimised, and in which energy consumption and efficiency have been estimated, see references [62,63].

The efficiency of a powertrain subsystem can be considered in different ways, based on the necessities of the research process [14,48]. Powertrain efficiency can be considered constant throughout the working conditions, thus, reducing the level of details of the vehicle model and lightening the computational heaviness of the model [13]. Conversely, it could be considered a 'dynamic' parameter, either defined analytically through a mathematical formula or stored in a map, depending on the powertrain working conditions. Powertrain efficiency usually varies in the operative field of electric motors, which is the most influential part of the electric powertrain [1,25,28,33,34].

PVM results are versatile and can be compared with real test data. A comparison between simulated results and real bench tests can assess the accuracy of the dataset computed through the numerical PVM [30,39,52,60,63–65]. In addition, this modelisation allows for local optimisation, both on the general vehicle performance and the specific subsystem side.

As mentioned, the biggest limitation of this model is the level of detail itself. The possibility to integrate it into other external programs, environments, or approaches, as will be explained, decreases when the model is more detailed. This means that the vehicle model results are deeply detailed (describing each subsystem), implying that more time is spent in computing the variables involved in the modelisation process of the vehicle for each subsystem considered. Conversely, with a low-detailed vehicle model, it is possible to consider it with other approaches since the required computational heaviness for the model is reduced to the necessary physical quantities to be determined [27].

4.2. VRP: Vehicle Routing Problem

One of the fields that 'sees' the application of a vehicle model-driven approach, thanks to a lighter vehicle modelisation, is the vehicle routing problem (VRP), described in Figure 5. In this problem, the vehicle model is featured by a low level of detail, since the technical characteristics of the powertrain, gearbox, driveline, and HVAC are neglected. In this way, a rough estimation of energy consumption is performed, without the possibility of analysing where the energy is dissipated and which parameter influences the energy consumption. On the contrary, its light configuration allows the processing of the extended dataset, prompting resolution maps [47]. This method allows for assessing the implementation of EVs within the actual framework [5]. The vehicle model adopted for VRP helps to evaluate the electric energy demand to be delivered by the powertrain during the vehicle motion along a selected route. As depicted synthetically in Figure 4, average and constant acceleration and deceleration values are considered from the technical datasheet of the vehicle. Therefore, the speed and distance covered are computed through numerical integration [66,67]. This emphasises the fact that the effects of powertrain dynamics on energy consumption are neglected and discarded, together with the EMS algorithm. The path is parameterised (in terms of length and slope profiles) and concerns the charging infrastructure. Usually, the energy consumption is in a relationship with gross and tare weights through a linear load-dependent formulation, as reported in (8) [66,68,69]. Routes are generally discretised as nodes and directions. Decisions, i.e., whether to recharge the vehicle or continue, are taken according to constraints and penalty functions properly set up, borrowing typical strategies from multi-objective optimisation [21,66,67,70]. For these reasons, optimal SOC trajectory planning 'sees' the wide implementation of the VRP approach, since this problem represents an application that is very close to VRP. The results of the numerical experiments show an average energy estimation inaccuracy below 3% [39,67].

$$E_{wheels} = \alpha m + \beta \tag{8}$$

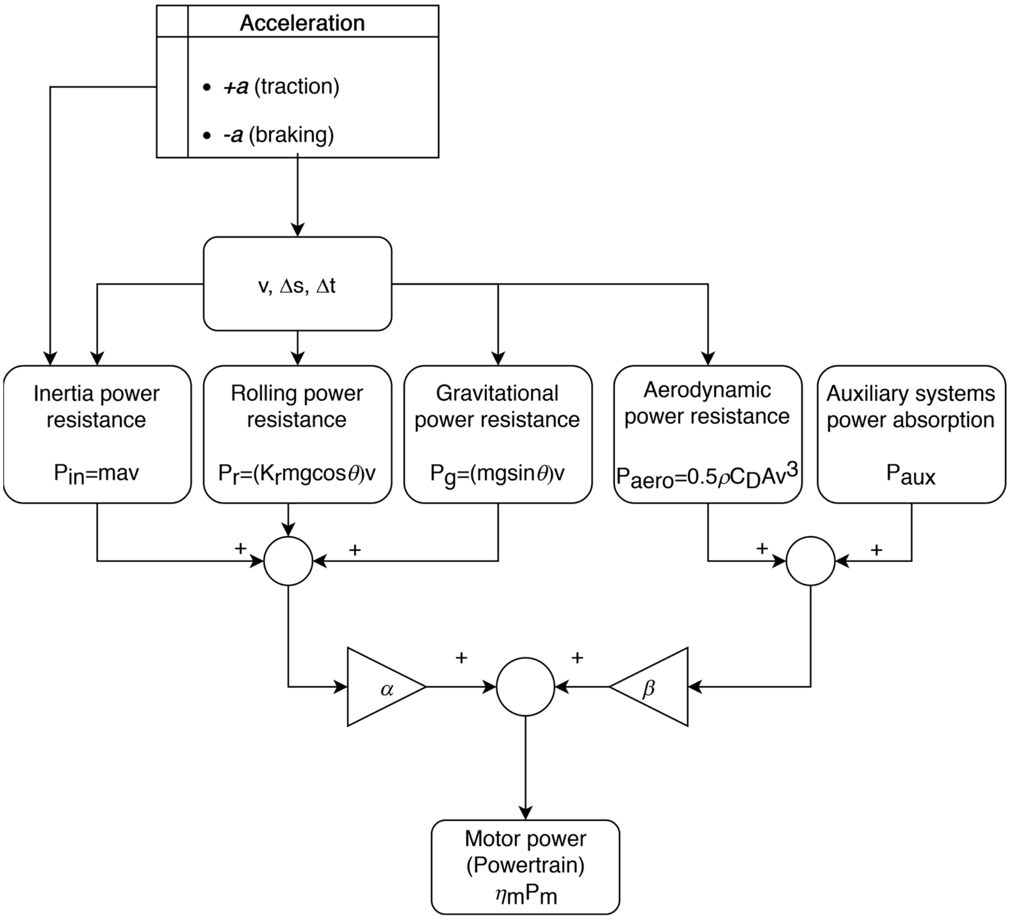


Figure 5. VRP vehicle model.

4.3. Multi-Objective Optimisation

The vehicle model-driven approach is useful to set multi-objective optimisation strategies, and identifying and improving weak points of the problem considered. It is convenient to exploit this simple vehicle modelisation as seen in Sections 4.2 and 4.3, to explore all critical aspects related to VRP and optimise the vehicle motion [66]. Nevertheless, multi-objective optimisation can be adapted and set on the technical arrangement of the vehicle itself. Since this approach is useful to evaluate the different technical characteristics of a single aspect of the problem, a constrained optimisation can lead to locally optimised vehicular subsystems to reduce the dissipation of energy delivered by the powertrain and increase the overall vehicle efficiency, as aforementioned in the previous sections [48,61]. A valuable example can be seen in [43]. Usually, the techniques used for multi-objective optimisation are the Pareto front analysis and genetic algorithms (GAs). Once the design variables are selected and the objective functions set up, together with penalty functions for unacceptable solutions to be discarded, results can be visualised through a map of solutions [47,48]. The advantage of this approach is the possibility of including different physical modelisation types through analytical formulations within the objective functions that must be considered and evaluated. This aspect is what makes this approach useful in evaluating different technical configurations of the vehicle's subsystems and characteristics, thanks to the always-increasing computational power of CPUs.

4.4. STR: Source-to-Range Model

Vehicle modelisation can also be taken into account in a broader analysis of energy consumption, considering all manufacturing processes behind the realisation of the vehicle itself. This approach is called source-to-range (STR) [40]. The novelty of this approach involves considering all of the energy wasted during the entire life cycle of the vehicle. It includes several steps, briefly depicted in Figure 6.

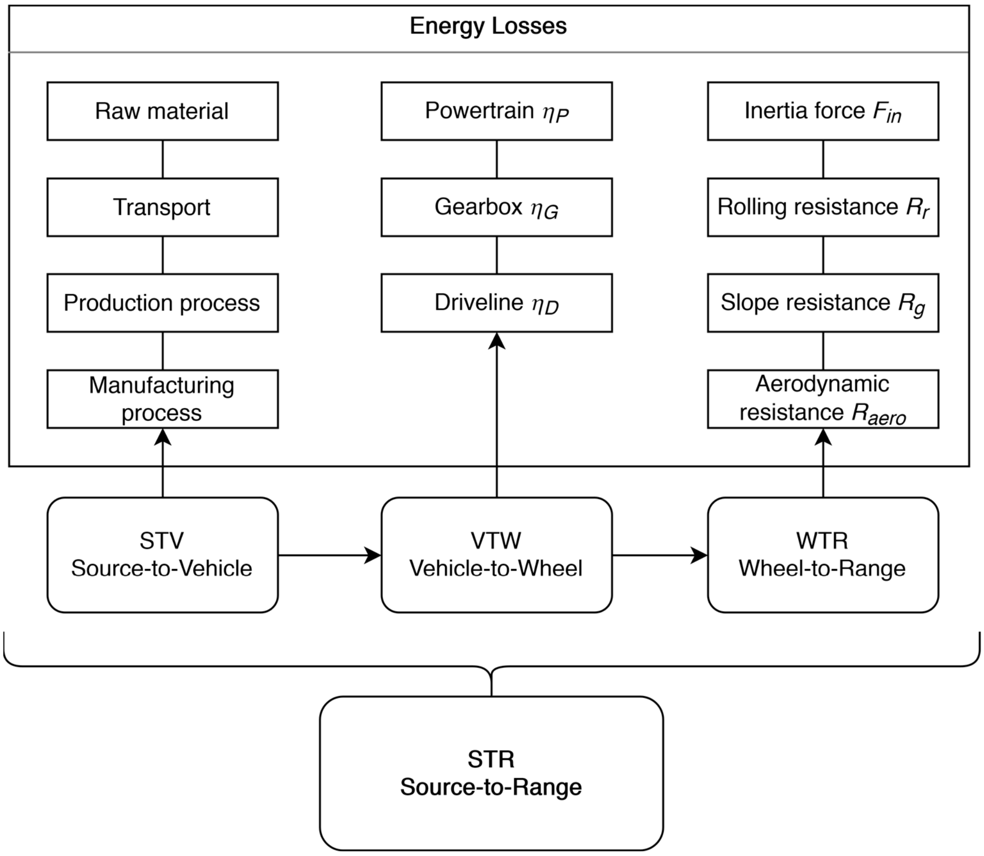


Figure 6. Source-to-range model and energy losses.

This approach involves the vehicle model already seen and described in previous sections, whose results are completed by the energy dissipated by production and manufacturing processes. It is useful to evaluate the environmental impacts of the whole life-cycle process, starting from the very first steps, such as raw material production and transport, or the industrial manufacturing processes that are involved in vehicle production, which are the most energy-demanding within the whole life-cycle of the vehicle [8]. In this way, the focus moves on what the drivers do not see when driving the vehicle. If the aim is to reduce, at most, the environmental impacts of human activities, this model is suitable for considering all energy consumed and wasted from the vehicle subsystems (not only during the physical motion across the street) [71]. The power of this approach involves considering every single vehicular subsystem (powertrain, battery pack, gearbox, driveline, wheel, etc.) and estimating the energy consumption starting from the beginning of its life (and, therefore, the supply of raw materials) [7]. Moreover, in this way, it is possible to identify the most energy-demanding process related to a specific subsystem and to proceed to local optimisation and correcting or proposing new processes that are more environmentally sustainable.

5. Data-Driven Analysis Approach

As mentioned before, an alternative approach to solving EV problems is the data-driven analysis approach. This method is useful when a large amount of data is available at the beginning of the analysis. Its blocks are described in the scheme presented in Figure 6. With this approach, the first step is constituted by clustering the data into groups. Big data can refer to driving cycles, driving behaviours, most journeys, traffic observations, or habits from real cases extracted through constant and pervasive monitoring of vehicular circulation [9,10,72–74]. Moreover, this approach allows for performing correlation analyses between variables of different natures, thanks to machine-learning techniques [75,76]. The main difference with respect to the vehicle model-driven approach is the absence of a vehicle model [23]. The data-driven analysis approach is capable of including various algorithms, and statistical evaluations can be performed on the data. This implies that the initially acquired dataset, which can be called a 'raw dataset', must be properly prepared to be constituted as a confident starting dataset prior to proceeding with the analysis. Within this branch, various approaches can be distinguished. Starting from the scheme of Figure 7, the focus will be set on the "processing" phase, which is the heart of the data-driven analysis approach and where the main differences with vehicle model-driven approaches are grouped. SWOT analysis related to Data Analysis-driven approach is briefly reported in Table 4.

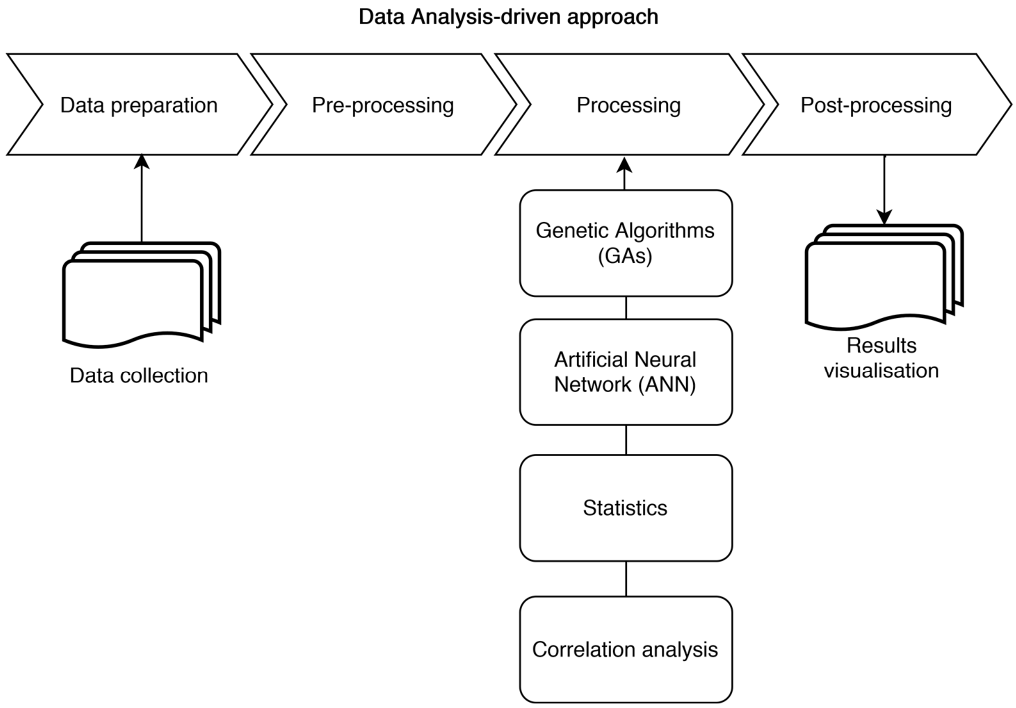


Figure 7. Data-driven analysis approach.

Table 4. SWOT analysis for the data-driven analysis approach.

	Strength	**Weaknesses**
Internal elements	Big data Machine learning	No technical analysis
	Opportunities	**Threats**
External elements	Extract patterns Evaluate behaviours	No vehicle model

5.1. Machine Learning

This type of process is mainly based on the use of two instruments: feedforward artificial neural networks (ANNs) and genetic algorithms (GAs) [77]. The advantages of ANNs include the ability to perform a large-scale learning and prediction process (LSLPP) or a simulation process (LSSP). When dealing with ANN, it is important to pre-process the available dataset, making it homogeneous. Therefore, this pre-processing is commonly called 'clustering', which groups data referred to similar characteristics into classes [45,73,78,79]. It is usual practice to prepare the data or assess the results through statistical evaluations, especially related to the variance distributions [23,78,80]. It is also possible to roughly evaluate energy consumption through empirical formulas applied to big datasets [81,82]. This means that evaluations are not performed with proper vehicle modelisation but through linear regression or least square reduction (LSR) [4,10,18,23,80,83]. The advantages of polynomial relationships are frequently exploited to relate the physical quantities of different natures; for example, the relationship between energy consumption and the road gradient or ambient temperature can be modelled according to a third-order polynomial [18,84]. In these cases, the difficulty stands with the correct estimation of coefficients, which can be computed with good accuracy through LSR. Different datasets, for example, taking into account the air conditioner factor on energy consumption, can be compared when undergoing the same processing phase. Estimations can be done on the average speed and greenhouse gas emissions in a citizen context [9].

Another interesting approach that is strictly linked with machine learning is the so-called Q-learning. This approach is capable of modelling the decision-making process based on (9)

$$Q_{i+1}(x,y) = p(x,y) + k\left[\sum_i P_i(x \vee x', y) Q_i(x', y')\right] \tag{9}$$

Q-values are the values assigned to certain decisions and are based on the "prize" p that depends on x possible states and y choices. $P_i(x \vee x', y)$ is the probability of changing the state when a decision y is chosen that is multiplied by the actual i-th $Q_i(x', y')$. This is summed up with all of the 'i' previous steps and multiplied by a bonus–malus coefficient $k \in [0;1]$. For k close to 1, the decision is more rewarding, and vice versa, it is more penalizing. Based on this Q-value relation, it is possible to build a decision tree with a customised constraints relationship. This approach is strongly implemented with the use of ANN, constituting a double-deep Q-learning network (DDQN), which is suitable and adopted to simulate EV decisions taken in a real environment [72].

5.2. Well-To-Wheel Problem (WTW)

This is an approach similar to the (already described) STR model. The main difference between the two approaches is the basis: the latter is a vehicle model-driven approach, and the former a data-driven analysis approach. This leads to estimating the whole energy demand of the production process without proper vehicle modelisation. Conversely, the estimation of energy consumed during the whole life-cycle of the vehicle is performed based on a wide dataset regarding the average values of energy consumption and according to empirical Formulas (7) and (8).

6. Hybrid Approach

As the possibility of merging the advantages offered by the two approaches was already explained, there is a third approach that is commonly called hybrid [44]. This approach is constituted by the implementation of both the data-driven analysis and vehicle model-driven approaches and is capable of increasing the levels of detail of the simulations performed. Usually, the methods derived by the data-driven analysis approach are implemented to pre-process and refine the starting dataset. In this way, various scenarios can be set, with each dataset describing a particular behaviour or travelling condition [16]. Therefore, the techniques from the vehicle model-driven approach are implemented; the vehicle model is, thus, able to perform simulations based on the different starting datasets [46,85,86]. The results can be compared and assessed. One can immediately understand both the potentialities and drawbacks. This kind of approach represents a highly time-consuming process (since gigabytes of data are usually processed) and requires very-high computational power, which is then turned into the high computational heaviness of the problem.

One of the most important paybacks that this approach is able to deliver is related to the dataset scenario. As aforementioned, the data-driven analysis approach is capable of extracting patterns (or behaviours) from real (or real-time) data [2,16,81]. Hence, the differentiation of data creates the basis for various starting scenarios since many patterns can be identified and extracted. The vehicle model is then exploited to validate (via a numerical analysis) these patterns, estimating the effects on the energy consumption and management of the EV [16,61,81,85–88]. Finally, the data-driven analysis approach can be exploited to refine the simulation results produced by the vehicle model-driven approach, to refine the final results through statistics [89]. Therefore, this strategy is able to set a deep analysis of the effects carried out by any driving behaviours or human decisions on the energy consumption of an EV, considering the vehicle dynamics itself [90]. The process is briefly depicted in Figure 8; Table 5 synthetically presents all strong and weak points of each approach considered and described.

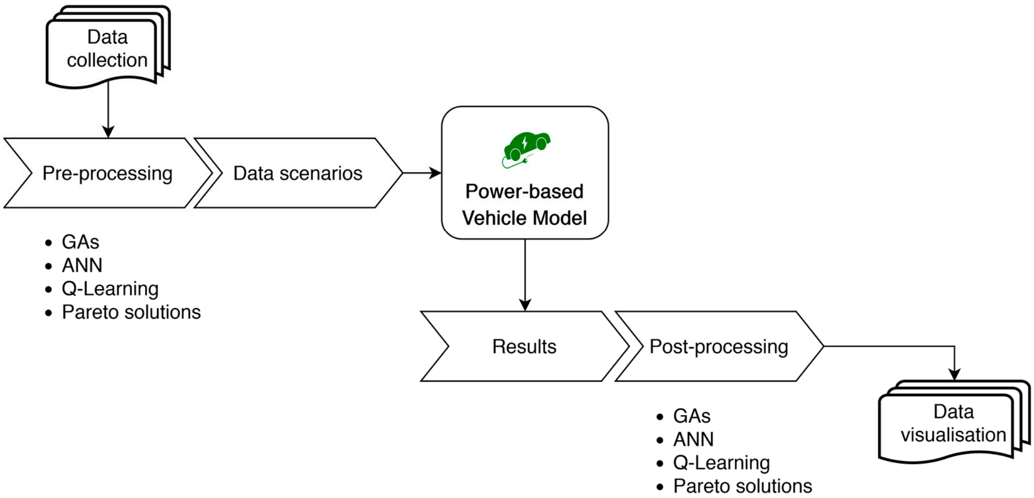


Figure 8. Hybrid approach for EV modelling.

Table 5. Different strategies to model the EV problems. Synthetically groups the pros and cons of the modelling approaches.

	Strategies to Evaluate EV Energy Consumption		
	Data-Driven Analysis	**Vehicle Model-Driven**	**Hybrid**
PROs	Evaluate trends [10,16,72]	Sensitivity analysis [27,48]	Merges advantages of DA-VM approaches
	Big data analysis for prediction [23]	Simulations on real data for prediction	More complete insight into the problem
	Real/real-time starting dataset [4,73]	Vehicle technical specs considered [24,44]	Statistics prediction on big data through vehicle model [86]
	Correlation/co-factor analysis [45]	Best working point identification	
	Interactions considered	Evaluation of vehicle performances [1,91,92]	
	Clustering/class comparison [78]	Vehicle-to-vehicle comparison [1,5,34]	
CONs	Global optimisation	Local optimisation [21]	Computational heaviness
	No knowledge of vehicle	No interactions with the surrounding systems/environment	

7. Discussion

A vehicle model-driven method is the best-fitting strategy to evaluate the performances and energy consumption from the technical characteristics of the real EV models considered. To evaluate the goodness of the actual subsystems, and to identify corrective actions to be carried on the equipment, this way represents the best approach. Several vehicle subsystems can also be taken into account with their own technical specifications. Therefore, a numerical vehicle model is always present and set up according to analytical relations with respect to motion resistances, inertia, and motion force acting. Modelling vehicle subsystems, such as the powertrain, the driveline, the driver. and so on, making the vehicle model more complete. Moreover, the advantages offered by this strategy can allow setting up an optimisation analysis on the vehicular subsystems and the vehicle itself, in order to identify the power losses and maximise their reduction. Within this approach, the different strategies that could be adopted were illustrated through forward and backward vehicle modelisation. This can be summarised as a local approach, useful to punctually evaluate the results. Conversely, when large datasets must be analysed, machine learning techniques can help. Dealing with big data acquired from real situations, it is possible to evaluate both fuel and energy consumption from driving cycles and the habits of real drivers. Therefore, data-driven analysis methods allow for estimating the average values of energy consumption. This strategy is commonly adopted to analyse and predict the presence of large numbers, constituting a population. The differences between statistical approaches and optimisation-based algorithm approaches (such as LSLPP and LSSP based on GA, NN, Q-learning, co-factorial, and binary models) were provided. These methods are useful in evaluating the effects of driving behaviours on large populations. The latter strategy can refer to a global approach since the evaluation process was broadly set on the whole dataset.

When real-based scenarios are required to virtually assess the vehicle model based on multiple cases, a hybrid approach is useful, due to its ability to cluster large starting datasets and extract patterns from final results after being processed through the numerical vehicle model. In this way, a deeper analysis can be done within each scenario, evaluating the interactions between the behavioural effects of real drivers and the vehicles.

8. Conclusions

Thanks to the progressive and worldwide diffusion of EVs in traffic, the need for accurate modelisation is required, e.g., better identifying critical aspects (to correct and adjust), enforcing weak points, and promoting strong points. Based on the different natures of the problem and, hence, on the results to be achieved, different approaches can be created to better fulfil the aim of the problem. Two parallel and alternative approaches (strategies) can be adopted to evaluate energy consumption, both starting from existing datasets. Vehicle model-driven approaches are more suitable to describe the vehicle dynamics and subsystems involved. The effects of each vehicular subsystem on the general performance can be evaluated, with the possibility of virtually testing different technical solutions and arrangements. The payback of implementing this approach involves the virtual prototype that can be created, considering the different technical specifications related to the vehicle under analysis. Moreover, the vehicle model-driven approach can be implemented into environmental simulations, to evaluate interactions with traffic and infrastructure. Conversely, the effects related to driving styles and behaviours of drivers cannot be adequately considered. These can be accounted for if a data-driven analysis approach is chosen. Thanks to the use of statistics and global optimization techniques, this approach makes it possible to extract patterns and analyse trends from big data, delivering results that can be exploited to evaluate different solutions. A third hybrid approach can be identified, merging the advantages of the vehicle model and data-driven analysis approaches to consider more complete analyses, with the drawback of computational heaviness. In this way, various scenarios can be set, starting from a broad dataset, and their effects evaluated through the numerical vehicle model, with the final results examined through techniques used in a data-driven analysis approach. Since the emergence of virtual reality, the wide use of simulation tools has spread, increasing the performances of virtual models, reducing testing costs, and refining virtual models, to be as close as possible to performances in the real world.

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List of Abbreviations

ANN	artificial neural network
BEV	battery electric vehicle
BVM	backward vehicle model
CPU	central processing unit
DA	data analysis
DDQN	double deep Q-learning network
DoE	design of experiments
EMS	energy management system
EREV	extended-range electric vehicle
EU	European Union
EV	electric vehicle
FCEV	fuel cell electric vehicle
FTP	federal test procedure
FVM	forward vehicle model
GA	genetic algorithm
GHG	greenhouse gases
GPU	graphics processing unit
HEV	hybrid electric vehicle
HVAC	heating, ventilating, air conditioning
HWFET	highway fuel economy test
ICE	internal combustion engine
LSLPP	large-scale learning and prediction process
LSR	least square reduction
LSSP	large-scale simulation process
MHEV	mild hybrid electric vehicle
mHEV	micro-hybrid electric vehicle
NEDC	new European driving cycle
NN	neural network
OBD	on-board diagnostics
PHEV	plug-in hybrid electric vehicle
PI	proportional integral
PEM	power-based electric vehicle model
PFM	power-based fuel-engine vehicle model
PPM	power-based plug-in hybrid vehicle model
PVM	power-based vehicle model
SOC	state of charge
STR	source-to-range
SWOT	strength, weaknesses, opportunities, threats
VM	vehicle model
VRP	vehicle routing problem
WLTP	worldwide-harmonised light-duty vehicle test procedure
WTW	well-to-wheel

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