Urban vehicle design system

Master degree in Automotive engineering

Academic year 2024-2025

Supervisors:

Andrea Tonoli

Candidate:

Michele Francesco Pantusa

307961

Index

1. Electrification main issues background

The transition to electrical mobility has conditioned the automotive industry, requiring it to develop electric vehicles in a matter of extremely short time and in an intensely competitive scenario. This urgency clashes with the technical and engineering complexity of the design phase in which every parameter, from the battery to the weight of the vehicle, must be fine-tuned with the highest degree of accuracy. The crucial aspect of the problem is the battery management, which, while being more efficient of the electric motor than internal combustion engines, possesses much lower energy density than fossil fuels. This means that battery packs must be much heavier and larger, which has a direct impact on the vehicle architecture, mass distribution and, consequently, its dynamic performance.

An unrealistically calibrated battery with such values as an outrageously high energy density can produce simulation solutions that are theoretically optimal but unreal for the real world. This problem accentuates the requirement for an optimal tuning phase, where each of the input parameters, from the capacity of batteries to aerodynamic coefficient, via initial mass of the vehicle, must be defined in accordance with real industry values and the technological characteristics of the target vehicle. Care should be taken that the value of the initial mass is chosen depending on the type of vehicle which is to be designed: a city car will require a far lower mass value than would be typical for an SUV or an oversized vehicle, and this choice will have a very significant effect on the force, acceleration, and energy use calculations.

Apart from the battery, the construction of other components, such as the power unit, wheels and chassis system, also largely relies on the physical specifications set at the beginning of the process. The laws of dynamics, that control aerodynamic force, rolling resistance and inertial forces, must be invoked correctly in a bid to precisely simulate the car's performance over a driving cycle. The validity of such models really rests on a realistic set of inputs: biased or unrealistically idealized values can cause the optimization to go astray, producing solutions that are unrepresentative of the true structural and performance constraints.

In a situation where it is possible to get a product to market within an incredibly short time, the use of advanced optimization techniques, such as genetic algorithms, is essential. These models can iterate quickly and solve problems at their optimum, but their performance relies directly on the quality of the original data. All the parameters must be fine-tuned in such a way that the simulation model is within a set of values close to the real world. Only in this way can one reach a final product that not only is theoretically efficient, but also usable and competitive in the market.

2. Objective

The goal of this endeavor is to develop a system that has the ability to test numerous components and configurations of the same vehicle or a single component rapidly and accurately, with attention to all the variables involved. The main challenge is to have to perform, in a very short time, the recalculation of the chained variations that are the consequence of each change, in order to evaluate and combine the impact on the various interrelated subsystems in order to define an optimized solution. This approach is attempting to overcome the limitations of traditional prototyping, which has been characterized by time-consuming and laborious processes, where each modification involves long times for the recalculation and verification by hand of the relations among the variables involved. To confront this complexity, we determined that a genetic algorithm would be used, an optimization technique inspired by the natural process of evolution. This strategy enables the effective treatment of the different concatenated criteria, iteratively building a population of possible solutions and evolving them towards configurations that simultaneously satisfy the different requirements involved. The system, thanks to the ability of the genetic engine to explore huge solution spaces in very little time, will be able to perform recalculations in real time, propagating automatically and dynamically the changes in the subsystems and thus ensuring a global and coherent evaluation of the optimized solution.

The utilization of such an approach allows the time needed for prototyping to be significantly reduced, with the potential for testing various technological and design scenarios in a very short time. The genetic algorithm, in fact, allows the system to test various configurations virtually in parallel, resulting in an optimization process that determines the best compromise between performance, efficiency and compliance with the technical constraints imposed. The ability to include the recalculation of the concatenated variations is the novel kernel of such an approach as any change applied to a component instantly influences the entire system, fostering a global perception of the behavior of the vehicle.

3. Urban mobility vehicles

In the modern automotive industry one of the main obstacles is represented by the necessity of fast prototyping combined with the complexity of the calculus involved during the design process. Modifying many components in short periods of time it is a dispendious process that require an high number of resources. This contest is stressed when designing M0 urban cars or Kei cars, with compact dimension and specific normative restrictions lend much less maneuver space during design phase with a significant increase in terms of time.

The catch is to find an efficient methos to test and optimize components as the electric motor or the battery in an already defined vehicle (or not) without incur ins different in long designing phases and prototyping. The application of a genetic algorithm will offer powerful solution to solve the problem.

The genetic algorithm, inspired to natural evolution principles, will allow to rapidly explore an high amount of solution. They emulate evolutive processes through selection, crossover and mutation on a population of solutions. This approach grant to optimize simultaneously different interlinked subsystems taking in account the interdependencies defined by the theory of the secondary masses effect. By this theory the changes applied to one component will influence consecutively the other requiring an holistic approach to the design process.

Implementing a genetic algorithm, it is possible to reduce significantly the time and the effort needed to test different configurations of motor, battery or other components. This allows to accelerate the developing process but also the efficiency of the vehicle individuating optima solutions that could not emerge from traditional methods.

3.1 Definition

The designing and optimization of ultracompact vehicles are crucial aspects for automotive industry. Theese vehicles, ideated to going through the challenges of the urban mobility like traffic management and pollution, must respect specific restrictions in terms of dimensions and normatives. There are three relevant categories around the world , L7e heavy quadricycles in Europe, Kei car in Japan and A1 class in China. A clear comprehension of their characteristics, dimensions and respecting rules is fundamental to develop genetic algorithms able to rapidly prototype and optimal dimensioning of the components like electric motor or battery. [7] [8] [9] [11] [18] [19]

3.2 Heavy quadricycles L7e, Europe

Figure 1, Renault Twizy [14]

Heavy quadricycles classified in L7e category by European normative represent an intermediate solution between motorcycles and traditional cars, ideal for urban and extra-urban mobility [7] [8] [9] [11] [18] [19]

Main specifications:

Curb weight

- Weight for people transportation less than 450kg
- Weight for commercial transportation less than 600kg
- Theese regulated weights do not include the battery

Maximum power

- Pmax less than 15kW

Typical dimensions

- Length: 2,5m-3,7m
- Width: 1,5m
- Height: 1,4m-1,8m

Requirements and rules

- Homologation must follow EU regulation n. 168/2013, which indicates safety, environmental and productivity conformity requirements.

3.3 Kei car, Japan

Figure 2, Daihatsu Mini EV [15]

Kei cars (軽自動車) are a vehicle category typical and exclusive of Japan, created to promote efficient vehicle, low cost and agile on jammed urban roads. Moreover must be taken in account that BEV kei cars also compete with ICE cars as both motorizations falls under the same category. [7] [8] [9] [11] [18] [19]

Main specifications:

Maximum dimensions:

- Length: less than 3,40m
- Width: less than 1,48m
- Height: less than 2,00m

Engine

- Engine dimensions: less than 660 cm^3
- Maximum Power: 47 kW (64CV)

Requirements and Rules

- Tax and insurance cost reduction

- In some areas it is not required the proof of parking spot ownership (that is mandatory everywhere of the other cars)

3.4 A00 class, China

Figure 3, Keyton A00 [16]

In China class A00 identifies microcar or compact city cars, deigned to satisfy mobility needs in large Chinese cities. [7] [8] [9] [11] [18] [19]

Maximum dimensions:

- Length: 3,00m-3,50m
- Width: less than 1,50m
- Height: less than 1,50m

Engine

- Prevalently electric in order to follow government indications
- Limited power, in order to push optimization research

Requirements and Rules

- Government incentives subsidies for the purchase of electric vehicles and tax reduction
- License Plates and Registration, simplified registration procedures in cities with vehicle restrictions.
- Emissions Regulations, stringent standards to combat air pollution in urban areas.

3.5 Advantages

The category of ultracompact vehicles offer a series of significant advantages that make them particularly adapt to nowadays urban mobility. These vehicles are designed to answer effectively to modern cities challenges, characterized by street congestion, limited spaces and growing environmental worry.

One of the main advantages is the energetic efficiency. Thank to reduced dimensions and weight these vehicles have a better consumptions statistic with respect to traditional vehicles. Lighter vehicles will require less energy to move, which translates in a smaller energy consumption.

The environmental sustainability is strictly linked with energetic efficiency. Compact vehicles will always produce less pollutant emissions, which has a positive effect on air quality in urban areas air quality. The reduction of CO_2 and other pollutants contributes to climate change effects mitigation and improving public health.

The traffic congestion reduction is another crucial advantage. Compact dimensions allows to these vehicles to occupy less space on roads, easing traffic flux and making more agile the driving experience in more densely populated areas. The possibility to

use narrower lanes and parking in reduced spaces will ease the pressure on urban infrastructures, improving the overall transport sector efficiency.
From the economical point of view, maintenance costs of the category are generally smaller. Buying price tend to be lower, making them more accessible to a wider slice of population. Operative, maintenance, energy and insurance are generally smaller with respect to bigger vehicles.
Maneuverability is an ulterior strong point. Reduced weight and dimensions make this category extremely agile in urban traffic. These vehicles are able of smaller turning radius, this helps when parking and driving. This agility will reduce time and stress during urban travels.
These vehicles are also aligned with urban policies oriented to sustainability and to quality of life. Most of cities promote the use of ecological vehicles via bonuses, granting limited traffic area access and reduces parking fees.
Technological innovation is moreover pushed by the challenges that this category building and designing restriction are imposing. [10] [17] [20] [21] [32]

3.6 Market share

From OEM's economical point of view it is remarkable how microcar market is going to grow in upcoming years. This significant attention delivered to the category is crucial to understand the level of competition that will be present in the near future. Competition always means high levels of attention and speed in design and strategic processes. Individuating a winning factor or a predominant rapidity could means a strong leading of the vehicle sector. Moreover it is appreciable how the European and Asian markets will be the most relevant for microcar category. [10] [17] [20] [21] [32]

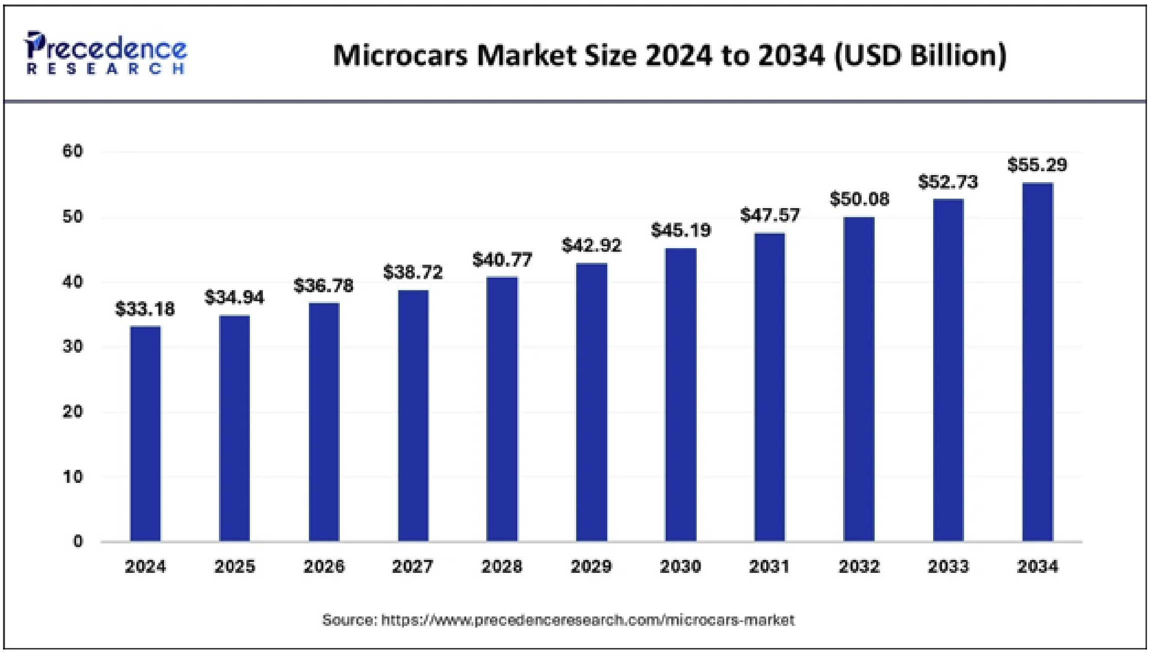

Figure 4, Microcar market, Precedence Research

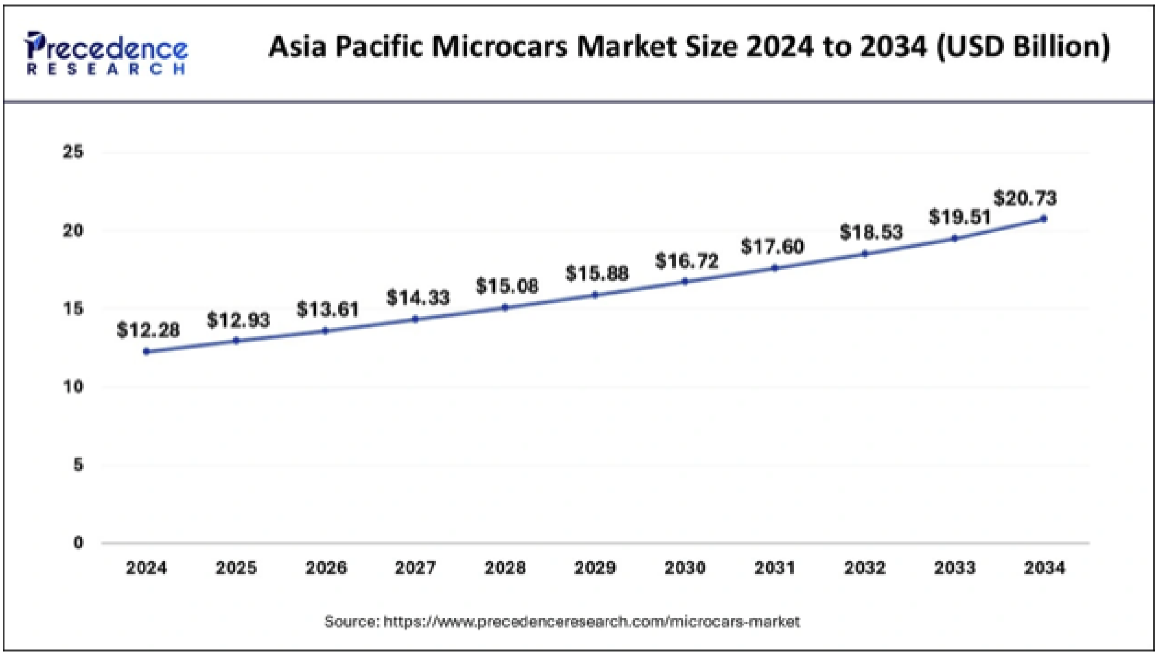

Figure 5, Asia Pacific microcar market growth prevision, Precedence Research

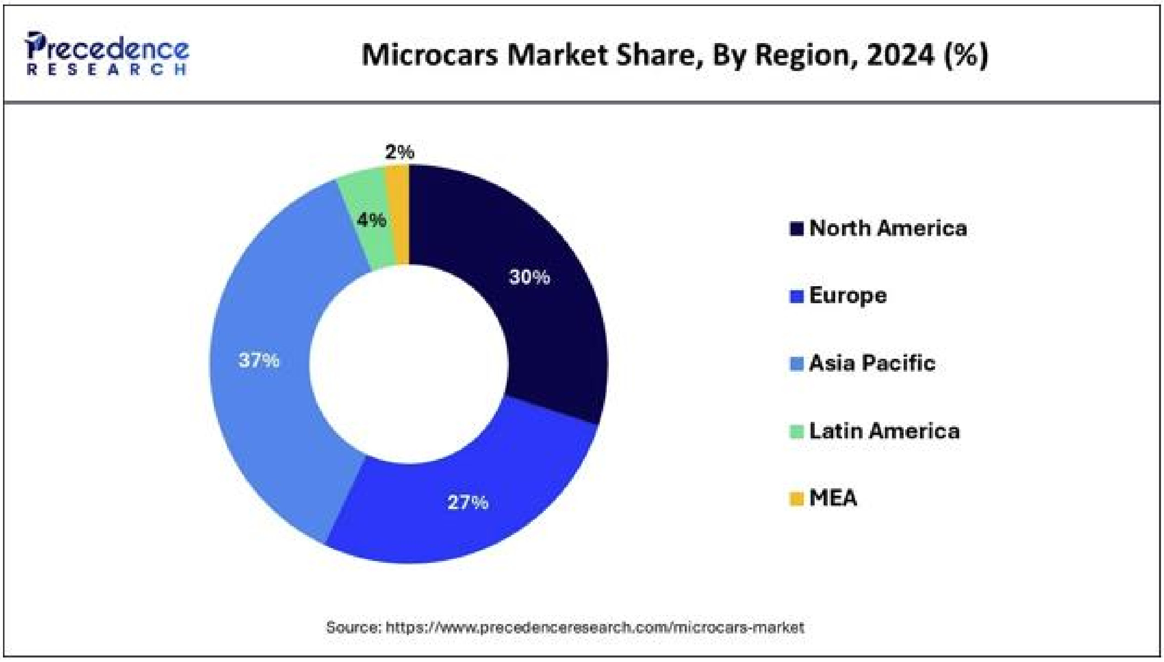

Figure 6, Microcar regional market share, Precedence Research

4. Report on urban vehicles and features analysis

A proper way to study this vehicle category is to analyze its market segment in order to understand each economic zone which chrematistics predominates.

More precisely several car models for each economic zone have been collected: EU, China and Japan. Once the data has been collected they have been confronted the three markets to visualize the differences and find the key features.

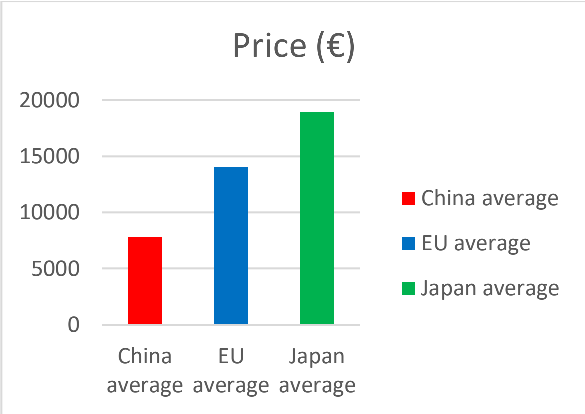

Figure 7, Microcar average regional price

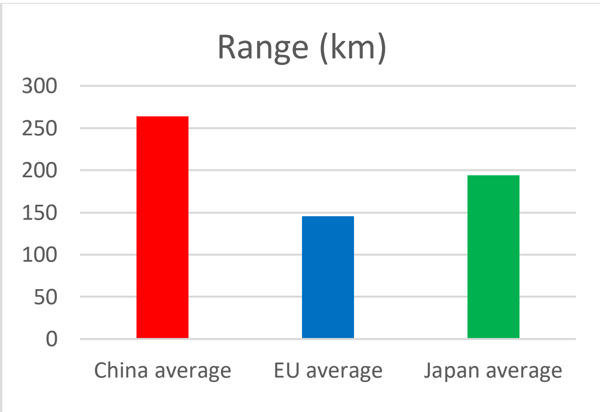

Figure 8, Microcar average regional range

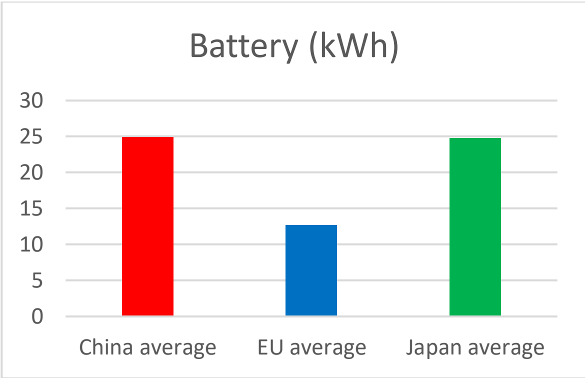

Figure 9, Microcar average regional battery

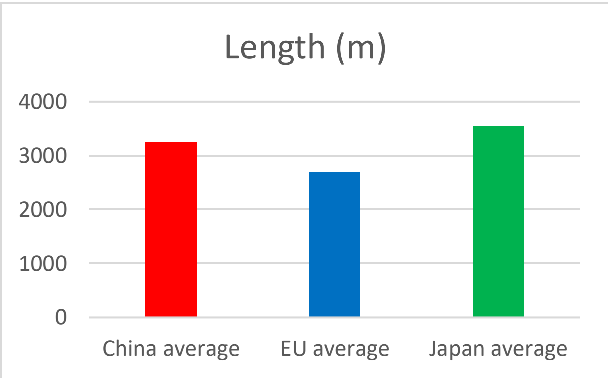

Figure 10, Microcar average regional length

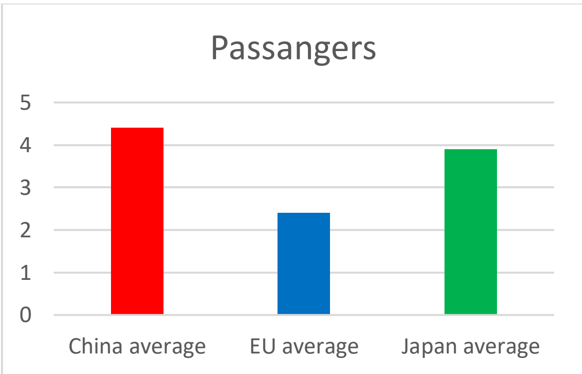

Figure 11, Microcar average regional number of passengers

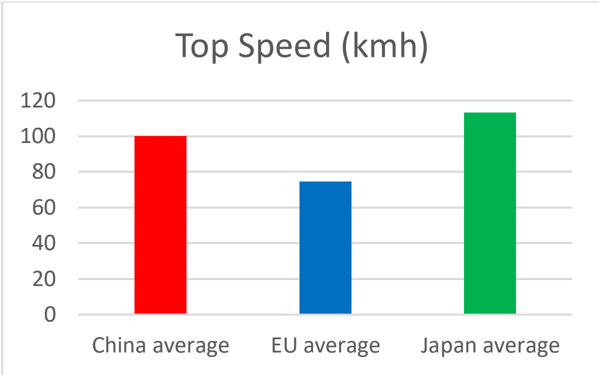

Figure 12, Microcar average regional top speed

From very first set of graphs it is clear how the Chinese seems the most competitive in terms of price and declare range. But to better understand which area of develop has not been yet paved these results have been expressed in population of points to recreate areas, in order to find blank spaces to insert the developing vehicle and so individuating its killer feature.

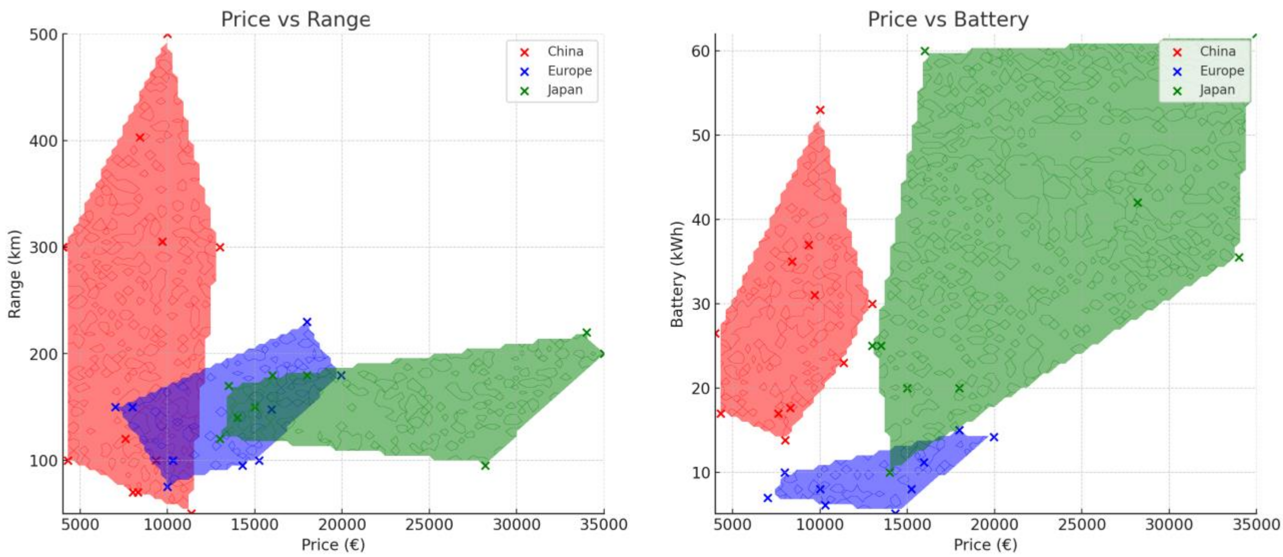

Figure 13, price-range confrontation (on the left), price- battery confrontation (on the right)

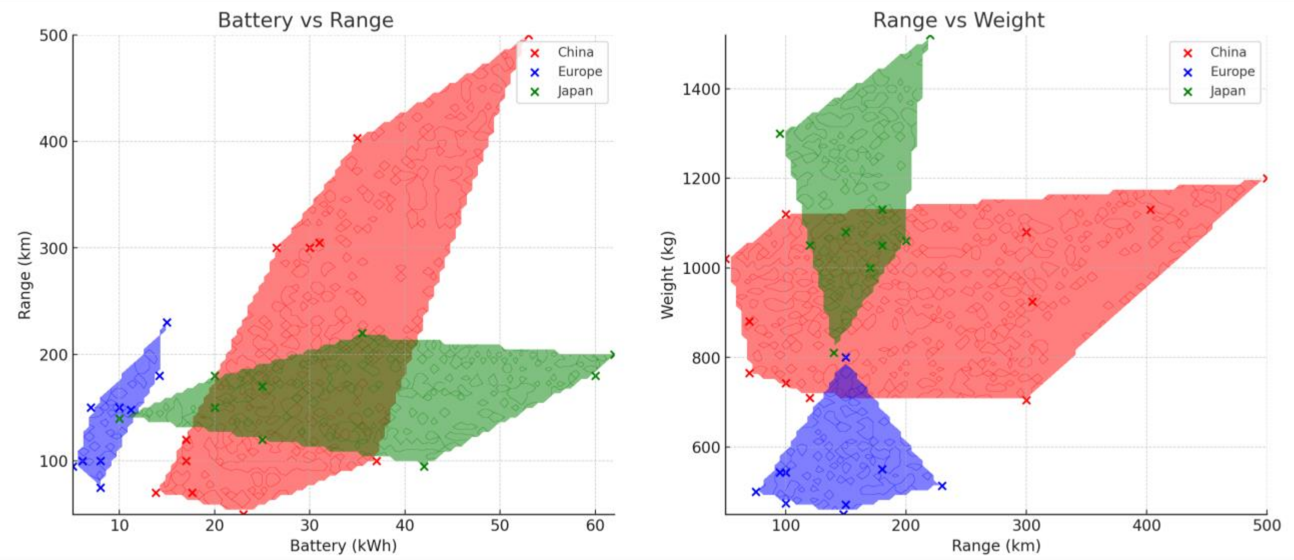

Figure 14, battery- range confrontation (on the left), range-weight confrontation (on the right)

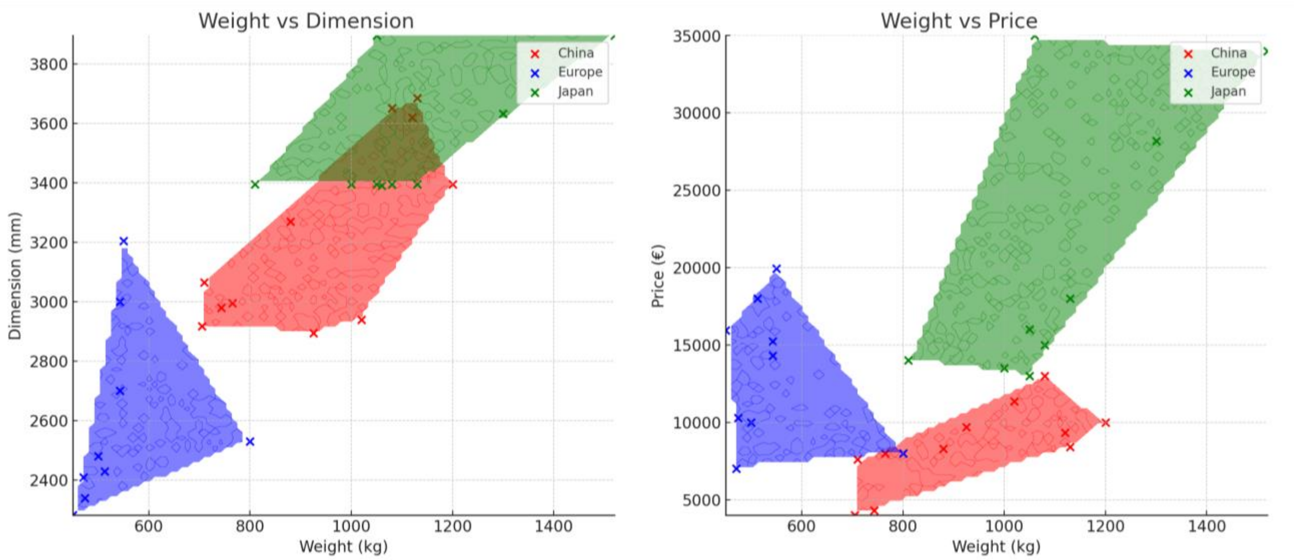

Figure 15, weight-dimension confrontation (on the left), weight-price confrontation (on the right)

Less populated areas will be the most successful for development.

Anyway it is also important to consider safety regulations for each country, passive safety will directly affect the total weight of a vehicle. It is easy to think about the chassis weight, improving passive safety could mean increasing its total weight.

China CNCAP:

- Active Safety:

- Advanced Driver Assistance Systems (ADAS): Includes automatic emergency braking (AEB), lane detection, blind spot warning, and vulnerable road user (VRU) detection.
- Driver Monitoring Systems (DMS): Monitors driver attentiveness and fatigue.
- Road Feature Recognition (RFR): Recognizes road signs and features to assist in safe driving.

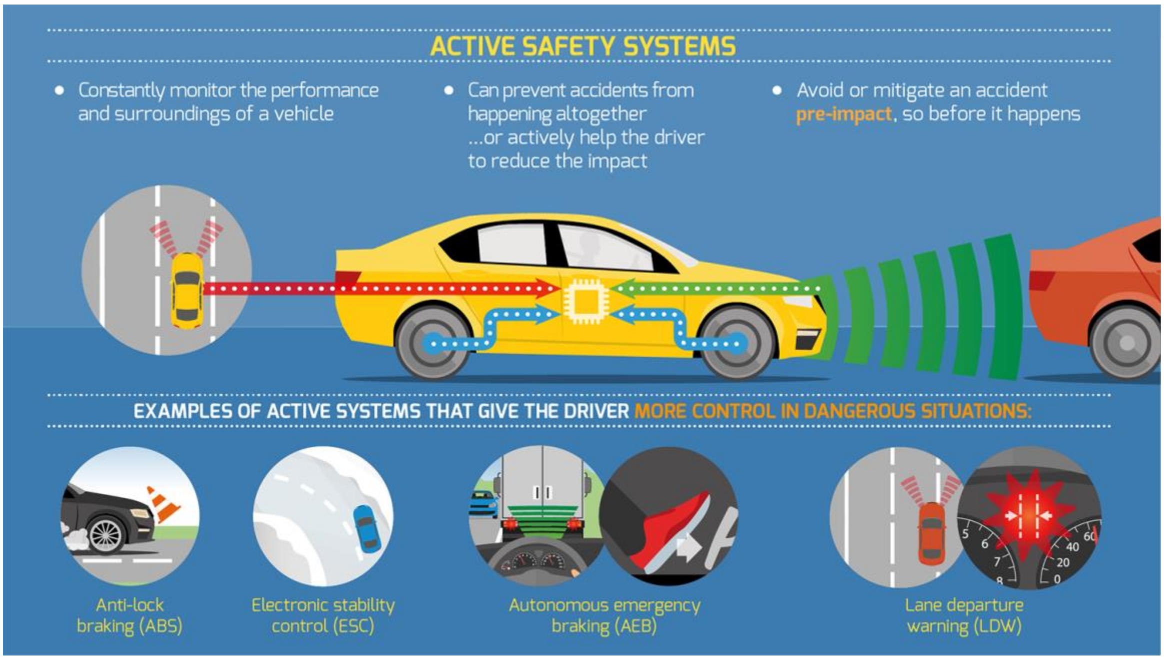

Figure 16, main ADAS systems

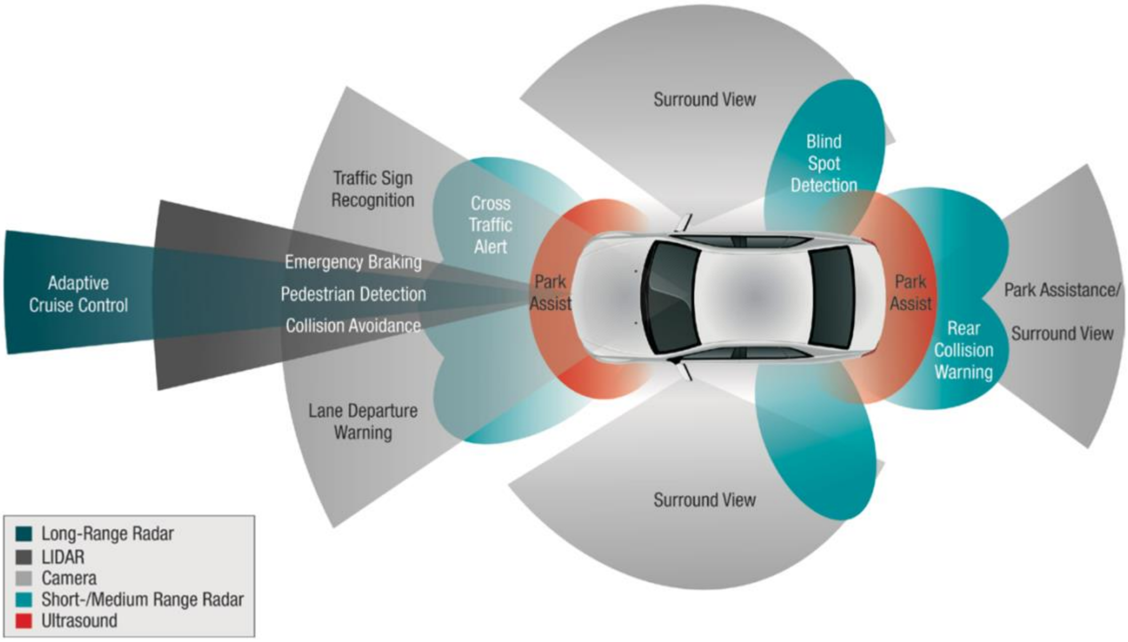

Figure 17, main ADAS systems sensors

- Passive Safety:
    - Frontal Impact Test: Evaluates the vehicle's ability to protect occupants in a head-on collision.
    - Side Impact Test: Assesses protection in the event of a side collision.
    - Pole Side Impact Test: Measures the vehicle's safety when it hits a pole or tree.
    - Whiplash Test: Tests the effectiveness of head restraints in preventing neck injuries during rear-end collisions.

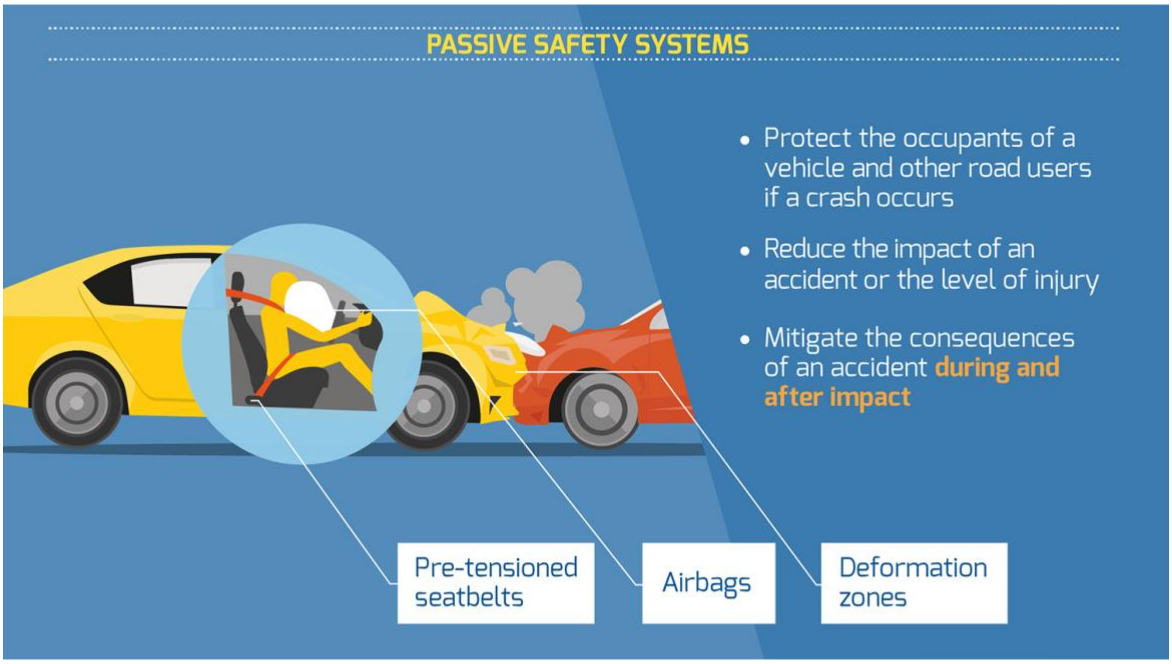

Figure 18, passive safety

European ENCAP and Japanese JNCAP:

- Active Safety:
  - Advanced Driver Assistance Systems (ADAS):
  - Automatic Emergency Braking (AEB): Detects potential collisions and applies brakes automatically.
  - Lane Departure Warning (LDW): Alerts the driver if the vehicle unintentionally drifts out of its lane.
  - Blind Spot Monitoring (BSM): Warns the driver of vehicles in the blind spot.
  - Pedestrian Detection: Identifies pedestrians and activates AEB if necessary.
  - Driver Monitoring Systems (DMS):
  - Monitors driver attentiveness and fatigue levels.

  - Road Feature Recognition (RFR):
  - Recognizes road signs and features to assist in safe driving.
  -

- Passive Safety:
  - Frontal Impact Test
  - Side Impact Test
  - Pole Side Impact Test
  - Whiplash Test

4.1 Developing points

Determination on which components OEM must focus resources and time is very important. Price, maximum range, internal volumes and safety are the most important areas of develop and they all must combine to obtain a winning product. Moreover Japanese OEMs must consider a motorization internal competition because a great part of kei cars mount a traditional internal combustion engine, this means that those specific vehicle, despite being less ecologically efficient, are going to be lighter, better internal volume efficient and wider operativity range. In general the main disputed characteristics are price, range and dimensions.

The article “Electric vehicles’ consumer behaviours: Mapping the field and providing a research agenda” gives a complete view on EV consumer preferences, combining bibliometric and thematic analysis. The study aims to identify main influencing factors the buying choice, as the price awareness, environment attention and individual perceptions. Gives spotlight to the role of policies and technological evolution in promoting the adoption of EVs. Moreover, defines the EVs consumer profile, underlining the attraction for new technologies and the sensibility to new environmental thematics. This article has been used to understand which factor are crucial for a new vehicle development and why they are so important. [10] [17] [20] [21] [32]

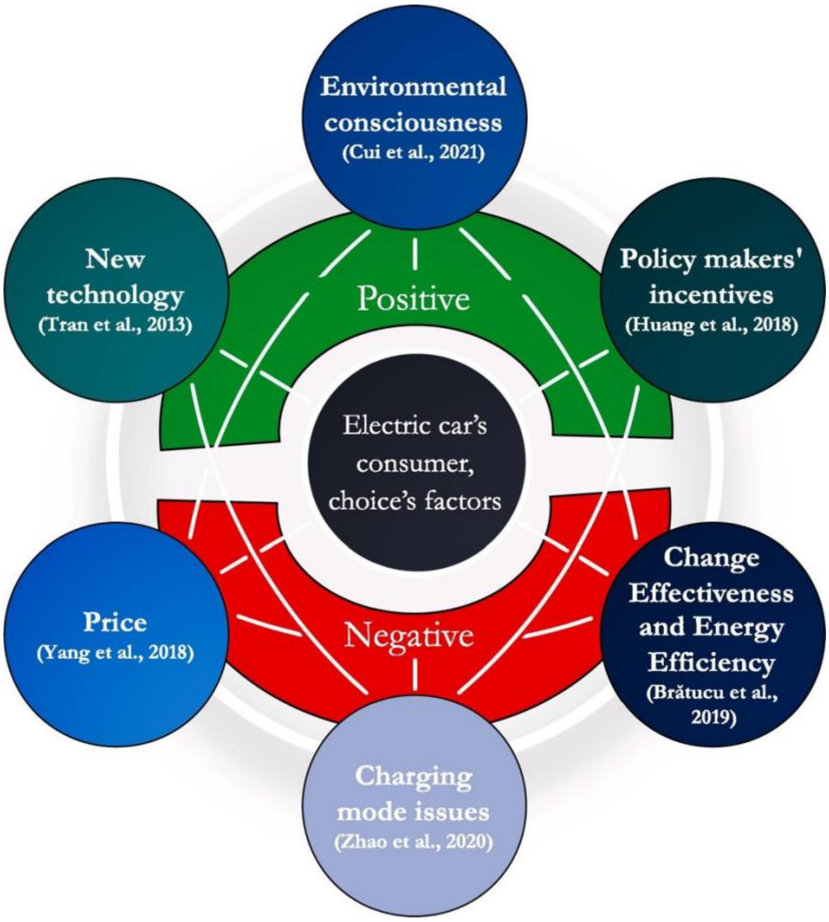

Figure 19, buyers perception of EV cars characteristics from article: Electric vehicles' consumer behaviours: Mapping the field and providing a research agenda

5. Study case

Recharge time is a crucial aspect for consumers, being able to recharge the car in short times could be a leading features in the market. A fast charge could also provide a solution for short maximum range due to small battery, indeed a small battery can lower the price and the dimension. To conjugate a reduced battery dimension with a useful range a swappable battery is the solution. Light and easy handling battery can shorten recharge times down to standard refueling ones. But finding a good compromise between battery capacity and other vehicle dimension could be a problem, a small change in battery capacity could significantly lower the resulting range. On the other hand a way to big battery could be impossible to be handled for swapping procedures. [22]

Figure 20, swappable battery concept by Gogoro [22]

Developing a car must follow several procedures requiring a huge amount of time and resources. It is possible to subdivide a car in 5 subsystems: Chassis, Battery, Power unit, Tires and internal volumes. Each of these subsystems is regulated by physical and dimensional relations, but most of these equations shares some physical quantities which means that every macro component cluster is interconnected. It happens to apply changes or upgrades to the components, even if small, this will generate cascade changes to all other components. For this reason, a rapid and automatic system will be extremely useful while designing. Algorithms are always a smart pick for these cases, after consistent research for an already existent solution the thesis evolved its scope from designing the vehicle itself to developing a genetic algorithm suitable for the rapid prototyping purpose.

6. Design methodology approach

During the development of a vehicle or one of its components several modification may be required, but being every component interconnected to others, one change can modify starting conditions for every components requiring new consequential modifications. This procedure it is time consuming and can lead to miscalculations. In these cases it possible to use a the theory of second masses for changes estimation. The theory only is not enough to reduce the computing time, it is a path that a powerful tool, such as the genetic algorithm, can use in order to facilitate development. [12] [13] [27] [28] [29]

6.1 Second masses theory

During the development phase when occurs a variation of primary mass (Δ) in a component the vehicle will not be anymore in equilibrium because subsystems are dimensioned for an initial value of mass M_0. The re-dimensioning of these subsystems to adapt to the new mass (M_0 + Δ) will produce further variations in mass, called secondary mass variations. Secondary masses can be divided in two modality:

- Simple secondary masses change: just one re-dimensioning cycle is considered
- Computed secondary mass change: an hypothetic iterative infinite cycle is considered, in which the secondary total variation converges to a bigger share of results

Usually a mass influence coefficient ($γ_i$) and a total vehicle coefficient (γ_V) are introduced, respectively, each subsystem singular contribution and sum of every subsystem contribution.

Base mathematical approximated solution

1. Total scaled mass (M^{Rs}):

The total mass of the vehicle after the scaling of the subsystems is given by:

$$M^{\mathrm{Rs}} = M^0 + \varDelta + (\varDelta\varGamma)$$

where:

- M_0 = initial mass (for which the subsystems are sized)
- Δ = primary mass variation (positive for increase, negative for reduction)
- $\Delta\ \Gamma$ = total secondary variation (depending on the coefficient Γ)

2. Secondary mass coefficient – Simple (Γ^s):

   Considering a single scaling cycle we have:

$$\Gamma^{\mathrm{s}} = \frac{\Delta_{secondary}}{\Delta}$$

   This coefficient indicates the ratio between the secondary mass variation (obtained after a single iteration) and the primary variation.

3. Secondary mass coefficient – Compounded (Γ^c):

   If the iterative process (compounding) is considered until convergence, the overall coefficient becomes:

$$\Gamma^{\mathrm{c}} = \frac{\Gamma^{s}}{1-\Gamma^{s}}$$

   (Valid if Γ^s is less than 1)

4. Vehicle influence coefficient (γ_V):

   It is the sum of the influence coefficients of the individual subsystems:

$$\gamma_V = \Sigma_{\mathrm{i}}\, \gamma_{\mathrm{i}}$$

   where γ_i represents the change (in kg) of subsystem i for every 1 kg change of the vehicle.

5. Mass change for subsystem i:

   The new weight of the subsystem, after scaling, is:

$$m_{\mathrm{i}}^{\mathrm{Rs}} = m_{\mathrm{i}}^{0} + \Delta\tau_{\mathrm{i}}$$

   where:

   - m_{i0} = initial mass of subsystem i
   - $\Delta\tau_i$ = secondary (additional) change for subsystem i

6. Influence coefficient for subsystem i – Simple:

$$\gamma_{\tau,\,\mathrm{i}} = \frac{\Delta\tau_{\mathrm{i}}}{m_{\mathrm{i}}{}^{0}}$$

Indicates how much the mass of the subsystem changes in percentage in a single scaling.

7. Influence coefficient for subsystem i – Compounded:

$$\gamma_{\tau,\,\mathrm{i}} = \frac{\frac{\Delta\tau_{\mathrm{i}}}{m_{\mathrm{i}}{}^{0}}}{1 - \left(\frac{\Delta\tau_{\mathrm{i}}}{m_{\mathrm{i}}{}^{0}}\right)}$$

This gives the coefficient when considering the infinite iterative (compounded) effect.

6.3 State of art

The first objective of the thesis was to use an already existing system to rapidly design and test components, however a system specifically developed for this purpose was not already implemented. Still, it is important to understand the work done by Lorenzo Nicoletti and Paul König both Phd at Technische Universität München. They worked on an efficient system to develop battery electric vehicles (BEV) that could support engineers during design phases. The research from the constatation that BEVs, having an higher powertrain efficiency with respect to ICEVs, they have lower energy density of their energy reservoir (fuel tank for ICEV and battery for BEV), this explain the inconvenient battery dimensions and weight. This complicate the battery integration in the vehicle directly affecting the maximum range. Their thesis aims to fill the gap building a tool able to model architecture of the vehicle taking in account the secondary effects of volume and mass. These aspects, generally ignored during the first phases of development, could have a significant impact on vehicle final weight and range. This tool identify potential conflicts and weaknesses in the first stages of BEV developing. [23]

In the state of the art, the thesis investigates the most important features of BEV architectures, i.e., different electric machine topologies (central or near-the-wheel) and battery integration principles (highfloor, mixedfloor and lowfloor). Highfloor and mixedfloor principles are emphasized for purpose-design vehicles.

The chosen tool in the vehicle architecture tool category is empirical and semi-physical models due to their ability to process few inputs, typically accessible in concept design phase. Empirical models are perfected in a database. The powertrain component requirements are what longitudinal dynamic simulation (LDS) translate into using the inputs in the tool.

A significant contribution of the thesis is the volumetric and gravimetric simulation of the elements. The mass model considers the different modules of the vehicle (chassis, body, exterior, interior, powertrain, etc.) and uses linear regressions or static values in order to represent the mass of single components. The volumetric simulation is based on dimensional chains to estimate installation space for main components, for example, the battery.

The verification and validation of the tool were performed by comparing simulation results with data from existing BEV vehicles. Validation determined a high accuracy of the tool with deviations for non-traditional vehicles such as BMW i3s. Deviations are attributed to the use of lightweight material (carbon fiber) not fully covered under the model.

Finally, the thesis uses the tool to quantify the impacts of different electrification schemes on future BEV designs. Notably, most importantly, the impacts of using different types of cells (pouch and cylindrical) and the possibilities of a new battery integration concept called Cell to Body (C2B) are evaluated. The results are that the C2B concept would make the vehicle autonomy be able to be increased quite considerably without affecting mass and consumption negatively. The optimization also helps to further support the potential of the C2B principle, achieving maximum independence and minimum battery energies for all three reference vehicles.

The thesis discovers that the developed tool can indeed support BEV design in the conceptual phase appropriately so that proper decisions on vehicle architecture and electrification strategy could be made by the designers. The limitations of the tool stem mainly from the use of empirical models that are not suitable for vehicles with substantially different characteristics compared to those vehicles used to calibrate the models.

The paper introduces a design system for battery electric vehicle (BEV) architecture that considers multiple parameters such as drivetrain topology, car components and dimension concept, with special attention paid to secondary mass and volume effects. The system, programmed on MATLAB, addresses the problem of data obsolescence through an open and updateable model architecture. It functions by means of several key steps:

1. Input initialization: important design parameters like top speed, desired range and acceleration time are established, maintaining inputs low enough to be utilized at the concept design stage.
2. Component database: car components are defined within empirical models, which are outputs of a benchmark analysis and grouped in a centralized database governed via SQL.
3. Longitudinal Dynamic Simulation (LDS): solves vehicle dynamics issues to create more design parameters such as required power and battery power through a quasi-static approach of reduced computational burden. LDS is aware of performance, calculated vehicle loss, and topologic requirements.
4. Dimension volumes and mass estimating of the component based on empiric models derived from database-based information.

Feasible architecture output: following convergence, the resulting vehicle architecture can be viewed and analyzed, with outputs including LDS results (power, torque, speed, consumption, range, battery energy) and interior concept (headroom, legroom, passenger compartment dimensions).

One of the important features is the automatic updating of empirical models within the SQL database. When data is added, a MATLAB script reads the data and updates the linear regressions and constant values, thus addressing data staleness and improving the accuracy of the tool. [24] [25]

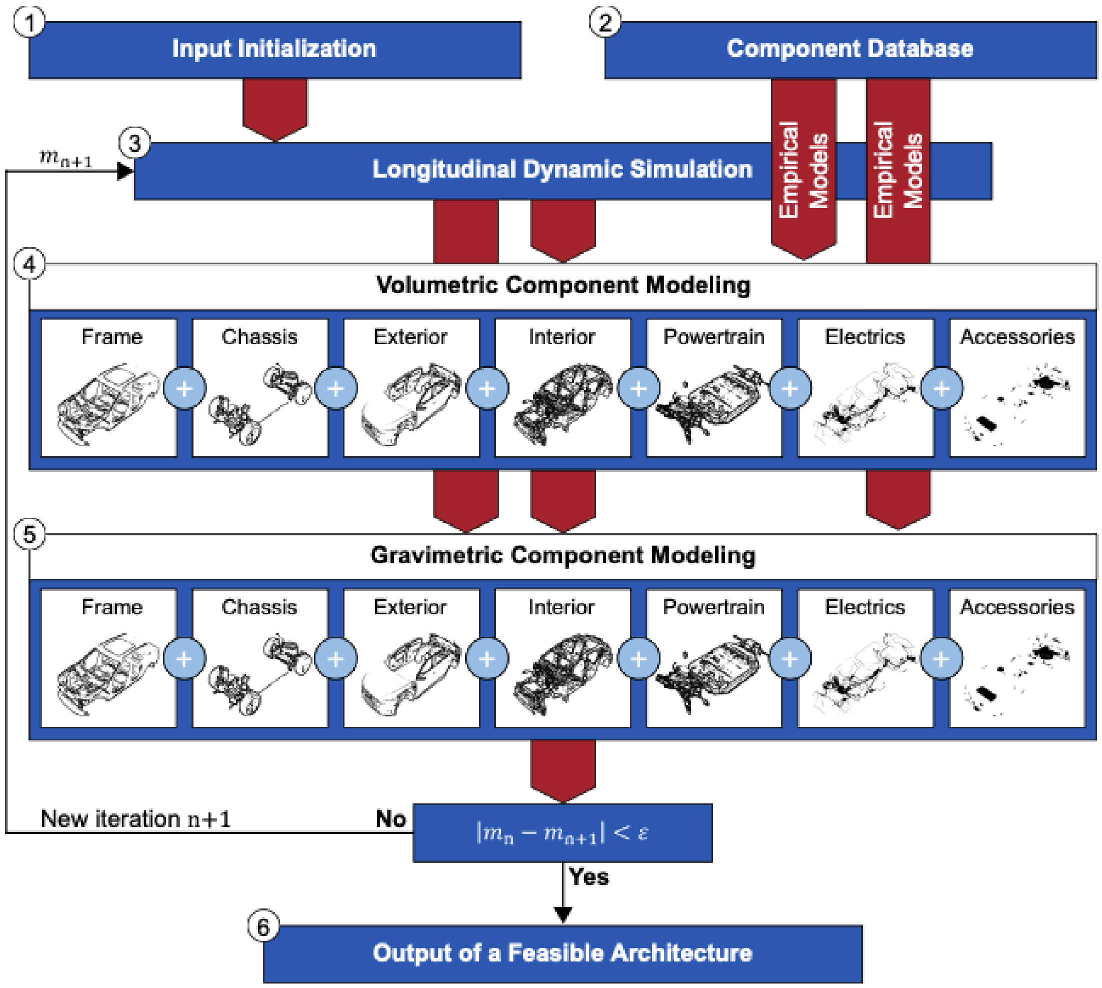

Figure 21, Nicoletti thesis tool structure [24] [25]

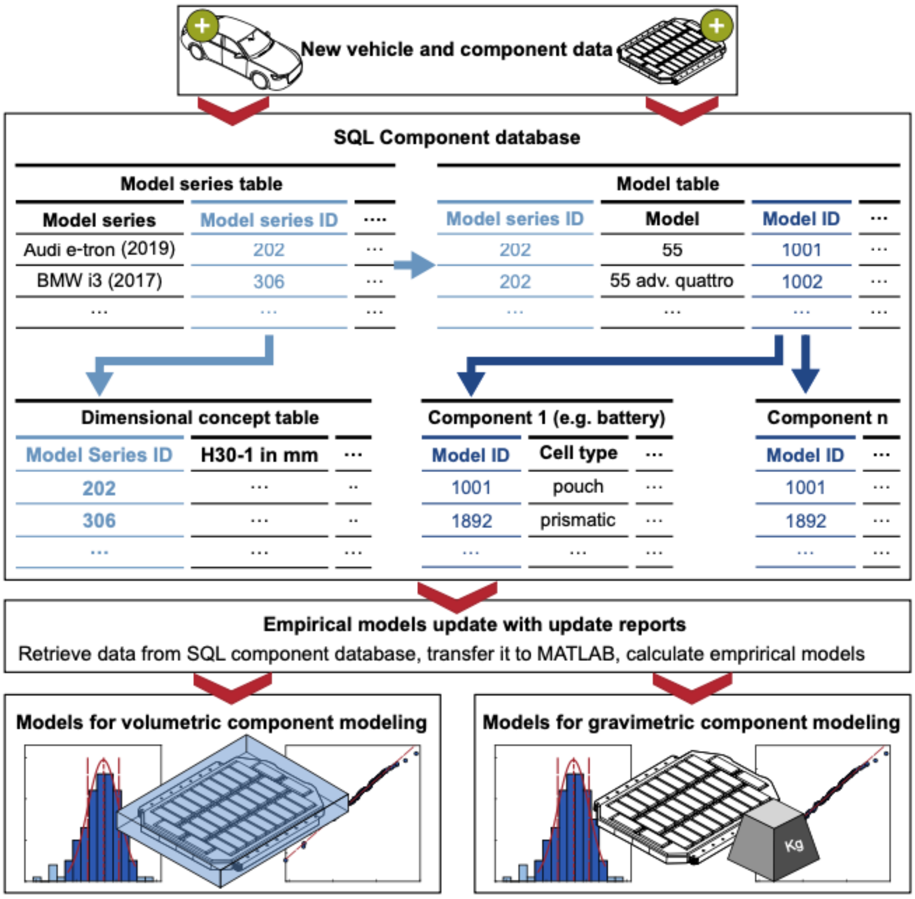

Figure 22, Nicoletti thesis SQL database working principle for the developed model [24] [25]

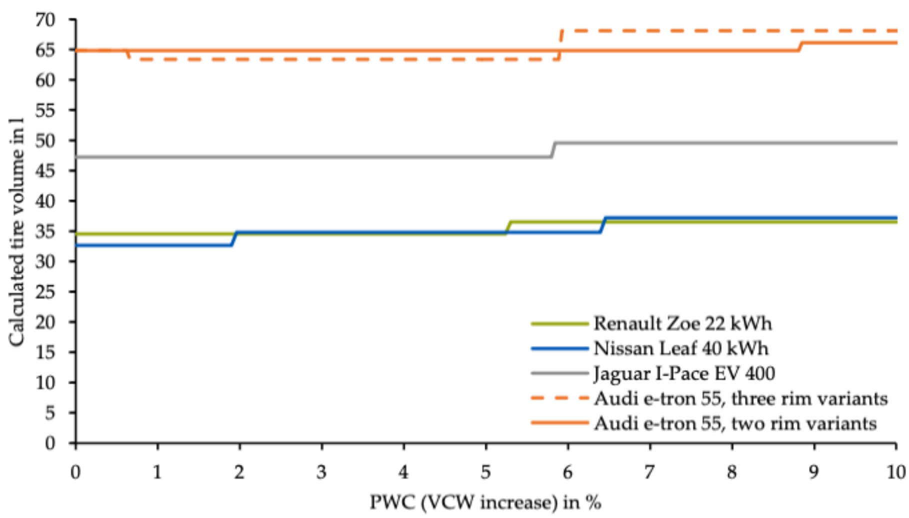

Figure 23, Interdependency between secondary volume change (SVC) of the wheel and the primary

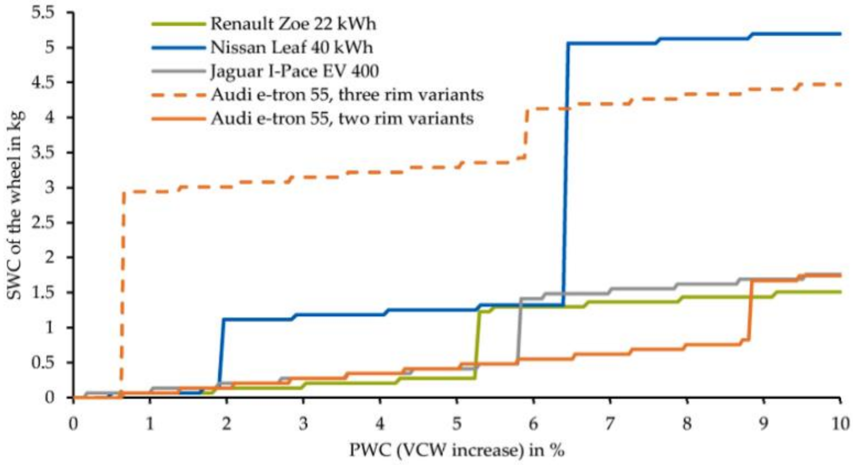

Figure 24, Interdependency between SWC (secondary weight change) of the wheel and PWC (primary weight change).

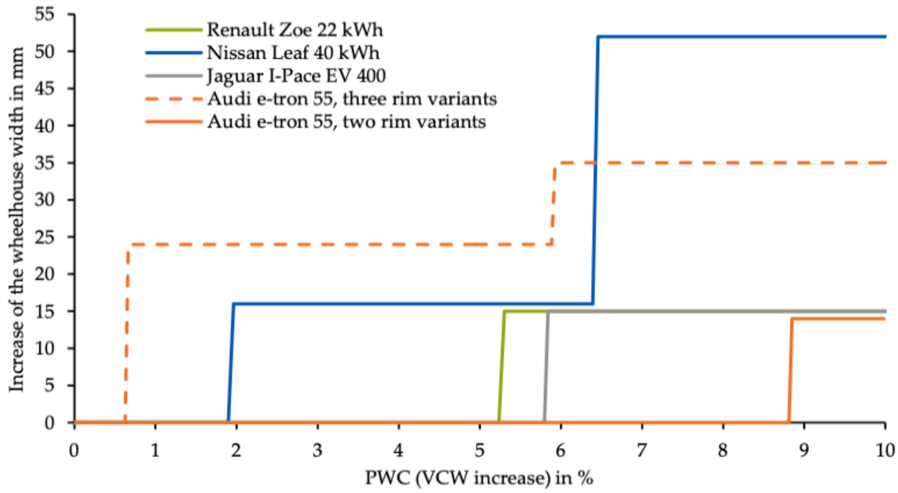

Figure 25, Interdependency between wheelhouse width and PWC (primary weight change).

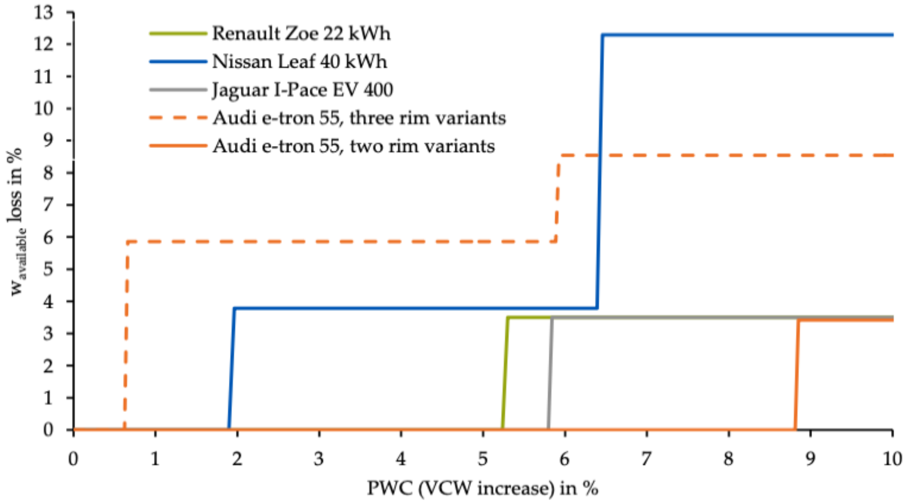

Figure 26, Interdependency between the SVC (secondary volume change) at vehicle front end and the PWC (primary weight change).

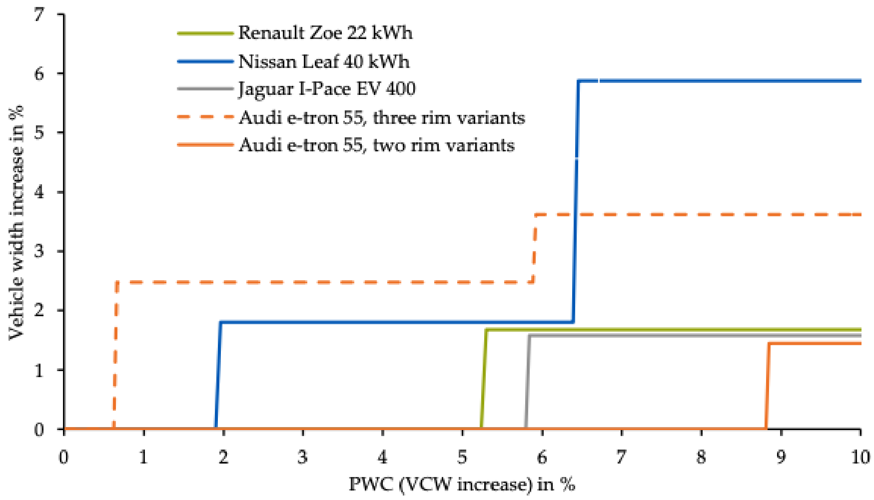

Figure 27, Interdependency between the vehicle width and the PWC (primary weight change).

The proposed model will borrow ideas from what was done by Nicoletti, some of the fundamentals such as the simulation of the gravimetric and volumetric characteristics of the components staying the same. Instead of using databases to estimate and calibrate the empirical models, a genetic algorithm approach will be used. [24] [25]

This means that the system will be able to rapidly traverse the space of possible solutions, dynamically and in real time optimize the selection and placement of the components, and dynamically and in real time optimize the choice. The check parameters and boundaries will be optimized "on the fly" depending on the specific needs of the project, thus facilitating fast and efficient prototyping. [24] [25]

Shorty, employing the fundamental principles of the Nicoletti system, implementation of a genetic algorithm eliminates the static database need and has greater flexibility and speed in examining and regulating the components of the conceptual phase. [24] [25]

6.3 Genetic Algorithm

Genetic algorithms are an optimization paradigm based on the natural process of evolution, trying to replicate selection, reproduction and mutation that, in nature, allow species to evolve slowly to better adapt to their surroundings. In the real world, instead of directly looking for the best solution, we start with a population of randomly generated solutions and, through successive iterations, each solution "evolves" as a result of natural selection, crossover and mutation. The basic idea is that, although each single mutation or recombination is random, the process as a whole will favor the combinations that are most capable of solving the problem, continually improving the quality of the solutions. [1] [2] [3] [4] [5] [6] [26] [27] [28]

The theoretical underpinnings for this approach are found in Darwin's concepts, which first appreciated that the battle for existence aided the most desirable variations, but it was not until John Henry Holland, in the 1970s, turned Darwin's principles into the vocabulary of computing that a population of solutions could be demonstrated, if correctly examined using a fitness function, to develop in a manner akin to a naturally occurring species. Holland also introduced important concepts such as patterns, which demonstrate how certain substructures of chromosomes are capable of repeating and mixing in such a way that, though created randomly, lead to a systematic improvement of the solutions. [1] [2] [3] [4] [5] [6] [26] [27] [28]

Genetic algorithms mechanism of operation is interesting because, during a cycle in iterations, the best solutions have greater chances of replicating themselves and transferring the most advantageous traits to the "offspring.". During the crossover process, the genetic information of the parents is merged to create new combinations that can be better than the previous solutions, and mutations introduce a degree of randomness that guarantees new regions of the search space are visited, thus preventing the algorithm from getting stuck in a local minimum. This evolutionary process, in a way analogous to collective learning, allows us to solve difficult problems, even when the objective function is nonlinear or discontinuous, where the traditional method of derivatives or gradients fails. [1] [2] [3] [4] [5] [6] [26] [27] [28]

Within the model of your MATLAB, the system will be dependent on that drawn in Nicoletti's project, but instead using an avenue where information processing is through mere evolution of the chromosomes, without the need for maintaining a stationary database of members. This means that, instead of relying on preconceived and manually updated empirical models, the system will utilize the strength of genetic algorithms to search and optimize the solution space autonomously and dynamically. This feature not only facilitates rapid prototyping, but also allows for real-time adjustment of parameters based on design needs, facilitating an adaptable and responsive system that changes as the problem changes. [1] [2] [3] [4] [5] [6] [26] [27] [28]

In effect, genetic algorithms are an extremely adaptable and evolutionary methodology, capable of incorporating Darwin's principle of natural selection into a computational process that, through successive improvement, leads to optimal solution finding, with the added advantage of not having to use complicated static data structures, but rather to constantly adapt to the requirements of the given problem. [1] [2] [3] [4] [5] [6] [26] [27] [28]

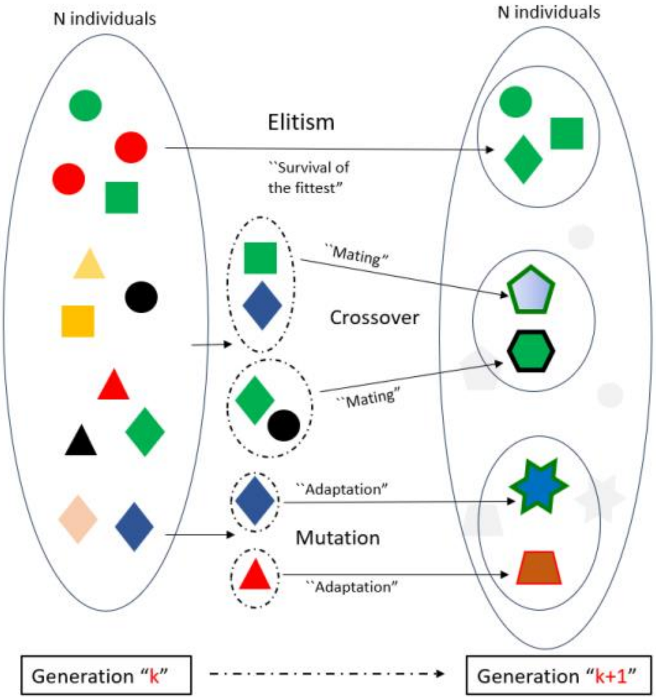

Figure 28, explanation of new recombined and evolved generation genesis

7. Code developing process

This MATLAB code uses a genetic algorithm to determine the optimal parameters of an electric vehicle to minimize simulated energy usage (in kWh). The code, which is inside the main function, ensures that it sets up the problem, runs the simulation of the driving cycle and subsequently "evolves" the design variables until an optimal solution is achieved. [1] [2] [3] [4] [5] [6] [12] [13] [26] [27] [27] [28] [29]

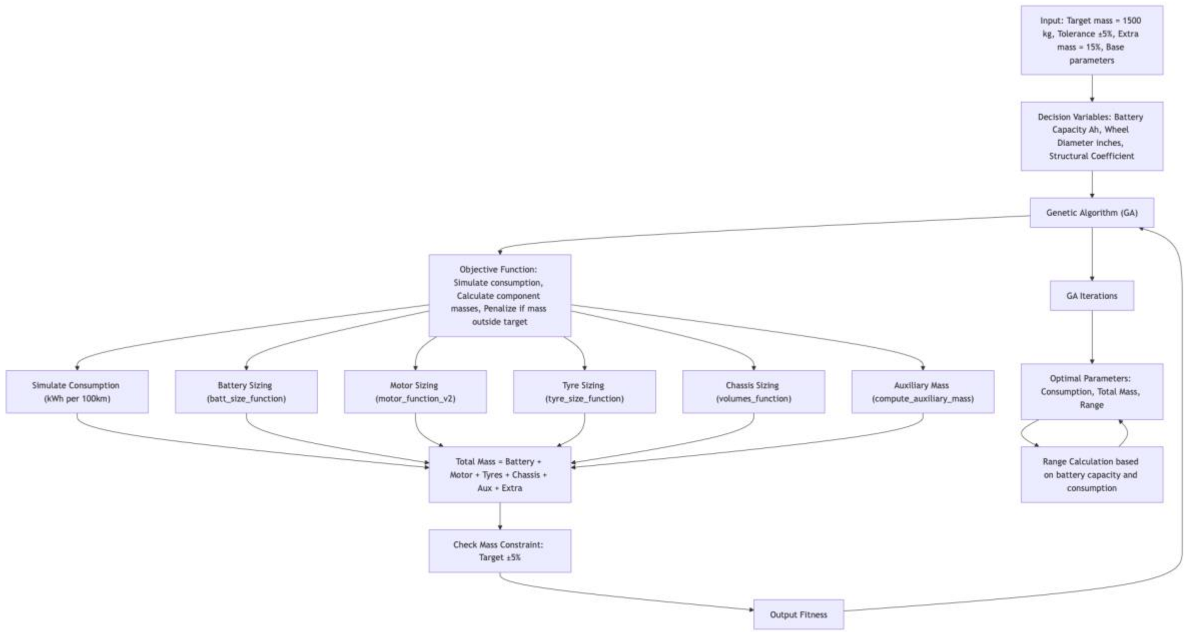

Figure 29, main genetic algorithm flow diagram

At the beginning of the program, both console and all variables are deleted, so the environment is blank. Immediately thereafter, a group of constant parameters with regard to the vehicle is defined, such as the aerodynamic coefficient, the acceleration time from 0-100 km/h, the size of the vehicle, the characteristics of the battery cell (capacity in Ah, voltage and weight) and other parameters determining the dynamic and structural behavior of the vehicle. These values are gathered in a params structure, which is then passed to the subsequent functions so that all of the simulation and calculation of the components happen using the same basic conditions.

Once the parameters are established, the driving cycle type is chosen, in this case 'wltp' (but the code could also function with 'nedc' and 'cltc'). In addition, the user defines an initial mass of the vehicle and a percentage tolerance is calculated which defines minimum and maximum values for the total mass of the vehicle. The minimum and maximum values are used both when verifying the overall sizing after completing the optimization process, and when imposing penalties on the objective function in the event that the sum of components falls outside the desired range. [1] [2] [3] [4] [5] [6] [26] [27] [28]

The variables to be solved for are three: the battery capacity (in units of kWh), the rim diameter (in inches) and the estimated mass of the vehicle. There are lower and upper limits on these variables, and they are passed to the GA engine by the ga function of the MATLAB Optimization Toolbox. The GA options are such that the current iteration is reported, with a population size of 100 individuals and a limit of 100 generations. [1] [2] [3] [4] [5] [6] [26] [27] [28]

The objective function, changes the variable parameters of the params structure from the current values of the individual (i.e. candidate solution) and subsequently simulates using a proper simulation environment recalled by the relative function. This function, on the other hand, generates a speed profile based on the chosen driving cycle and calculates, with the help of physical models (considering aerodynamic forces, rolling resistance and inertial forces), the mechanical and electrical power required by the vehicle. The energy consumed is integrated over time and reported in kWh, and the distance travelled is also calculated, useful for the calculation of the specific consumption in kWh/100 km [1] [2] [3] [4] [5] [6] [26] [27] [28]

Then, after the simulation, the objective function proceeds to calculate the vehicle component sizes: some functions are called for the battery component sizing (batt_size_function), the motor (motor_function), the tyres (tyre_size_function) and for calculating the volumes (and the chassis mass) via (volumes_function). So, an estimate of the total mass of the components is calculated. If this mass, along with a further fixed mass (calculated as a percentage of the initial mass), is less than the previously established minimum limit, a penalty is applied (heavily increasing the value of the objective function) to guide the optimization towards solutions that respect the mass constraint. [1] [2] [3] [4] [5] [6] [26] [27] [28]

The result of the objective function is then a sum of the simulated energy consumption and penalties for mass deviations. The genetic algorithm employs this value to calculate the "fitness" of the individual; the aim here is to minimize the energy consumption, so a superior solution is one that gives a lower value. [1] [2] [3] [4] [5] [6] [26] [27] [28]

Once the GA completes its evolutionary cycle and passes back the optimal parameters, the code takes these values, reassigns them to the (params_optimal) structure and proceeds to run the simulation once again in order to compute the vehicle's specific consumption and range. Then the components (motor, wheels, chassis, battery) are summed up once more to calculate detailed masses of the parts, and finally, the code ensures that the combined weight of the components together with the fixed added weight equals or exceeds the minimum limit set. If the total weight is less than minimum, the code adds additional mass until the minimum limit is achieved and optimizes the parameters accordingly.

Finally, the program gives a series of summary outputs including the original mass, total masses of components, simulated energy consumed, power engine, specific consumption, range, battery capacity, diameter of the rims and the estimated masses for all the components.

These simulation support functions and, like run_simulink_simulation and those which create speed profiles (wltp_speed_profile, nedc_speed_profile, and cltc_speed_profile), are of a nature that they simulate the vehicle's behaviour over an arbitrary drive cycle mimetically, transforming a time sequence into a speed profile and calculating the energy required from the forces involved. These functions are integrated into the evolutionary process by creating dynamic information that is input into the fitness function.

Briefly, the code combines an accurate physical model of the vehicle with a genetic algorithm that continually tries to minimize energy use without infringing on structural limits (e.g., total weight) and reducing important design parameters. The resulting optimized design of the vehicle parameters is obtained automatically and dynamically and can be used to evaluate and improve the design of the electric vehicle in the conceptual phase.

The key of the GA optimization in this case is defining the search space for the three parameters that are optimizing. In particular, the vector of variables includes:

1. Battery capacity (in kWh):

This parameter is set to range from 30 to 31 kWh. These constraints, respectively defined in the lower bound (lb) and upper bound (ub) vectors, restrict the search to a highly constrained range. The GA is therefore "coerced" to search for the optimal solution within this little range, and this can turn out to be useful if you have an inkling that the optimum capacity is approximately 30 kWh, but still you would like to reserve space for any possible corrections.

2. Circle diameter (in inches):

Here both the lower and upper bounds are 18, so the diameter of the circle is not variable: it is a parameter with a fixed value. The GA will thus always be supplied with the same value for this parameter, and actually will not get it as a variable to optimize. This is a standard procedure when a certain parameter is considered already defined or not impacting the problem to be solved.

3. Estimated total mass of the vehicle:

This parameter is limited by a range calculated as a function of the initial vehicle mass. The user enters an initial mass (e.g., 1500 kg) and, using a percentage tolerance of ±5%, the lower and upper limits (total_mass_min and total_mass_max) are determined. In this way the GA is searching for solutions having an "acceptable" total mass close to the initial value, such that the resulting configuration is not greatly distant from what is being expected.

The lower and upper limits are thus passed to the `ga` function in the program flow, where they serve to maintain each generated individual (i.e. each parameter vector candidate) within these limits. The target of the fitness function, established in (objective_consumption), is to decrease the simulated energy consumption, having penalties in case the total weight of the car components (calculated through the corresponding functions for battery, engine, wheels and chassis) is not equal to the estimated weight or does not meet the enforced limits.

The main inputs of the system are:
- The constant parameters defined in `params` (for example, aerodynamic coefficient, acceleration time, vehicle dimensions, etc.).
- The initial mass of the vehicle, directly put in the code.
- The type of driving cycle (in our example 'wltp', but 'nedc' or 'cltc' can also be utilized as well).
- The interval of the three variables to be optimized.

The last output is the optimal values of the parameters (battery capacity, rim diameter and estimated total mass) that minimize the objective function, together with a set of simulation results, for instance, total energy consumption, specific consumption in kWh/100 km, estimated range and the masses of the individual components.

That is, the upper and lower bounds define the "container" out of which the GA will be required to search for the optimal solution, constraining the search space to real and viable values for all the variables, and not allowing the evolutionary process to seek out configurations that, for example, would result in the vehicle being too light or too heavy compared to the design specifications. This technique is used to keep the optimization on the most important parameters, making the final solution more effective and user-friendly.

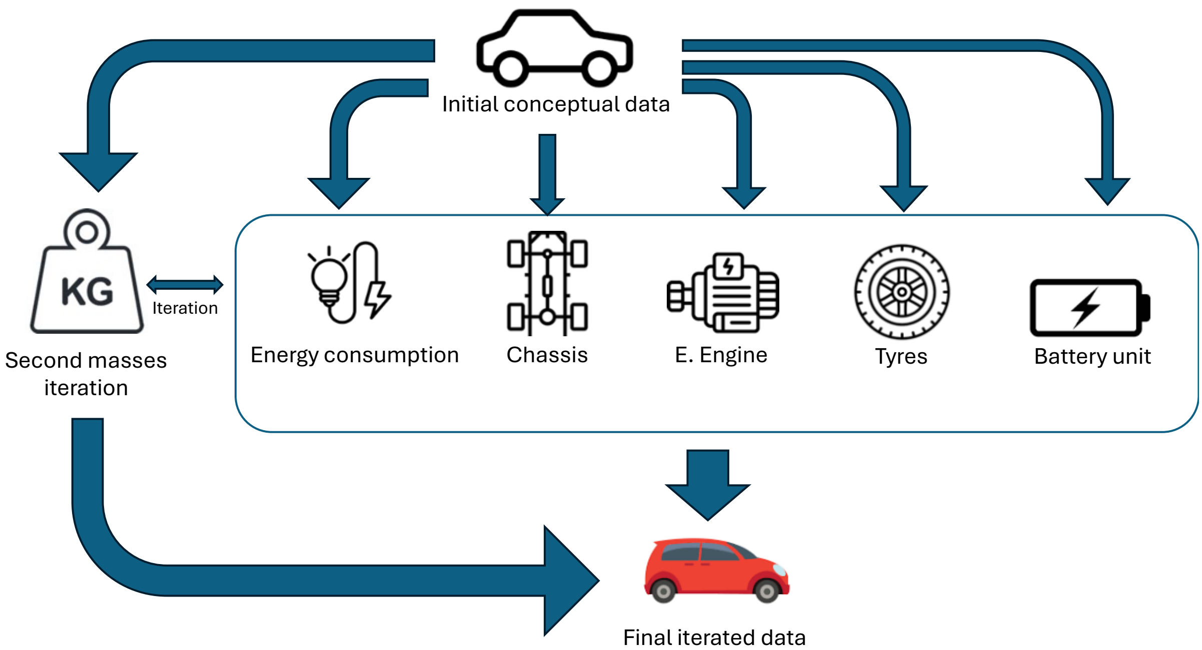

Figure 30, main algorithm working principle inspired to Nicoletti's one

7.1 Main systems virtualization

The code is split into a number of functions that collectively mimic and optimize the electric vehicle's behavior through a genetic algorithm. Below is an example of each part in action, explaining both the mechanisms of computation and physical laws upon which the computations are based. [24] [25] [26] [27] [29] [30] [31] [33] [34]

Main function

This function marks the start of the optimization. Here, the surroundings are established by clearing the console and the variables present, some predefined constants that characterize the vehicle are established (e.g., the aerodynamic coefficient, time of acceleration, dimensions, cell properties of the battery, etc.) and a structure (params) is established that accumulates all this information. An important point is defining the lower and upper limits for the optimization variables: the first variable is the battery capacity (between 30 and 31 kWh), the second one is the diameter of the rim in inches (here 18, hence non-variable) and the third is the total estimated vehicle weight within a tolerance level of ±5% of the initial weight. These are limits that minimize the search space and ensure that the solutions generated are realistic and do not allow for configurations that would make the vehicle too heavy or too light. With these parameters set, the GA is executed with the MATLAB ga function, which calculates the objective function (objective_consumption) trying to optimize the simulated energy consumption.

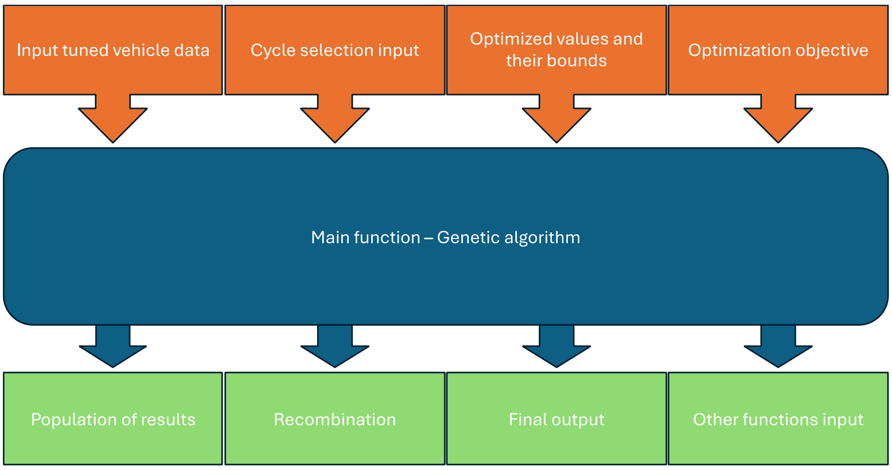

Figure 31, main function (GA) inputs and outputs

Fitness function

This is the essence of the optimization. This function receives as argument a vector of variables (the three quantities defined above) and the structure of the fixed parameters. Its purpose is to return the "cost" (in this case, the simulated energy cost) of the candidate configuration.

First, the vector values are inputted in the appropriate fields of the params structure. In the second step, the (run_simulink_simulation) function is called, which runs the car behavior simulation on a driving cycle (for example, WLTP) and returns the cumulative energy consumption (in kWh). Then the specific consumption (kWh/100 km) is calculated.

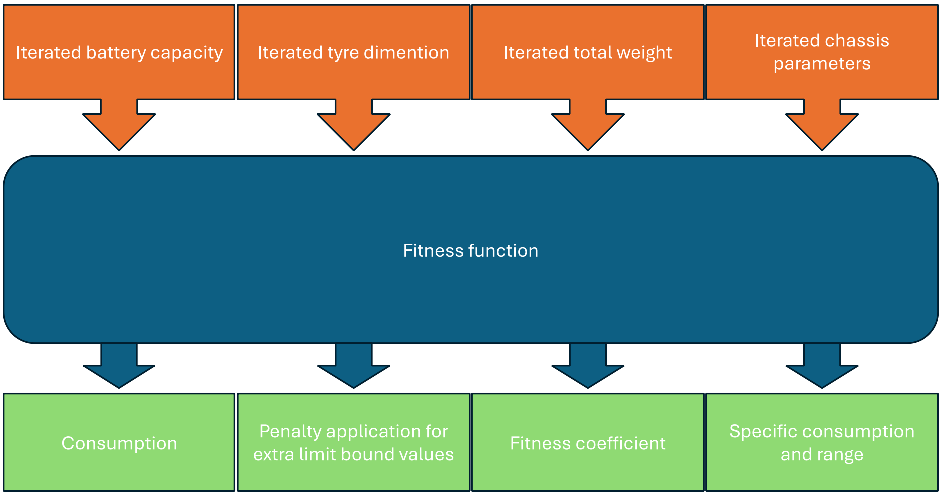

Figure 32, fitness fucntion inputs and outputs

Then, in order to ensure that the setup does not deviate from structural constraints, the function invokes other functions that dimension the major components: the battery, the motor, the wheels and the chassis (volumes_function). The total of the masses of the components is evaluated against the predicted mass; any differences create penalties (multiplied by a significant factor) which are appended to the consumption value. In this way, the GA will be inclined towards solutions that not only minimize consumption but also satisfy the design constraints with respect to mass.

Extra components weights

In the end it is considered an extra mass addition due to all other vehicle components which don't have a function to be iterated (suspensions, alternator, infotainment, seats, exc..). Each of theese extra weight is considered inside the relative nearest subfunction with a scaling factor coming from average of same components mounted on other same category vehicles: Alternator and cooling are scaled on the basis of motor dimension and power, seats on the basis of number of passengers and internal volumes, infotainment and auxiliaries power usage inside consumption simulation function. Each of these addons are iterated, called and updated simultaneously with other vehicle components and function being directly dependent for those components as scaling factor additions.

Vehicle simulation

This approach uses a simulation based on the laws of vehicle dynamics. It first creates a drive cycle (via generate_drive_cycle) that provides a time series of speeds. The current acceleration (derivative of the speed with respect to time) is calculated and some fundamental physical laws are used:

Aerodynamic Drag:

$$F_{\mathrm{a}} = ½ \cdot \rho \cdot C_d \cdot A \cdot v^2$$
$$(\rho: air\ density, C_d: drag\ coefficient, A: frontal\ area, v: speed)$$

Rolling Resistance:

$$F_{\mathrm{r}} = m \cdot g \cdot rr$$

$$(m: vehicle\ mass, g: gravitational\ acceleration, rr: rolling\ resistance\ coefficient)$$

Inertial Force:

$$F_{\mathrm{i}} = m \cdot a$$

$$\left(a: acceleration, a = \frac{dv}{dt}\right)$$

Total Force:

$$F_t = F_{\mathrm{a}} + F_{\mathrm{r}} + F_{\mathrm{i}}$$

Mechanical Power:

$$P_m = F_t \cdot v$$

Regenerative braking Power:

$$P_{reg} = P_m$$

$$(when\ is\ negative\ value)$$

Electrical Power:

$$P_{\mathrm{e}} = \frac{P_m}{\eta} - P_{reg}$$

$$(\eta: overall\ efficiency)$$

Energy Consumption:

$$E = \int P_{\mathrm{e}} dt$$

$$(Convert\ E\ from\ Joules\ to\ kWh)$$

Summing them up, we have the total force required. Multiplying by the velocity gives the mechanical power, which, divided by the system-wide efficiency, equals the required electrical power. Integrating the power with respect to time gives the energy dissipated (in Joules), which is converted to kWh. The traveled distance is also computed by integrating the velocity, and this proves useful in the calculation of the specific consumption.

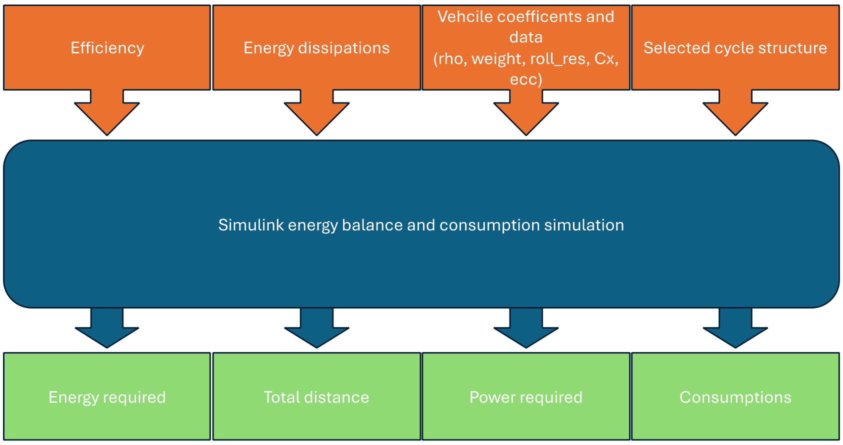

Figure 33, energy consumption simulation function inputs and outputs

Battery sizing

This function determines the battery size from the capacity required and parameters such as the state of charge (SoC), the capacity per cell (in Ah), the cell voltage and the mass per cell. Starting with the battery capacity (in kWh) as input data (GA variable), the function converts this value to ampere-hours based on the pack nominal voltage. It then computes the number of cells in series (to achieve the nominal voltage of the pack) and in parallel (to deliver the needed capacity). The product of the two figures equals the number of cells, and multiplying by the weight of a single cell provides the overall weight of the battery. Moreover is consider an estimated factor (derived from average of same weight/category batteries, that scale with weight) to add extra weight in order to consider battery hull, cables and battery related systems and components.

Capacity Conversion:

$$Ah = \frac{kWh \cdot 1000}{V_p}$$
$$(V_p: nominal\ pack\ voltage)$$

Cells in Series and Parallel:

$$n_s = ceil\left(\frac{V_p}{V_c}\right) \qquad n_p = ceil\left(\frac{Ah}{A_c}\right)$$
$$(V_c: cell\ voltage, A_c: cell\ capacity\ in\ Ah)$$

Total Cells and Mass:

$$N = n_s \cdot n_p \qquad m_{batt} = N \cdot m_c$$
$$(m_c: mass\ per\ cell)$$

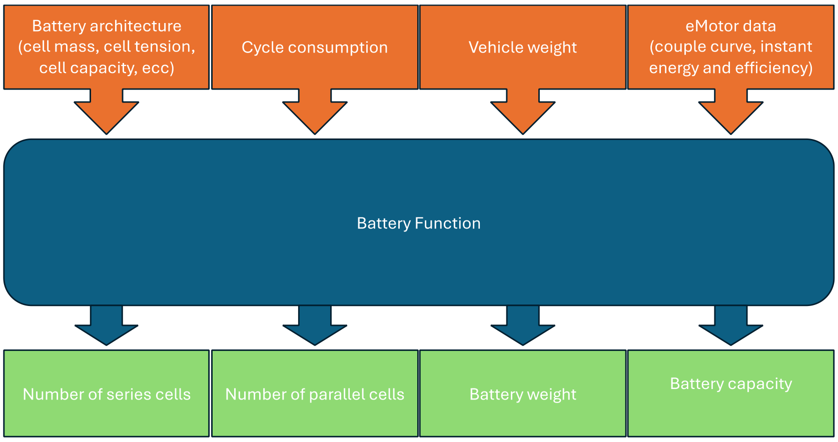

Figure 34, battery function inputs and outputs

Motor sizing

The motor sizing is done with various driving conditions in mind to estimate the maximum power requested. The function uses the selected driving cycle and, similar to (run_simulink_simulation), calculates the acceleration and the forces involved. In addition to the power required by the driving cycle, some cases are considered:

- 0-100 km/h acceleration,
- Constant top speed (where rolling resistance and drag forces prevail),
- Ascending a slope (calculating the component of the gravitational force

In each case, the power required is calculated (force times velocity divided by efficiency), an average is taken, a margin of safety is included, and, in kW terms, the mass of the engine is estimated based on an empirical formula (0.75 kg per kW).
Following physical correlation are used inside the motor function model to determine motor characteristics, using driving cycle emulated required energy (from Simulink function). The model estimate engine power on the basis of total maximum power required by the cycle, exported to a typical torque curve.

Instantaneous Acceleration

The instantaneous acceleration is computed as the change in velocity over the change in time:

$$a = \frac{\Delta v}{\Delta t}$$

$$where:$$
$$(\Delta v)\ is\ the\ change\ in\ velocity$$
$$(\Delta t)\ is\ the\ change\ in\ time.$$

Aerodynamic Drag Force

The aerodynamic drag force is given by:

$$F_{\text{aero}} = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v^2$$

$$\begin{gathered} with: \\ (\rho): air\ density (approximately\ 1.225 kg/m^3), \\ (C_d): aerodynamic\ drag\ coefficient \\ (A): frontal\ area\ of\ the\ vehicle \\ (v): vehicle\ speed. \end{gathered}$$

Rolling Resistance Force

The force due to rolling resistance is calculated as:

$$F_{\text{roll}} = m \cdot g \cdot rr$$

$$\begin{gathered} where: \\ (m): total\ mass\ of\ the\ vehicle, \\ (g): gravitational\ acceleration, \\ (rr): rolling\ resistance\ coefficient. \end{gathered}$$

Inertial Force

The inertial force required to accelerate the vehicle is given by Newton's second law:

$$F_{\text{inertia}} = m \cdot a$$

Total Force and Instantaneous Power

The total force that the engine must overcome is the sum of these three forces:

$$F_{\text{total}} = F_{\text{aero}} + F_{\text{roll}} + F_{\text{inertia}}$$

The instantaneous power required at a given speed is then:

$$P = \frac{F_{\text{total}} \cdot v}{\eta}$$

$$where (\eta)\ is\ the\ efficiency\ of\ the\ engine.$$

Specific Scenarios

The function also calculates the required power for several realistic driving scenarios:

Scenario 1: 0 to 100 km/h Acceleration

Acceleration:

$$a_{\text{accel}} = \frac{v_{\text{final}}}{t_{\text{acc}}}$$

$$where\ (v_{\text{final}} = \frac{100}{3.6})$$
$$(conversion\ from\ km/h\ to\ m/s)\ and\ (t_{\text{acc}})\ is\ the\ acceleration\ time.$$

Forces:

$$F_{\text{inertia, accel}} = m \cdot a_{\text{accel}}$$

$$F_{\text{roll, accel}} = m \cdot g \cdot rr$$

$$F_{\text{aero, accel}} = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v_{\text{final}}^2$$

$Power$:

$$P_{\text{accel}} = \frac{\left(F_{\text{inertia, accel}} + F_{\text{roll, accel}} + F_{\text{aero, accel}}\right) \cdot v_{\text{final}}}{\eta}$$

Scenario 2: Constant Maximum Speed on a Flat Road

Forces:

$$F_{\text{aero, max}} = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v_{\text{max}}^2$$

$$F_{\text{roll, max}} = m \cdot g \cdot rr$$

Power:

$$P_{\text{vel max}} = \frac{\left(F_{\text{aero, max}} + F_{\text{roll, max}}\right) \cdot v_{\max}}{\eta}$$

Scenario 3: Overcoming a Maximum Grade at a Moderate Speed

Conversion of Grade to Angle:

$$\theta = \arctan\left(\frac{\text{grade (\%)}}{100}\right)$$

Forces:

$$F_{\text{grade}} = m \cdot g \cdot \sin(\theta)$$

$$\mathit{Additionally, at\ a\ moderate\ speed}\ (v_{\text{grade}})$$
$$F_{\text{aero, grade}} = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v_{\text{grade}}^2$$

$$F_{\text{roll, grade}} = m \cdot g \cdot rr$$

Power:

$$P_{\text{grade}} = \frac{\left(F_{\text{grade}} + F_{\text{roll, grade}} + F_{\text{aero, grade}}\right) \cdot v_{\text{grade}}}{\eta}$$

Final Engine Power and Mass Estimation

The engine power is estimated by taking the average of the powers calculated for the drive cycle and the three scenarios, then adding a 10% safety margin:

$$P_{\text{engine, max}} = 1.1 \times \text{mean}\left(P_{\text{cycle}}, P_{\text{accel}}, P_{\text{vel max}}, P_{\text{grade}}\right)$$

Converted into kilowatts:

$$P_{\text{engine, kW}} = \frac{P_{\text{engine, max}}}{1000}$$

The engine mass is then estimated using a ratio:

$$m_{\text{engine}} = P_{\text{engine, kW}} \times 0.75$$

Converting RPM to Angular Velocity

To convert the engine speed from revolutions per minute(RPM)
to angular velocity in radians pers econd:

$$\omega\ (\text{rad/s}) = \frac{2\pi \cdot \text{RPM}}{60}$$

Instantaneous Power from Torque

The instantaneous power produced by the engine at a given angular velocity
is the product of the torque and the angular velocity:

$$P(\omega) = T(\omega)$$

$$where:$$
$$(T(\omega))\ is\ the\ torque\ (in\ N \cdot m)\ as\ a\ function\ of\ angular\ velocity\ (\omega)$$
$$(P(\omega))is\ the\ power\ in\ watts$$

Finding the Maximum Engine Power using double approach to improve accuracy, using torque system as requirements checking system

The maximum engine power is found by determining the maximum value of (P(ω)) a long the engine operating range.

Analytical Method Using the Derivative

1. $Compute\ the\ derivative\ of\ the\ power\ function\ with\ respect\ to\ (\omega)$:

$$\frac{dP}{d\omega} = \frac{d}{d\omega}[T(\omega) \cdot \omega] = T(\omega) + \omega \cdot \frac{dT}{d\omega}$$

2. $Set\ the\ derivative\ equal\ to\ zero\ to\ find\ the\ optimal\ angular\ velocity\ (\omega_{\max})$:

$$T(\omega_{\max}) + \omega_{\max} \cdot \frac{dT}{d\omega}|_{\omega_{\max}} = 0$$

3. $Solve\ for\ (\omega_{\max}), and\ then\ determine\ the\ maximum\ power$:

$$P_{\max} = T(\omega_{\max}) \cdot \omega_{\max}$$

Example Torque Model

A simplified model for the torque curve might be:

$$T(\omega) = \begin{cases} T_{max}\ , & if\ \omega \leq \omega_t \\ T_{max}\ [1 - k\ (\omega - \omega_t)]\ , & if\ \omega > \omega_t \end{cases}$$

$$where:$$

$$(T_{\max}) is\ the\ maximum\ (flat)\ torque,$$
$$(\omega_t) is\ the\ threshold\ angular\ velocity\ where\ torque\ begins\ to\ drop,$$
$$(k) is\ a\ constant\ representing\ the\ rate\ of\ decrease\ in\ torque\ beyond\ (\omega_t).$$

Using this model:

1. $For\ each\ angular\ velocity\ (\omega), compute\ the\ corresponding\ torque\ (T(\omega))$.
2. $Calculate\ the\ instantaneous\ power\ (P(\omega) = T(\omega) \cdot \omega)$.
3. $Find\ the\ value\ (\omega_{\max})\ at\ which\ (P(\omega))\ is\ maximized$.
4. $The\ maximum\ engine\ power\ is\ then$:

$$P_{\max} = T(\omega_{\max}) \cdot \omega_{\max}$$

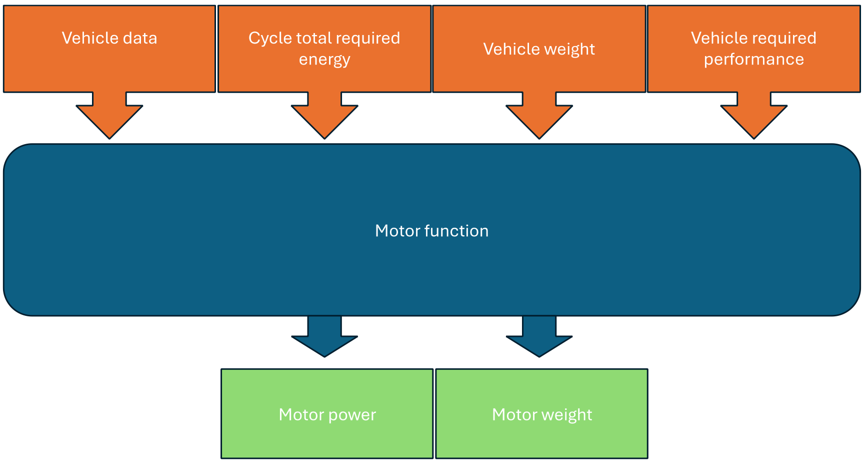

Figure 35, motor function inputs and outputs

Wheel sizing

This operation addresses the issue in a geometric as much as an energetic sense. It first translates the rim diameter (in inches) into millimeters and, together with the width and aspect of the tire, arrives at the overall wheel diameter, from which an effective radius (in meters) is calculated. The wheel weight is approximated with empirical equations taking into account the rim and tire. Furthermore, using the relationship weight, pressure and contact area (Area=Weight Pressure Area=Pressure Weight), the function approximates the contact area of the tires and, combining this data with an approximation of the energy losses (J/m), calculates the energy lost in deformation and friction when rolling.

Geometry:

$$d_{mm} = d_{in} \cdot 25.4$$
$$h = W \cdot \left(\frac{AR}{100}\right)$$
$$d_{total} = d_{mm} + 2 \cdot h \qquad r_{eff} = \frac{d_{total}}{2 \cdot 1000}$$
$$(d_{in}: diameter\ in\ inches, W: tire\ width\ in\ mm, AR: aspect\ ratio)$$

Wheel Mass:

$$m_{circle} = 0.036 \cdot d_{in}^2$$
$$m_{tire} = 0.009 \cdot W$$
$$m_{wheel} = m_{circle} + m_{tire} \qquad m_{wheels} = 4 \cdot m_{wheel}$$

Contact Area:

$$A_{contact} = \frac{m \cdot \frac{g}{4}}{P_{tire}}$$
$$(P_{tire}: tire\ pressure)$$

Energy Loss:

$$E_{loss} = e_{ref} \cdot \left(\frac{P_{ref}}{P_{tire}}\right) \cdot d$$
$$(e_{ref}: reference\ energy\ loss\ per\ meter, d: distance\ traveled;\ convert\ E_{loss} to\ kWh)$$

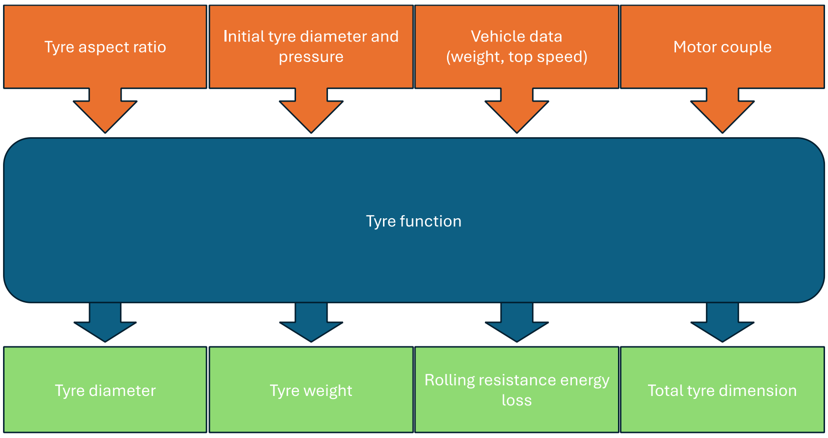

Figure 36, tyre fucntion inputs and outputs

Volume and chassis mass calculation

This function calculates the volume inside the car (for the people) and then deducts it from the outer volume (calculated using the overall dimensions) to arrive at the available volume in the chassis. To this, a structure coefficient is added – empirically determined as a function of initial vehicle weight – that decides the percentage of that volume taken up by the load-carrying structure. By multiplying the material volume by the material density (in this case 2700 kg/m^3, typical for aluminum), the chassis mass is determined.

Internal Volume:

$$V_{in} = \left(\frac{L - 2sp_{side}}{1000}\right) \cdot \left(\frac{W - 2 \cdot sp_{side}}{1000}\right) \cdot \left(\frac{H - sp_{floor} - sp_{roof}}{1000}\right)$$

External Volume:

$$V_{ex} = \left(\frac{L}{1000}\right) \cdot \left(\frac{W}{1000}\right) \cdot \left(\frac{H}{1000}\right)$$

Chassis Volume and Mass:

$$V_{ch} = V_{ex} - V_{in}$$

$$V_{mat} = V_{ch} \cdot k \qquad m_{chassis} = V_{mat} \cdot \rho_{mat}$$

$$(sp\_side: side\ wall\ thickness, sp\_floor: floor\ thickness, sp\_roof: \text{roof thickness, k: structural coefficient, ρ\_mat: material density})$$

Structural Coefficient:

A structural coefficient is used to estimate the actual volume of the chassis occupied by the structural material (aluminum or steel). The coefficient does not remain constant but is assigned as a linear function of the original total weight of the car. The argument is that big cars will occupy more structural space to carry bigger loads. The coefficient is determined by first assigning a minimum and maximum value (for instance, 0.02 and 0.05) and a minimum and maximum vehicle mass (for instance, 500 kg and 2500 kg).

The coefficient is then given by:

$$C_{\text{struct}} = C_{\min} + \left(\frac{C_{\max} - C_{\min}}{\text{Mass}_{\max} - \text{Mass}_{\min}}\right) \times (\text{Mass}_{\text{initial}} - \text{Mass}_{\min})$$

$$This\ value\ is\ clamped\ between\ (C_{\min})\ and\ (C_{\max})\ to\ ensure\ realistic\ limits$$

Chassis Mass Estimation:

The actual volume of material used in the chassis is estimated by multiplying the chassis volume by the structural coefficient:

$$\text{Volume}_{\text{material}} = \text{Volume}_{\text{chassis}} \times C_{\text{struct}}$$

Then, using the material density $((\rho_{\text{material}}))$, the chassis mass is estimated as:

$$\text{Mass}_{\text{chassis}} = \text{Volume}_{\text{material}} \times \rho_{\text{material}}$$

Incorporating a Safety Sizing Factor

In practice, chassis design must consider uncertainties, variability of loads, and conservatism of design. One way of incorporating these is by the application of a safety sizing factor. This factor moves the estimated mass of the chassis higher so that the design will be sufficiently robust relative to commercial standards.

Determining the Safety Factor

One such technique is to find the safety factor from the total vehicle mass to a reference mass of commercial vehicles. For example, let the average total vehicle mass of similar trucks be Mass_{ref}. Then, a safety factor SF can be found as a linear function of the deviation of the actual total vehicle mass from this reference mass:

$$SF = 1 + \gamma\left(\frac{\text{Mass}_{\text{initial}} - \text{Mass}_{\text{ref}}}{\text{Mass}_{\text{ref}}}\right)$$

Here, (γ) is a tunable parameter (e.g., 0.05 or 0.1) that determines how aggressively the safety factor increases with increasing mass. The idea is that a heavier vehicle might require a proportionally stronger frame.

Applying the Safety Factor

$$\text{Mass}_{\text{chassis, final}} = SF \times \text{Mass}_{\text{chassis}}$$

This adjustment specifies that the mass of the chassis is not only a function of material and geometric properties but also has a buffer for tolerating practical design uncertainty and commercial vehicle comparisons.

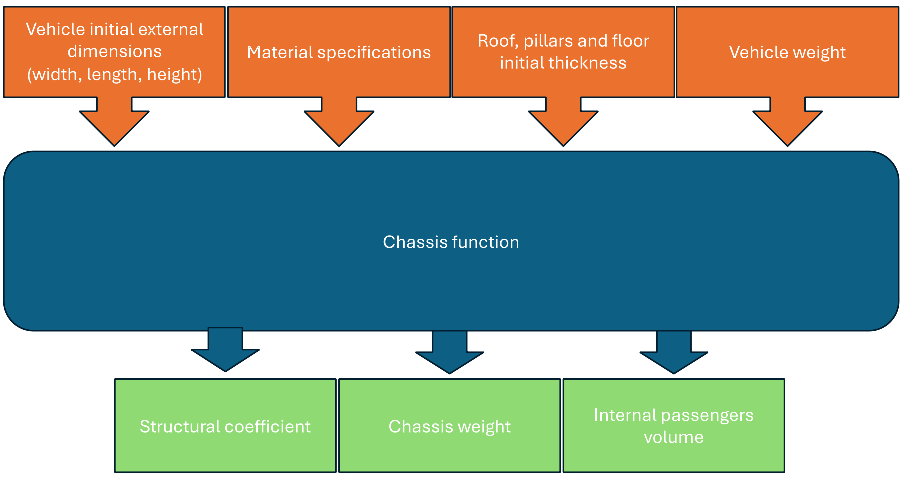

Figure 37, chassis function inputs and outputs

Drive cycle generation

The generate_drive_cycle function selects the speed profile based on the cycle type (WLTP, NEDC, CLTC). It calls one of the predefined functions (wltp_speed_profile, nedc_speed_profile, cltc_speed_profile) dividing the total cycle time into intervals, setting for each interval a target speed value (in km/h). Transitions in each interval made realistic by the speed transition function describing the speed oscillation, simulating controlled acceleration or deceleration, subject to a common maximum acceleration. Finally, the velocities are transformed into m/s in order that the calculations are carried out always in the dynamics. These procedures are based on the kinematics laws: velocity and acceleration have a relationship given by the derivative with respect to time, and the trace of the acceleration impacts the calculation of the forces and the power required.

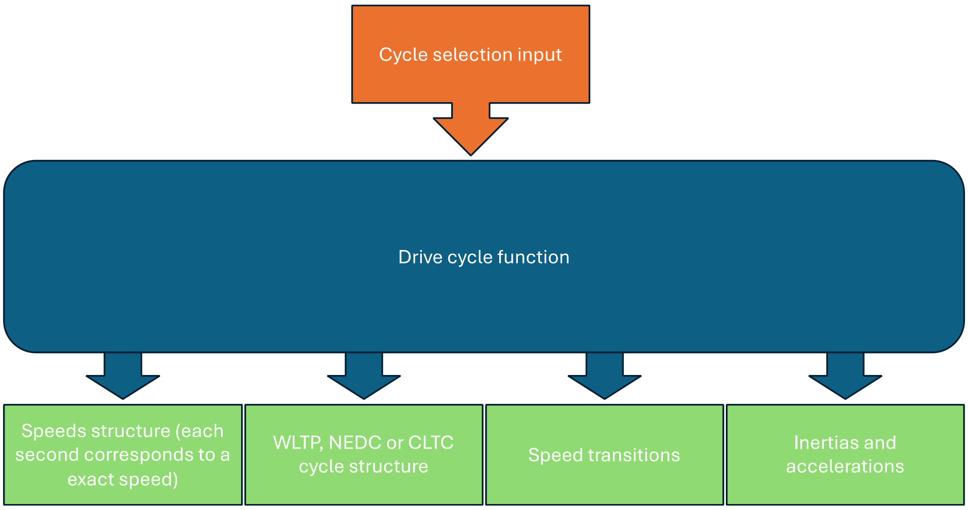

Figure 38, drive cycle function inputs and outputs

GA output function

Finally, this function (optional) saves the history of best fitness of each iteration of genetic algorithm to a variable that is thereafter released to the MATLAB workspace. This may be used to monitor the optimization progress and check the convergence of the GA.

7.2 Genetic algorithm tuning

The model is highly sensitive to input values and should be well-tuned so that the initial parameters reasonably estimate the desired industry and vehicle. For example, when an unrealistic energy density battery (too high relative to that normally achieved in the market) is entered, the model may provide too optimistic outcomes that cannot be achieved in the real world. This would provide a configuration that, while reflecting a diminished simulated energy expenditure, does not respect the real physical and technological limitations, sacrificing the overall reliability of the simulation.

This is valid for every input parameter: the initial mass of the vehicle value, the aerodynamic coefficient, the rolling resistance, etc., should be selected in accordance with the vehicle that will be designed. For instance, if the aim is a city car, the initial mass must be set to usual values (e.g. 1000–1200 kg), whereas for an SUV or a big vehicle the value may be much greater.

Tuning consists of methodically testing and fine-tuning such inputs, possibly with the use of real data from production cars or industry comparison techniques, such that the model remains in a realistic range. It is only in this way that the optimization that comes from the genetic algorithm is able to produce good and meaningful outputs to car design.

8. Validation of methodology

The validation of the algorithm results has been settled up imposing initial values of well known and defined (by data point of view) vehicles and tuning missing one to the correspondent category. More precisely the vehicles selected are FIAT 500e and Renault Twizy: battery, power, initial weight, tires dimension and dimensions have been imposed and other non given initial input data have been tuned to the correspondent vehicle data. The validation test has been simulated in WLTP cycle being the known values cyecle configuration. Below are listed fixed and tuned values and the initial input configuration. [35][36][37][38]

The simulation found an optimized configuration almost identical with the real one, it is important to consider that these empirical data, for now, will differ from real ones because not every aspect has been implemented and simulated under the related function. This have a minimal effect on final results and it is already considered as future upgrade. Battery temperatures, dynamic battery efficiency, dynamic motor efficiency, road condition, tires degradation or auxiliary (cooling system for example) systems dynamic energy utilization are not yet considered. Battery dynamic discharge efficiency, temperature depending, could change the overall energy requirements of the cycle.
As underlined before in Phd Nicoletti thesis, secondary masses effect have a significant impact on overall masses even when a only single component is modified. In the images depicted below, reproposed again from Nicoletti and König work, it is possible to appreciate the effect of primary and secondary masses and volumes. It is crucial to underline how evident small changes can evolve with cascade effects.

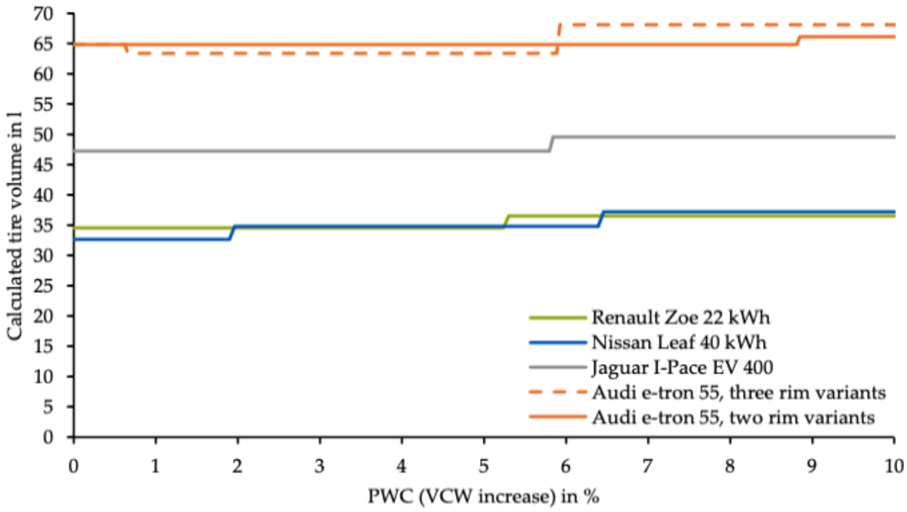

Figure 39, Interdependency between secondary volume change (SVC) of the wheel and the primary

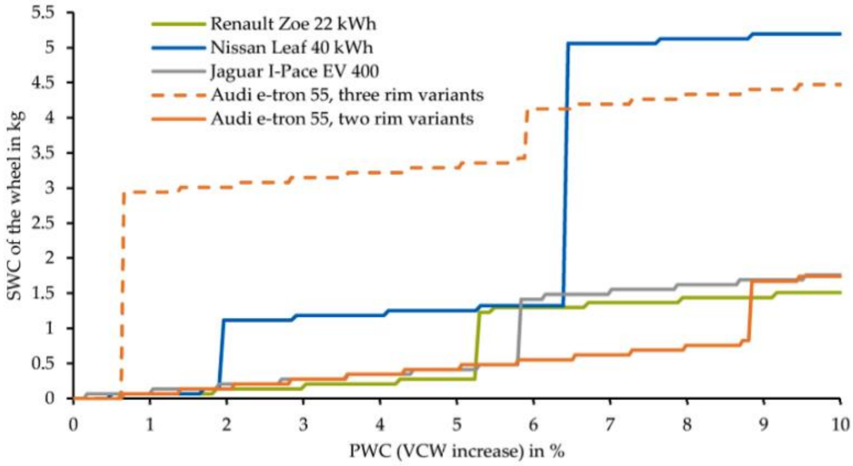

Figure 40, Interdependency between SWC (secondary weight change) of the wheel and PWC (primary weight change).

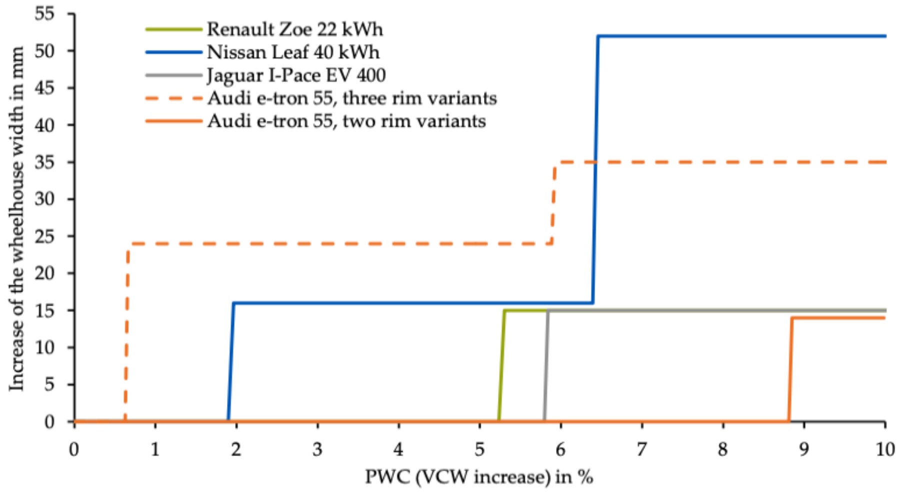

Figure 41, Interdependency between wheelhouse width and PWC (primary weight change).

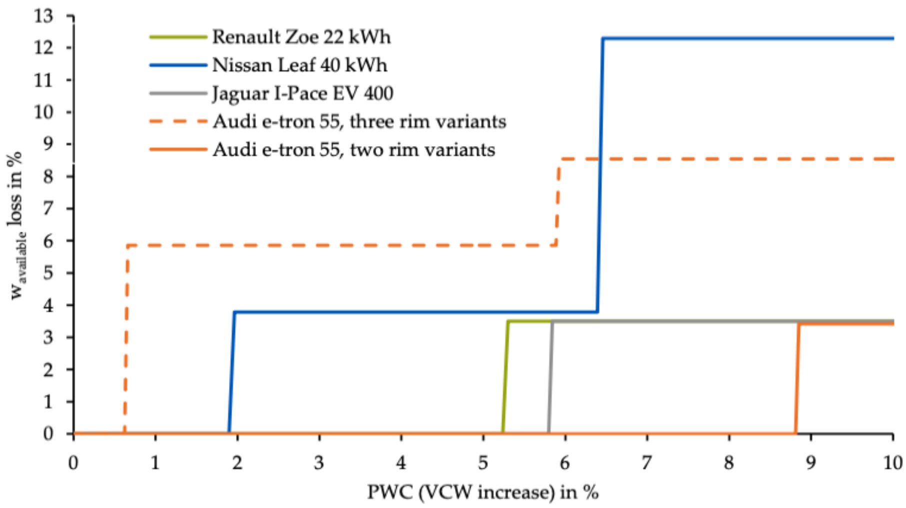

Figure 42, Interdependency between the SVC (secondary volume change) at vehicle front end and the PWC (primary weight change).

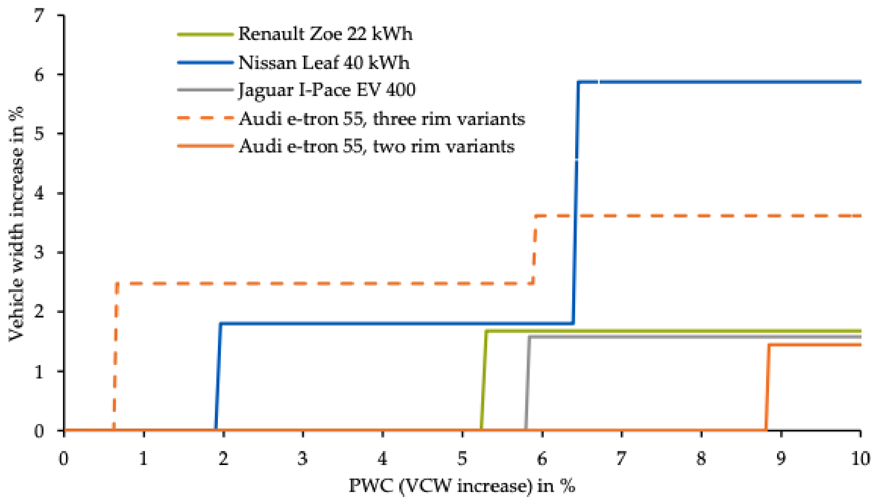

Figure 43, Interdependency between the vehicle width and the PWC (primary weight change).

FIAT 500e validation test

Fixed data (constants)	
Cell Capacity	60 Ah
Cx	0.32
Max speed	135 km/h
0-100 time	9 s
Total efficiency	0.85
Car width	1683 mm
Car height	1527 mm
Chassis Material	Alluminum
Cell Voltage	3.65 v
Cell weight	0.9 kg
Battery pack nominal Votlage	394 v
Motor max rpm	12000,00

Figure 44, empirical FIAT 500e data and GA not iterated constants

Unit	Initial input data	units	Value	GA output data	unit	Difference (%)
Total Weight	1365	kg	Total Weight	1296,00	kg	-5,05
Motor Weight	70	kg	Motor Weight	79,00	kg	12,86
Battery Weight	182	kg	Battery Weight	194,00	kg	6,59
Chassis Weight	160	kg	Chassis Weight	175,00	kg	9,38
Tyres Weight	74	kg	Tyres Weight	70,00	kg	-5,41
Range	190	km	Range	193,20	km	1,68
Battery capacity	23,7	kWh	Battery capacity	24,73	kWh	4,35
Spec. Consumes	13	kWh/100km	Spec. Consumes	12,80	kWh/100km	-1,54
Tyres dimension	17	Inches	Tyres dimension	17,00	Inches	0,00
Motor Power	70	kW	Motor Power	73,16	kW	4,51

Figure 45, FIAT 500e empirical data used by GA iterations

Figure 46, WLTP GA results used as validation: iterated FIAT 500e values

Renault Twizy validation test

Fixed data (constants)	
Cell Capacity	20 Ah
Cx	0,64
Max speed	80 km/h
0-45 time	6,1 s
Total efficiency	0.90
Car width	1190 mm
Car height	1460 mm
Chassis Material	Steel
Cell Voltage	3.7 v
Cell weight	1,2 kg
Battery pack nominal Votlage	52 v
Motor max rpm	10000

Figure 47, empirical Renault Twizy data and GA not iterated constants

Value	Initial input data	units
Total Weight	450,00	kg
Motor Weight	25,00	kg
Battery Weight	100,00	kg
Chassis Weight	100,00	kg
Tyres Weight	30,00	kg
Range	105,00	km
Battery capacity	6,10	kWh
Spec. Consumes	5,80	kWh/100km
Tyres dimension	13,00	Inches
Motor Power	15,00	kW

Value	GA output data	unit	Difference (%)
Total Weight	427,00	kg	-5,11
Motor Weight	26,30	kg	5,20
Battery Weight	108,30	kg	8,30
Chassis Weight	110,30	kg	10,30
Tyres Weight	30,00	kg	0,00
Range	107,10	km	2,00
Battery capacity	6,33	kWh	3,77
Spec. Consumes	5,91	kWh/100km	1,90
Tyres dimension	13,00	Inches	0,00
Motor Power	16,34	kW	8,93

Figure 48, Renault Twizy empirical data used by GA iterations

Figure 49, WLTP GA results used as validation: iterated Renault Twizy values

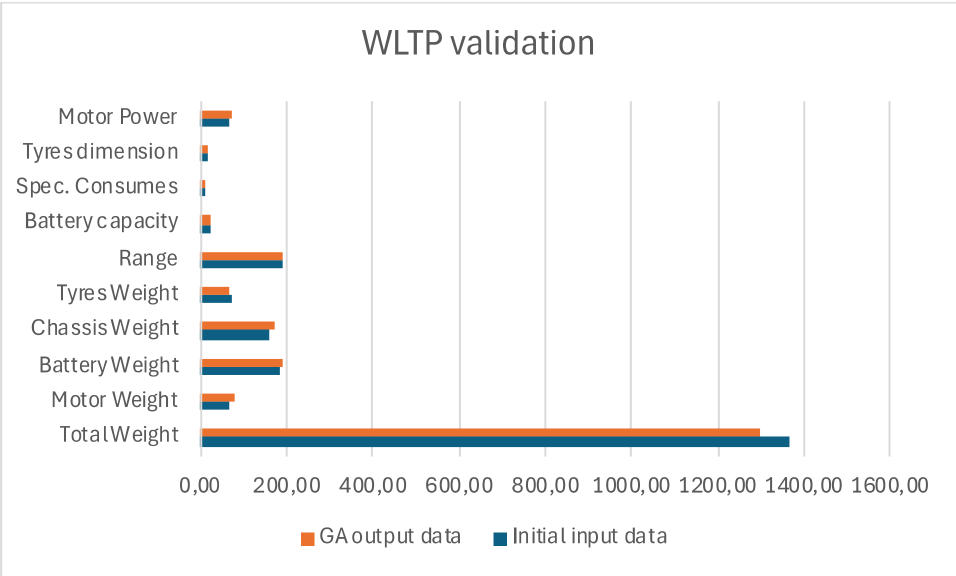

Figure 50, empirical-WLTP difference FIAT 500e

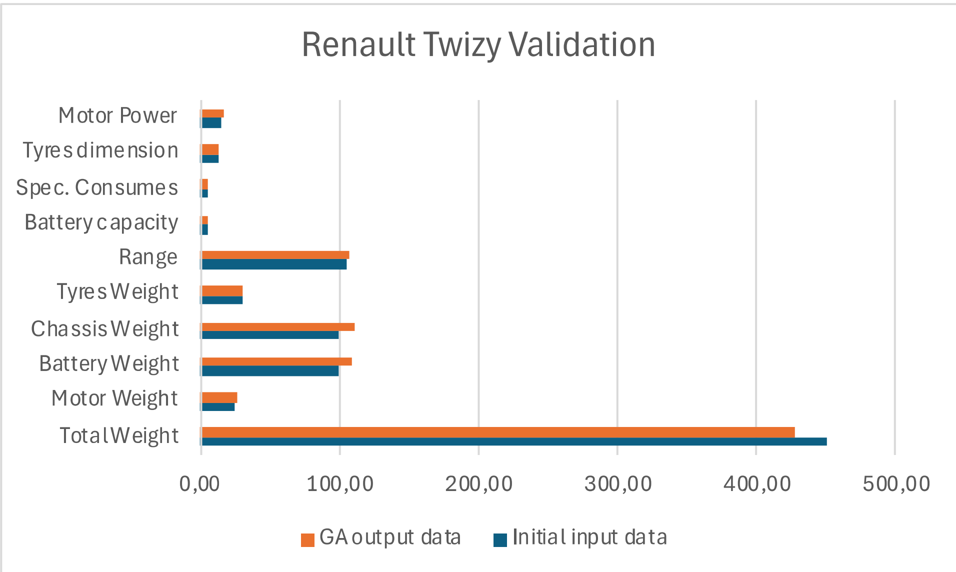

Figure 51, empirical-WLTP difference Renault Twizy

It is appreciable, as declared before, that the difference is minimal considered the non yet implemented function, this is a validation of the algorithm. Moreover a genetic algorithm must be validated by sensibility point of view, to do this when extrapolating final values in conclusion chapter has been decided to use this WLTP iterated result as reference sample and work on a single component for each run, more precisely for the selected component has been imposed a much lower value, a much higher value and a value similar to the first run of WLTP validation (showcased before). This very last imposed value will be the reference to understand if the sensibility of the algorithm is acceptable.

In the end, as final validation of algorithm sensibility, it has been set free of any constraints imposing only a growing initial weight input.

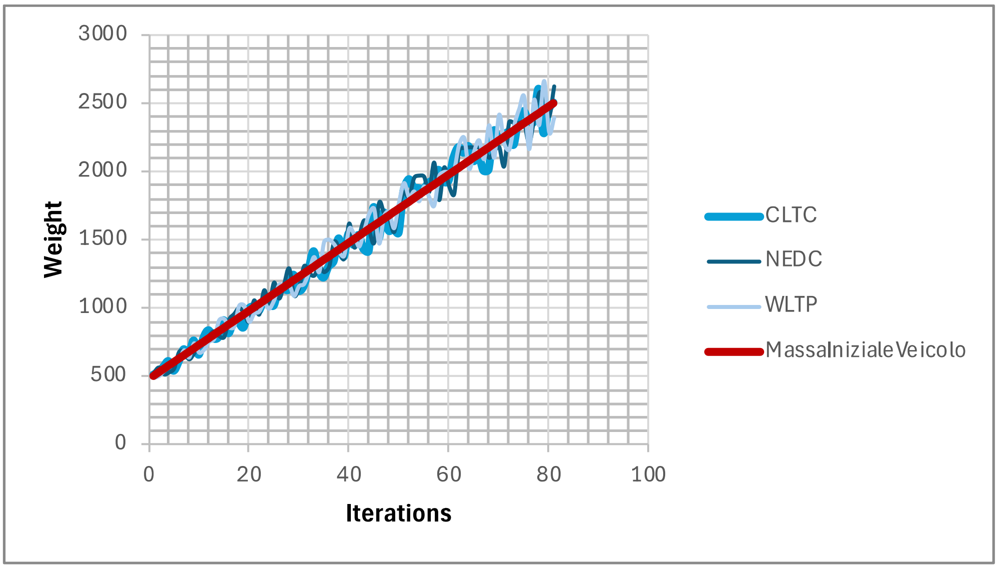

Figure 52, weight evolution along 100 iterations of GA

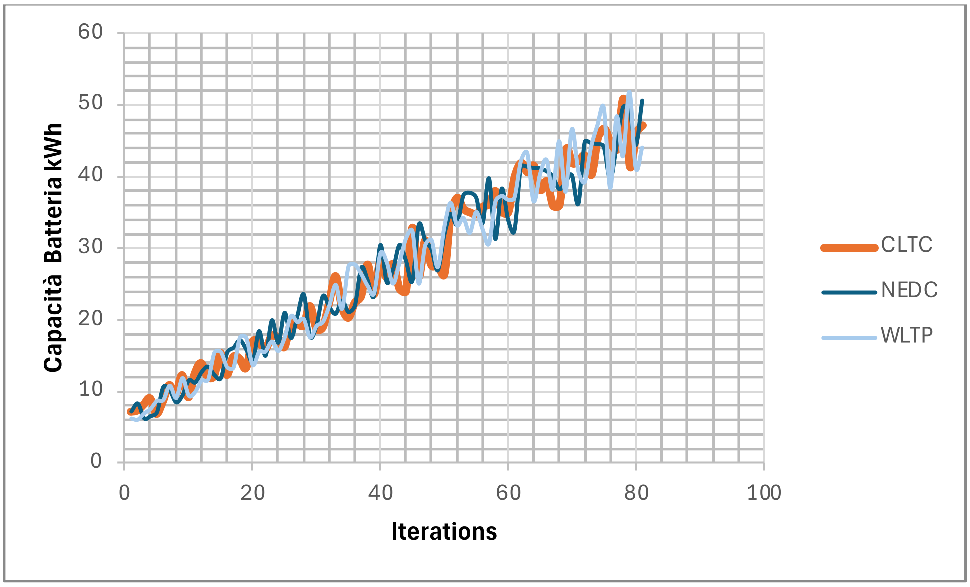

Figure 53, battery capacity evolution along 100 iterations of GA

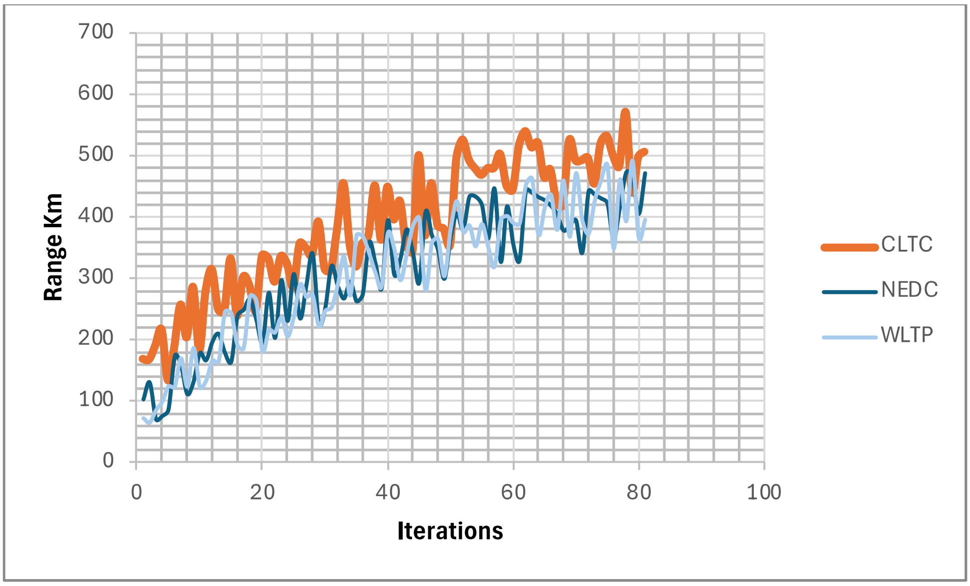

Figure 54, range evolution along 100 iterations of GA

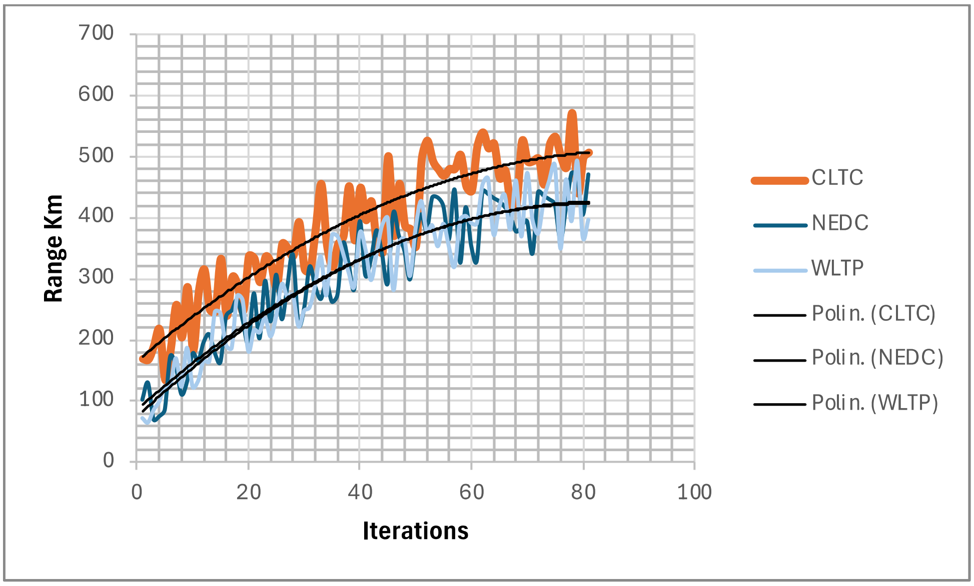

Figure 55, range evolution with trend lines

It is possible to appreciate the difference between 3 cycles evolution, whilst CLTC cycle has better results since is less demanding. Total weight grows with given tolerance being less strict each iteration. Bigger oscillations with heavier vehicle are expected since the algorithm has more freedom to adjust other components. Also battery capacity oscillations growth is depending from augmented algorithm freedom to design. The three graphs are results of the same simulation so values from same number of iteration corresponds to the same optimized vehicle configuration. Furthermore in figure 55 it is possible to appreciate how maximum ranges tend to reduce growth rate after each iteration, this could be an interesting case of study highlighting potential limitation for maximum range.

9. Results

Being the very purpose of the project to emulate and test various components on a selected vehicle has been decided to emulate a real designing phase situation. The main car systems has been set as the FIAT 500e ones and modify one system per time emulating a change in just one component and verify the overall car system working condition and feasibility. This means that the FIAT 500e yet iterated values have been imposed as comparison values do determine how a one system change would interact with others.

First of all the GA (genetic algorithm) has been tested with other two different cycles: NEDC and CLTC.

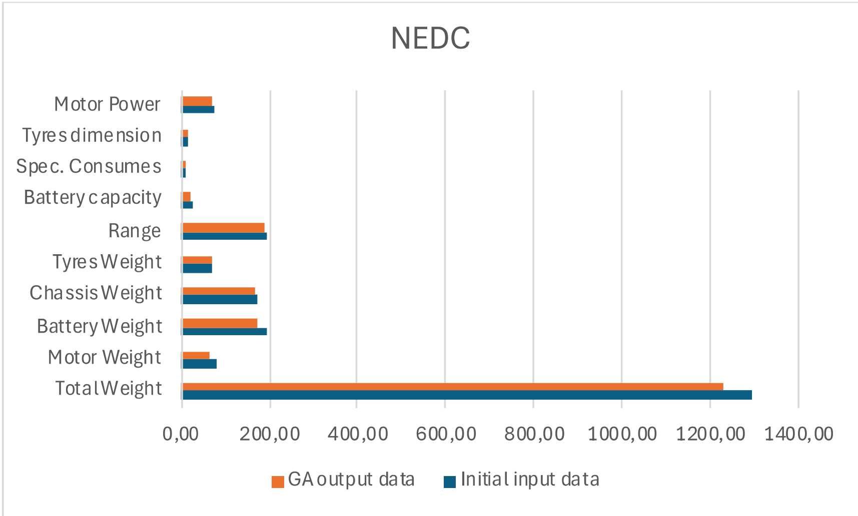

Figure 56, empirical-NEDC difference

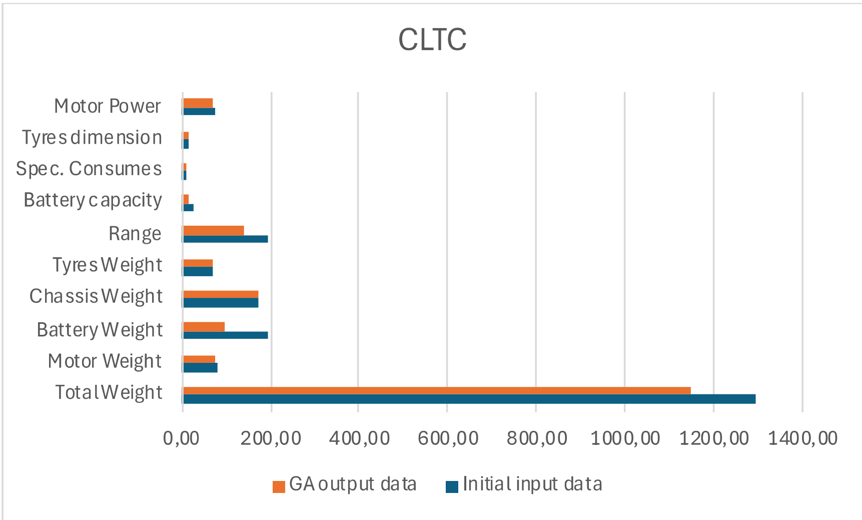

Figure 57, empirical-CLTC difference

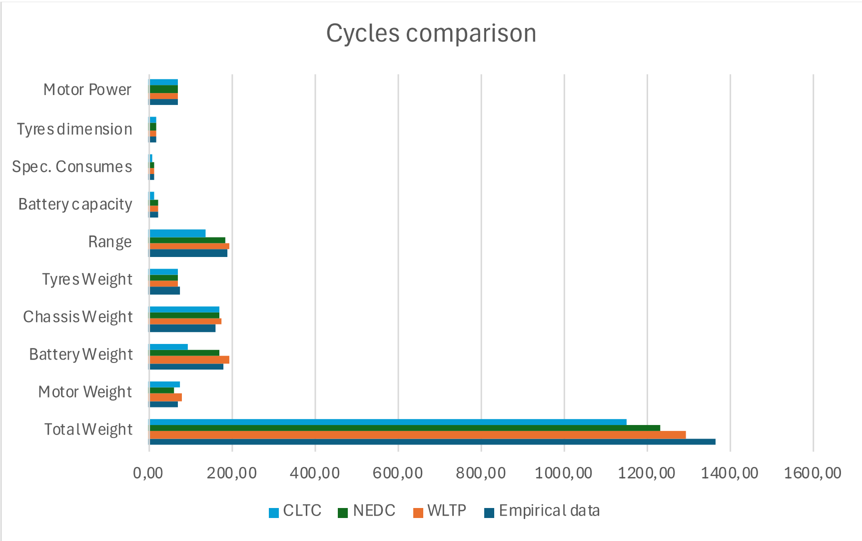

Figure 58, cycles and empirical data general comparison

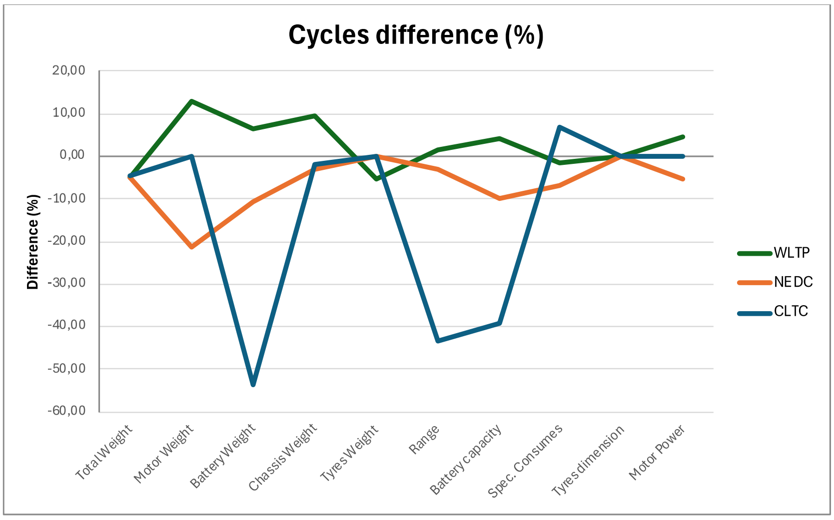

Figure 59, driving cycles differences with respect to empirical data

Value	GA output data	unit	Difference (%)
Total Weight	1231,00	kg	-5,02
Motor Weight	62,30	kg	-21,14
Battery Weight	173,20	kg	-10,72
Chassis Weight	170,00	kg	-2,86
Tyres Weight	70,00	kg	0,00
Range	187,00	km	-3,21
Battery capacity	22,31	kWh	-9,79
Spec. Consumes	11,90	kWh/100km	-7,03
Tyres dimension	17,00	Inches	0,00
Motor Power	69,40	kW	-5,14

Figure 60, NEDC results

Value	GA output data	unit	Difference (%)
Total Weight	1150,00	kg	-11,27
Motor Weight	75,00	kg	-5,06
Battery Weight	97,00	kg	-50,00
Chassis Weight	170,20	kg	-2,74
Tyres Weight	70,00	kg	0,00
Range	138,30	km	-28,42
Battery capacity	15,63	kWh	-36,80
Spec. Consumes	11,30	kWh/100km	-11,72
Tyres dimension	17,00	Inches	0,00
Motor Power	70,52	kW	-3,61

Figure 61, CLTC results

It is evident how maximum ranges of the vehicles show that the sizing is conservative, as the energy demand of the cycle is lower. This happens because, despite the consumes improvement, these two cycles are less demanding and the GA tends to size battery and total weight in terms of total consumption and since has not been imposed a minimum battery the total capacity may be seems conservative but it is calculated to be sufficient to fulfill cycle requirements.

Considering the battery one of the most decisive, or the most decisive (especially on light vehicles), component on a BEV it has been tested in 3 different configurations (15 kWh, 20 kWh and 40 kWh). The powertrain has been kept the same in order to maintain continuity between tests and the sample test. Also the tire diameter has been kept the same in order to follow the already discussed philosophy of one component swap and test.

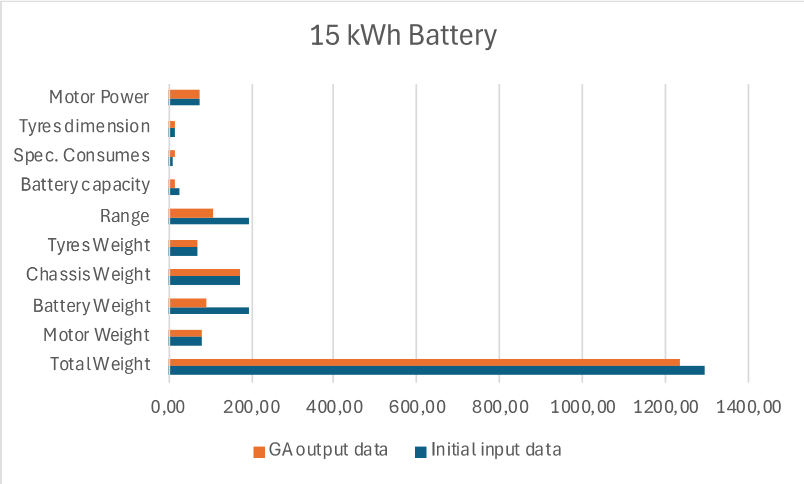

Figure 62, 15 kWh battery simulation difference with respect to first iterated WLTP results

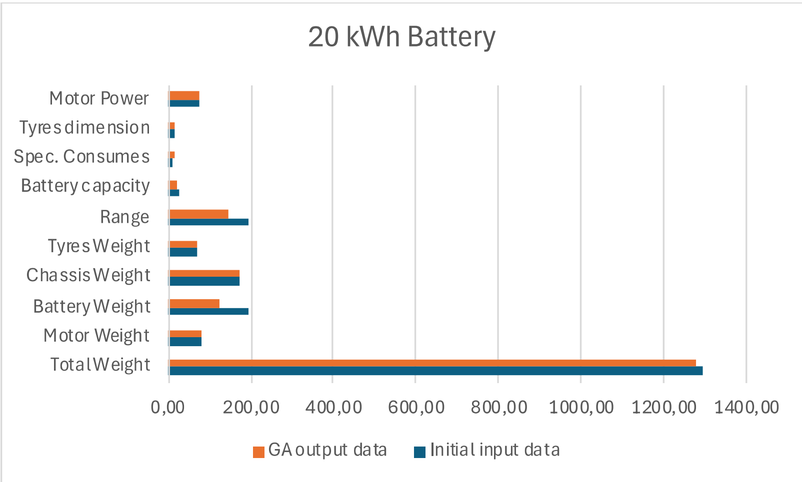

Figure 63, 20 kWh battery simulation difference with respect to first iterated WLTP results

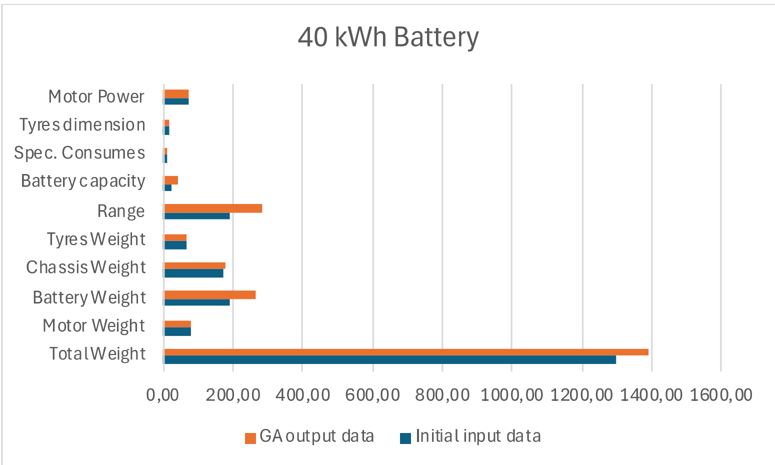

Figure 64, 40 kWh battery simulation difference with respect to first iterated WLTP results

Predictably the range grows with battery despite the weight increase. It is interesting to appreciate how the total chassis weight grows with battery weight, has been settled a safety factor inside the chassis function in order to take in account battery dimensions and weight to assure structural endurance.

Tires are important in terms of consumption and safety, influencing directly vehicle stability. The tire dimensions tested are 14, 18 and 21 Inches. Theoretically higher consume should be expected with bigger tires. Powertrain has been maintained the same always for consistency reasons.

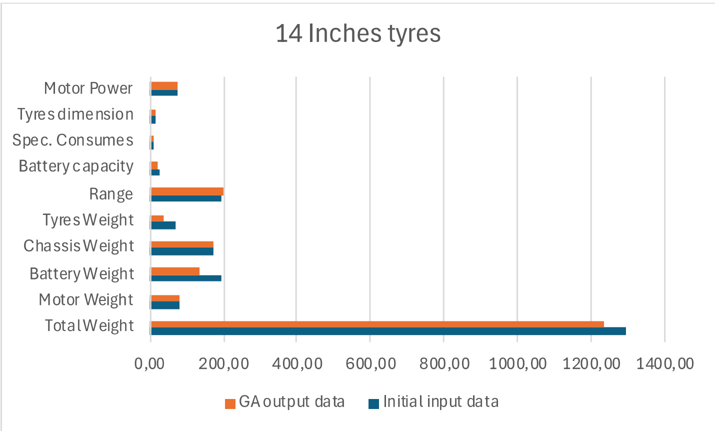

Figure 65, 14 inches tire simulation difference with respect to first iterated WLTP results

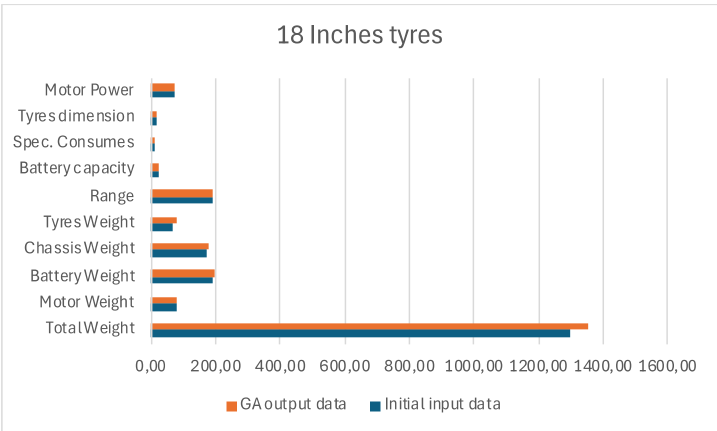

Figure 66, 18 inches tire simulation difference with respect to first iterated WLTP results

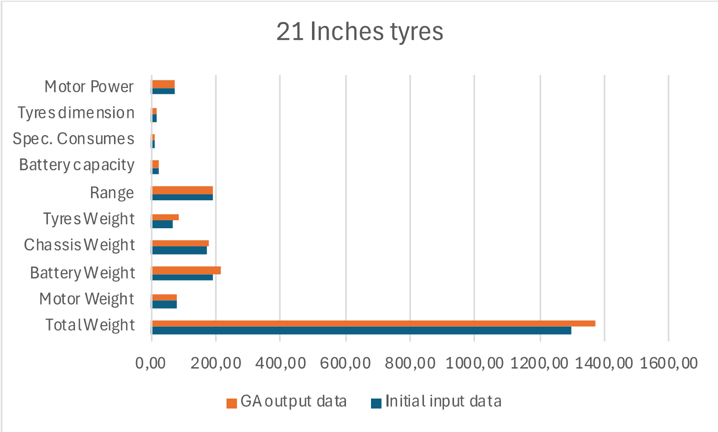

Figure 67, 21 inches tire simulation difference with respect to first iterated WLTP results

Battery weight changes sensibly since energy requirements of the test cycle are lower for smaller tires and higher for bigger tires. The change in battery dimensions also modify the chassis.

Until now the total weight has been set as input starting point similar to 500e one, now would be interesting test a radical change of this parameter. It is important to check which resulting components the code would give and it is also important for verification reasons, indeed being this a much invasive change will indirectly test the algorithm stability. The system has been tested with initial masses of 700kg and 1500 kg, higher values have not been considered since they would be reasonably far from targeted segment and not tuned, and inconsistent results would be expected.

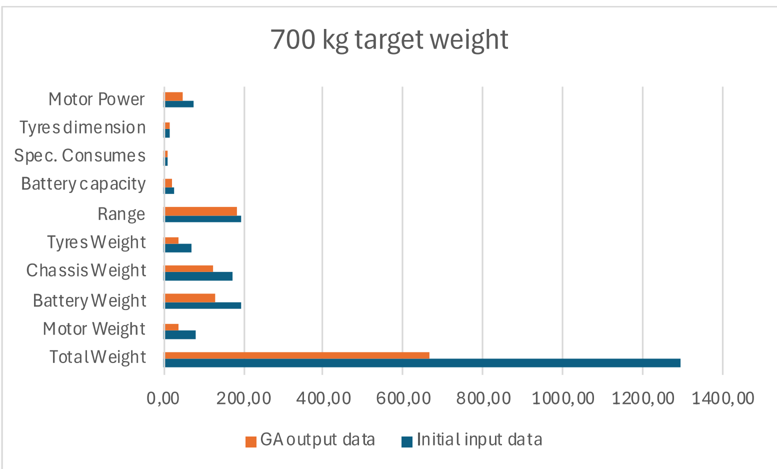

Figure 68, 700 kg total target weight simulation difference with respect to first iterated WLTP results

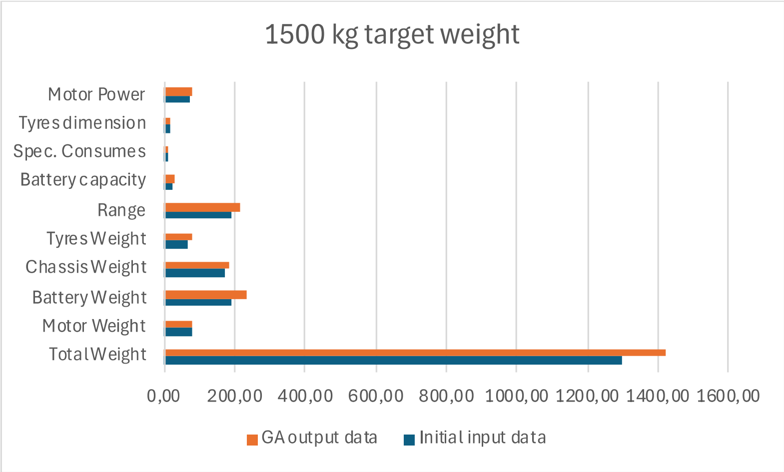

Figure 69, 1500 kg total target weight simulation difference with respect to first iterated WLTP results

Lighter vehicle results to have smaller tires, battery and motor but with a maximum range similar to the original one. Heavier car is going to have much bigger component, also tires would be larger, despite higher consumption, for safety reason.

Moreover, has been considered a change in Cx to emulate external vehicle changes, for example a change of the rear view mirror since they are the most aero drag generator component and even a small change can have remarkable effect.

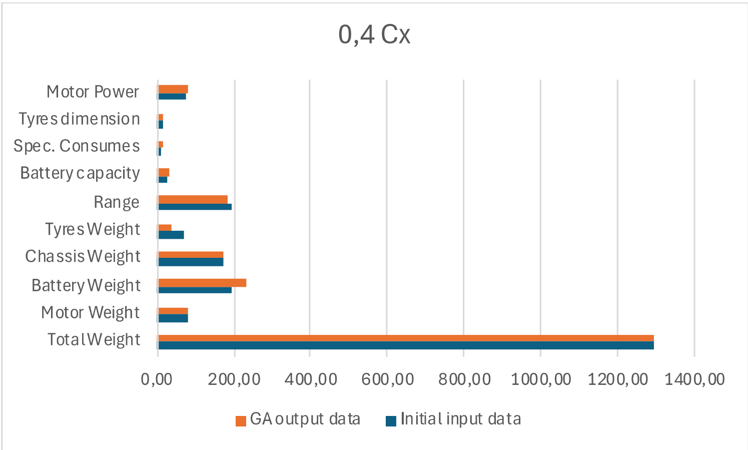

Figure 70, 0,4 Cx simulation difference with respect to first iterated WLTP results

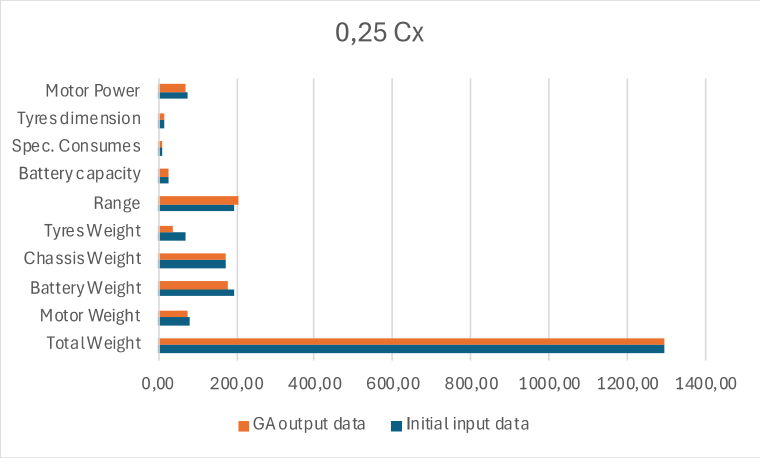

Figure 71, 0,25 Cx simulation difference with respect to first iterated WLTP results

Higher aerodynamic coefficient corresponds to higher consumes and so higher energy requirements, this result in bigger motor, bigger battery but lower range.

In the end a change in battery architecture has been performed, modifying cell distribution, energy density ratios and battery weight allocation

Fixed data (constants)	
Cell Capacity	60 Ah
Cx	0.32
Max speed	135 km/h
0-100 time	9 s
Total efficiency	0.85
Car width	1683 mm
Car height	1527 mm
Chassis Material	Alluminum
Cell Voltage	3.65 v
Cell weight	0.9 kg
Battery pack nominal Votlage	394 v
Motor max rpm	12000,00

Figure 72, initial 500e architecture

Fixed data (constants)	
Cell Capacity	3,5 Ah
Cx	0.32
Max speed	135 km/h
0-100 time	9 s
Total efficiency	0.85
Car width	1683 mm
Car height	1527 mm
Chassis Material	Alluminum
Cell Voltage	3.65 v
Cell weight	0,045 kg
Battery pack nominal Votlage	394 v
Motor max rpm	12000

Figure 73, modified battery architecture

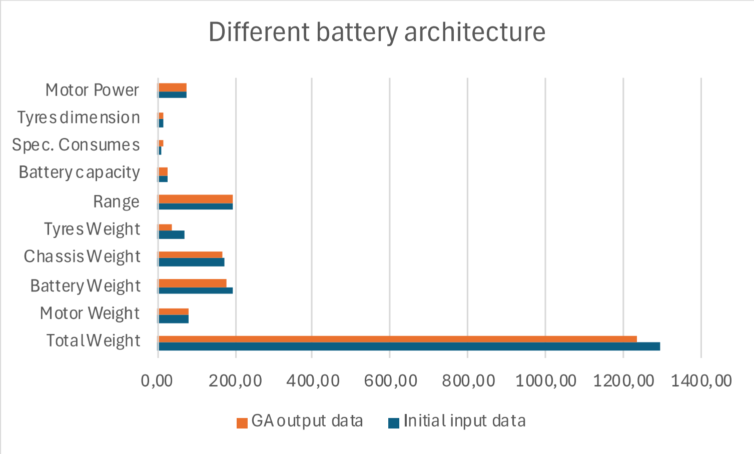

Figure 74, battery architecture change simulation difference with respect to first iterated WLTP results

Despite a very similar maximum range the new architecture results in a smaller and lighter vehicle, since energy density of the battery is higher. It can be observed that the code adjusts the capacity without extensively modifying the vehicle configuration, in order to maintain consistent results. The new architecture must still comply with operational standards, despite altering the arrangement and number of cells. Additionally, there are slight changes to the chassis to accommodate modifications in the utilized volume and weight distribution.

Passengers number homologation have a significant role on weight, above all on small cars. In the showed case the maximum number of passenger of the FIAT 500e has been reduced by one.

Value	500e	unit
Total Weight	1296,00	kg
Motor Weight	79,00	kg
Battery Weight	194,00	kg
Chassis Weight	175,00	kg
Tyres Weight	70,00	kg
Range	193,20	km
Battery capacity	24,73	kWh
Spec. Consumes	12,80	kWh/100km
Tyres dimension	17,00	Inches
Motor Power	73,16	kW

Value	GA output data 4 passengers	unit	Difference (%
Total Weight	1221,00	kg	-5,79
Motor Weight	79,00	kg	0,00
Battery Weight	194,00	kg	0,00
Chassis Weight	169,00	kg	-3,43
Tyres Weight	70,00	kg	0,00
Range	198,79	km	2,89
Battery capacity	24,73	kWh	0,00
Spec. Consumes	12,44	kWh/100km	-2,81
Tyres dimension	17,00	Inches	0,00
Motor Power	73,16	kW	0,00

Figure 75, comparison with passengers number reduction

Moreover, a second approach to result has been proposed. More precisely, instead of constraining a singular component, has been constrained a singular characteristic or not imposing at all a constrain. For no-constrain simulation a singular characteristic has been set to increase from a starting value to an ending value by imposed dimension steps. In figure 74 and 75 the simulation has been tuned with a target range of 200 km, instead in in figure 76, 77 and 78 no static constraints have been imposed but a dynamic range set to grow at each iteration.

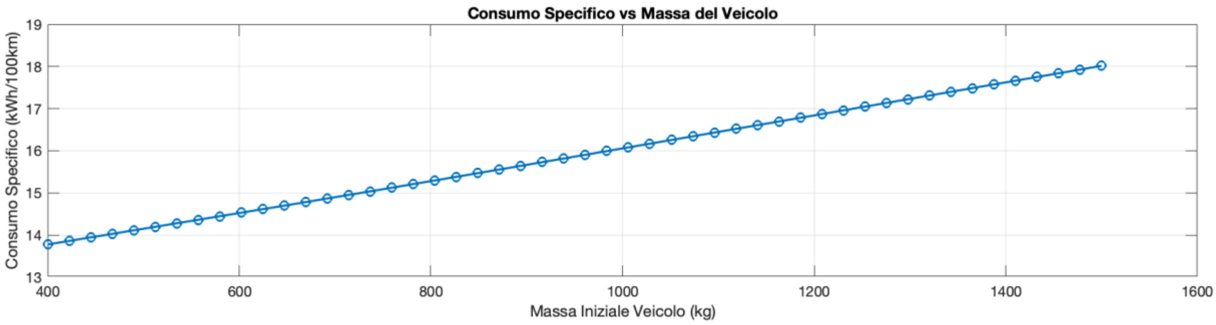

Figure 76, specific consumes-vehicle mass comparison

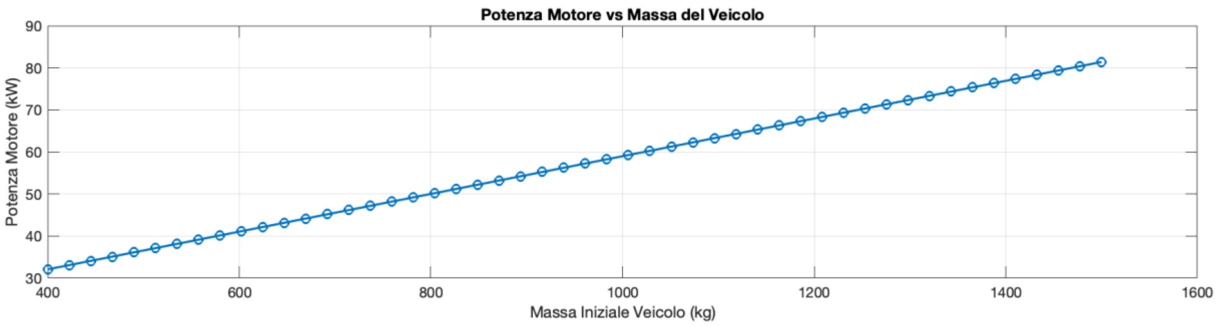

Figure 77, power-vehicle mass comparison

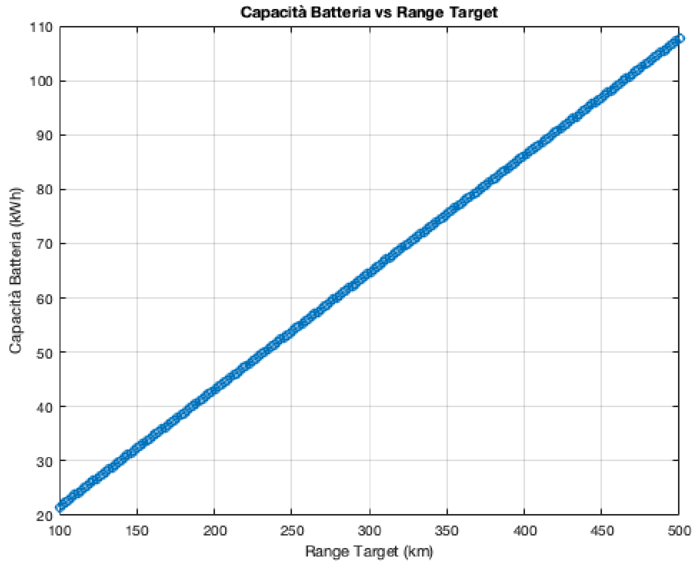

Figure 78, battery capacity-range comparison

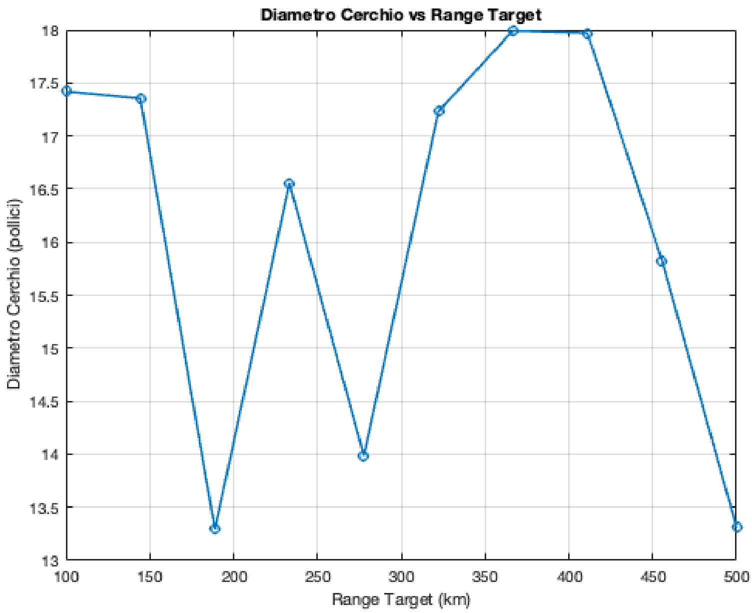

Figure 79, tire dimension-range comparison

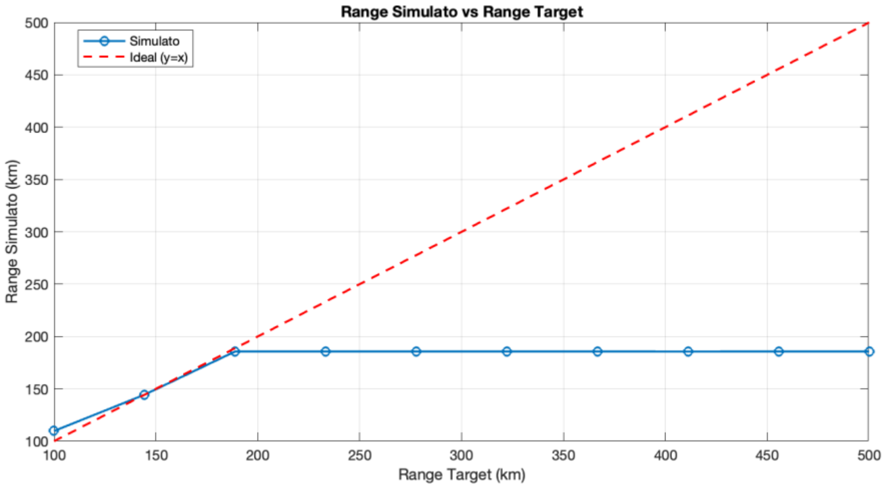

Figure 80, emulated range-ideal range

10. Conclusion and future upgrades

In terms of the ultimate developments and possible refinements, the project is open to a variety of possible developments that go way beyond the optimization of already established parameters. The goal is to incorporate further sub-functions with the capability to simulate larger quantity and precision of components that make up a vehicle in an increasingly more detailed and realistic manner. For example, it is supposed to have modules which are dedicated in the suspension system, thermal system, electronic control, and electronic dynamic efficiency , in an effort to obtain an overall model closer to reality. These sub-tasks, constructed in modular way, will enable further expansion and upgrades with small effort.

At the same time, a 3D representation and advanced simulation environment is to be built. The goal is to convert the numerical results, such as physical parameters, component position and the dynamic involved into point clouds that can be processed to form a three-dimensional mesh. This will act as a 3D prototype, which will make data easily comprehensible and usable, for internal purposes of analysis as well as for presenting. This 3D graphical representation not only enhances the comprehension of the model, but also enables one to visually check the integration and consistency of the different parts of the vehicle.

With a view to interoperability and flexibility, project conversion to Python is also planned, developing a tool set to facilitate automatic file generation in .stl and .3mf. These formats are standard in 3D printing and CAD design, providing seamless switching from the virtual model to physical prototype and facilitating direct integration with digital manufacturing processes.

Another level of innovation is the integration with Large Language Model (LLM) algorithms and, possibly, the use of ChatGPT APIs. With this integration, it would be possible to have an easy and fast tuning of the input parameters and the required outputs. Users would be able to interact with the system in natural language, get suggestions, adjust parameters in real-time and immediately see the impact of such adjustments on the simulated model. This is an approach based on artificial intelligence that automates model refinement and adaptation, creating a cutting-edge frontier to not only make the optimization process more precise, but also highly interactive and user-friendly.

In the end, the potential for code creation is enormous: while on the one hand, addition of sub-functions to simulate other car parts will render the model increasingly detailed and realistic, on the other hand, integration with 3D visualization software and conversion programs into standard formats for physical modeling, coupled with support from LLM algorithms, will render the system extremely interconnected. This will allow to seamlessly shift from simulation to visualization and, finally, to prototyping, allowing for an iterative and imaginative design process that dynamically adapts to the vehicle's development needs.

Figure 81, large language model (LLM) structure

Figure 82, 3D printing prototyping

Bibliography

1. Deb, K. (2001). "Multi-Objective Optimization Using Evolutionary Algorithms". John Wiley & Sons.
2. Haupt, R. L., & Haupt, S. E. (2004). "Practical Genetic Algorithms". Wiley.
3. Articolo: Chong, K. T., & Shim, H. S. (1999). "Structural Optimization of an Automotive Body with Genetic Algorithms". *Journal of Materials Processing Technology*, 89-90, 352-356.
4. Goldberg, D. E. (1989). "Genetic Algorithms in Search, Optimization, and Machine Learning". Addison-Wesley.
5. Cacciabue, P. C., & Amaldi, P. (1998). "Modeling Driver Behavior in Automotive Environments". *Safety Science*, 28(2), 115-128.
6. Articolo: Back, T., Fogel, D. B., & Michalewicz, Z. (1997). "Handbook of Evolutionary Computation". IOP Publishing Ltd. and Oxford University Press.
7. Regolamento (UE) n. 168/2013 del Parlamento europeo e del Consiglio del 15 gennaio 2013 relativo all'omologazione dei veicoli a motore a due o tre ruote e dei quadricicli.
8. Ministero del Territorio, delle Infrastrutture e dei Trasporti del Giappone: Specifiche delle kei car.
9. Associazione Cinese dei Produttori di Automobili (CAAM): Rapporti sul settore automobilistico.
10. Articolo Accademico: Wang, H., & Kimble, C. (2011). *"Segmenting the Chinese Car Market: The Challenge of Teaming Mass Production and Individualism"*. Management Decision, 49(4), 594-613.
11. Ministero delle Infrastrutture e dei Trasporti: Informazioni sulle categorie di veicoli.
12. Articolo Accademico: Abagnale, C., Cardone, M., et al. (2015). *"Electric Powertrain Optimization for a Lightweight Quadricycle: A Case Study"*. *Energy Procedia*, 81, 622-633

13. Articolo Accademico: Sugiura, M., & Taishi, M. (2000). *"Development of Next-Generation Kei Car with Improved Fuel Efficiency"*. *SAE Technical Paper*.
14. **Wikipedia.** (n.d.). *Quadricycle (EU vehicle classification) [Immagine di Renault Twizy].* Recuperato da https://en.wikipedia.org/wiki/Quadricycle_%28EU_vehicle_classification%29#/media/File:Renault_Twizy_P6180123_(cropped).jpg
15. **Carscoops.** (2022, marzo). *Daihatsu says cheap Chinese EVs pose a threat to Japan's iconic kei cars.* Recuperato da https://www.carscoops.com/2022/03/daihatsu-says-cheap-chinese-evs-pose-a-threat-to-japans-iconic-kei-cars/
16. **Keyton Auto.** (n.d.). *Keyton A00 Electric Sedan.* Recuperato da https://www.keytonauto.com/keyton-a00-electric-sedan.html
17. **Precedence Research.** (n.d.). *Microcars Market: Key Takeaways.* Recuperato da https://www.precedenceresearch.com/microcars-market
18. **LeddarTech.** (2024, giugno). *White Paper: A Comprehensive Overview of C-NCAP 2024 Regulations (Versione 1.0) [PDF].* Recuperato da https://leddartech.com/app/uploads/dlm_uploads/2024/06/White-Paper_A-Comprehensive-Overview-of-C-NCAP-2024-Regulations_V1.0_EN-5.pdf
19. **National Agency for Automotive Safety and Victims' Aid (NASVA).** (n.d.). *About.* Recuperato da https://www.nasva.go.jp/mamoru/en/about/about.html
20. **Articolo (Consumers' preferences for electric vehicles: The role of status and reputation).** (n.d.). Recuperato da https://www.sciencedirect.com/science/article/pii/S136192092200356X

21. **Articolo (Electric vehicles' consumer behaviours: Mapping the field and providing a research agenda).** (n.d.). Recuperato da https://www.sciencedirect.com/science/article/pii/S0148296322005410
22. **Gogoro.** (n.d.). *Battery swapping smart tech makes city living easy and clean.* Recuperato da https://www.gogoro.com/news/battery-swapping-smart-tech-makes-city-living-easy-and-clean-gogoro/
23. **World AutoSteel.** (2013). *Estimation of Secondary Mass Effects in Vehicle Design [PDF].* Recuperato da https://www.worldautosteel.org/download_files/Other%20Reports/Estimation%20of%20Secondary%20Mass%20Effects%20in%20Vehicle%20Design_201303.pdf
24. **Tecnische Universität München (TUM).** (n.d.). *[Parametric Modeling of Battery Electric Vehicles in the Early Development Phase].* Recuperato da https://mediatum.ub.tum.de/1647238
25. **Tecnische Universität München (TUM).** (n.d.). *[Methodik zur Auslegung von autonomen Fahrzeugkonzepten].* Recuperato da https://mediatum.ub.tum.de/1688955
26. **ICAR – CNR.** (2017). *[Documento tecnico].* Recuperato da https://intranet.icar.cnr.it/wp-content/uploads/2017/02/RT-ICAR-CS-03-17.pdf
27. **Benvenuti, D.** (n.d.). *Genetic Algorithms [Tesi di laurea].* Recuperato da https://www.roma1.infn.it/exp/nemo/AHEN/Thesis/DarioBenvenuti/05_Ric_Genetic_Algo.pdf
28. **Shikh Farshi, C.** (n.d.). *[Tesi di laurea].* Recuperato da https://amslaurea.unibo.it/id/eprint/5843/1/Christian_Shikh_Farshi_tesi.pdf

29. **Articolo (A review: high power density motors for electric vehicles).** (n.d.). Recuperato da https://iopscience.iop.org/article/10.1088/1742-6596/1706/1/012057/pdf
30. **Politecnico di Torino. A Review of Multi-Phase Permanent- Magnet Synchronous Motors** (n.d.). *[Tesi di laurea].* Recuperato da https://webthesis.biblio.polito.it/30903/1/tesi.pdf
31. **EMC Elettronica.** (n.d.). *L'elettronica di potenza nei veicoli elettrici e ibridi.* Recuperato da https://it.emcelettronica.com/lelettronica-di-potenza-nei-veicoli-elettrici-e-ibridi
32. **ENEA.** (2021). *Tecnologie per la penetrazione efficiente del vettore elettrico negli usi finali [PDF].* Recuperato da https://www2.enea.it/it/Ricerca_sviluppo/documenti/ricerca-di-sistema-elettrico/adp-mise-enea-2019-2021/tecnologie-per-la-penetrazione-efficiente-del-vettore-elettrico-negli-usi-finali/report-rds_ptr_2021_196.pdf
33. **Automoto.** (n.d.). *Cerchi grandi vs. cerchi piccoli: le prestazioni cambiano eccome.* Recuperato da https://www.automoto.it/prove/cerchi-grandi-vs-cerchi-piccoli-le-prestazioni-cambiano-eccome.html
34. **SAE International.** (2017). *Experimental evaluation of rotational inertia, tire rolling resistance: A twin roller chassis dynamometer [Atti di convegno].* Recuperato da https://saemobilus.sae.org/papers/experimental-evaluation-rotational-inertia-tire-rolling-resistance-a-twin-roller-chassis-dynamometer-2017-36-0212
35. Renault Group. Renault Twizy Brochure. Available at: https://cdn.group.renault.com/ren/it/transversal-assets/brochures/X091VEVPTWZ/brochure.pdf?utm_source=chatgpt.com

36. Al Volante. Renault Twizy Urban – First Drive Review. Available at: https://www.alvolante.it/primo_contatto/renault_twizy_1_urban
37. Quattroruote. Renault Twizy: Dimensions, Battery, Motor, and Performance. Available at: https://www.quattroruote.it/news/ecologia/2020/07/28/renault_twizy_dimensioni_batteria_motore_prestazioni.html
38. Wheel-Size.it. Renault Twizy 2020 – Wheel and Tire Dimensions. Available at: https://wheel-size.it/size/renault/twizy/2020/