POLITECNICO DI TORINO

Master's Degree in Automotive Engineering
Propulsion System Development

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Genetic Algorithm optimization of Fuel Cell/Battery propulsion system components

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Per Aspera ad Astra

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ABSTRACT

After the collective take of awareness towards a sustainable human impact on Earth, much of the attention has been focused on mobility and transports. Many international organisms, starting from European Commission, the American EPA (Environmental Protection Agency) and subsequently followed by the new rising economic powers like China and India, have taken actions. The common objective is a drastic reduction of noxious emissions from fossil fuel combustion and a lower footprint of transport sector on air pollution and greenhouse effect. These intentions have been concretized in regulatory laws and stringent limits that have led the OEMs to spend billions on more sophisticated technologies to comply with the imposed limits, avoiding hefty fines from the authorities. In parallel with the development of the existing conventional combustion engines solutions (downsizing, turbocharging, EGR and aftertreatment systems) and synthetic fuels, new frontiers were investigated. Electrified hybrid vehicles and full electric vehicles are now perceived by customers as a reality, and they are taking shares in the car fleet circulating in the cities around the world. Conversely, hydrogen propulsion is still seen as a “technology of the future” and underestimated when alternative green solutions are sought.

“Hydrogen is the future… and always will be” [1]

The above sentence ironically reflects the common opinion about hydrogen possibilities to open a breach on the market, despite looking promising for the premises from which it starts. However, this technology has evolved in the past years and thanks to obstinacy and economic efforts of some OEMs like Toyota and Hyundai, Fuel Cells are mature for mass production.

The objective of this thesis is the development of a methodology to determine the sizing of powertrain components in a Fuel Cell/Battery vehicle. The analysis will involve the study of the best powertrain configuration to optimize costs and performances in different missions and scenarios. For this purpose, an optimization procedure called Genetic Algorithm, able to autonomously find the best compromise, will be adopted. The GA procedure is coupled with a vehicle model in which Fuel Cell system model has been improved using experimental data to better represent the dynamic behavior of a real Fuel Cell. The study on the Fuel Cell will be focused on the influence of temperature and reagents supply on power generation. In conclusion, an applicative case will be investigate based on a generic mid-size Light Commercial Vehicle and an economic analysis on the different configurations is given to identify a cost-effective choice among them.

All the work has been carried out on MATLAB/SIMULINK environment.

CHAPTER 1: INTRODUCTION TO THE TOPIC

1.1 Need for new technologies for sustainable mobility

Since the effects of the human intervention into the natural ecosystems became more and more visible and intense, the cost in terms of loss of human lives and economic damages raised. Thus, the international authorities decided to make a common front against climate change. This intent culminated with the ratification of the Paris Climate Agreement in 2015 by the member states of United Nations Framework Convention on Climate Change (UNFCCC). The 175 Countries that signed the agreement on April 22, 2016, undertook to contain the increase in the global average temperature well below the 2 °C, threshold above pre-industrial levels, and to limit this increase to 1.5 °C, as this would substantially reduce the risks and effects of climate changes. The success of this could only pass through the reduction of greenhouse gases (GHG) for which the transport sector is responsible in large extent.

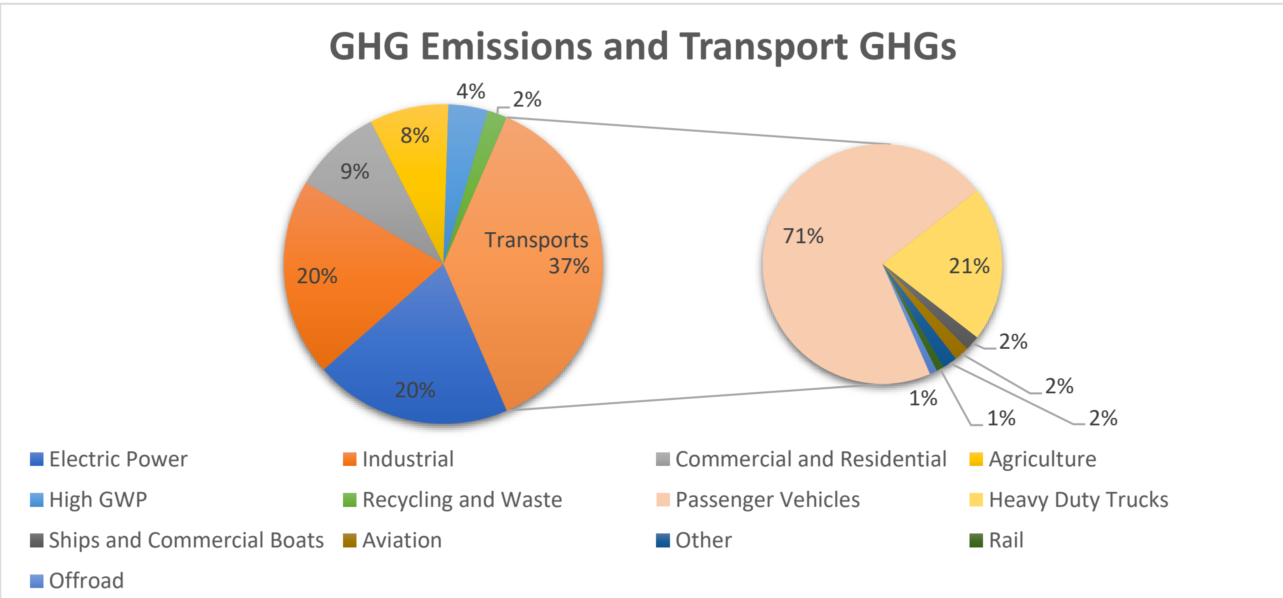

Figure 1: **GHG emissions and transport sector GHG emissions subdivided into vehicle types** [2]

A second factor on which attention has been focused is the emission of NOx from vehicles tailpipes. Nitrogen, combining with oxygen, gives rise to various compounds called NOx. Among these, the most important for atmospheric pollution are nitrogen oxide NO and nitrogen dioxide NO2. Nitric oxide is a colorless and odorless gas. It is formed in any combustion process in which air is used as an oxidizer, by reaction between oxygen and nitrogen at high temperatures. About 10% of NO, once released into the atmosphere, is transformed into nitrogen dioxide by the action of solar radiation.

Furthermore, in conditions of strong irradiation, nitrogen oxides participate in photochemical reactions that originate secondary pollutants (ozone, photochemical smog). Nitrogen oxides also contribute to the formation of acid rain and favor the accumulation of nitrates in the soil which can, in turn, significantly alter the environmental ecological balance. [3]

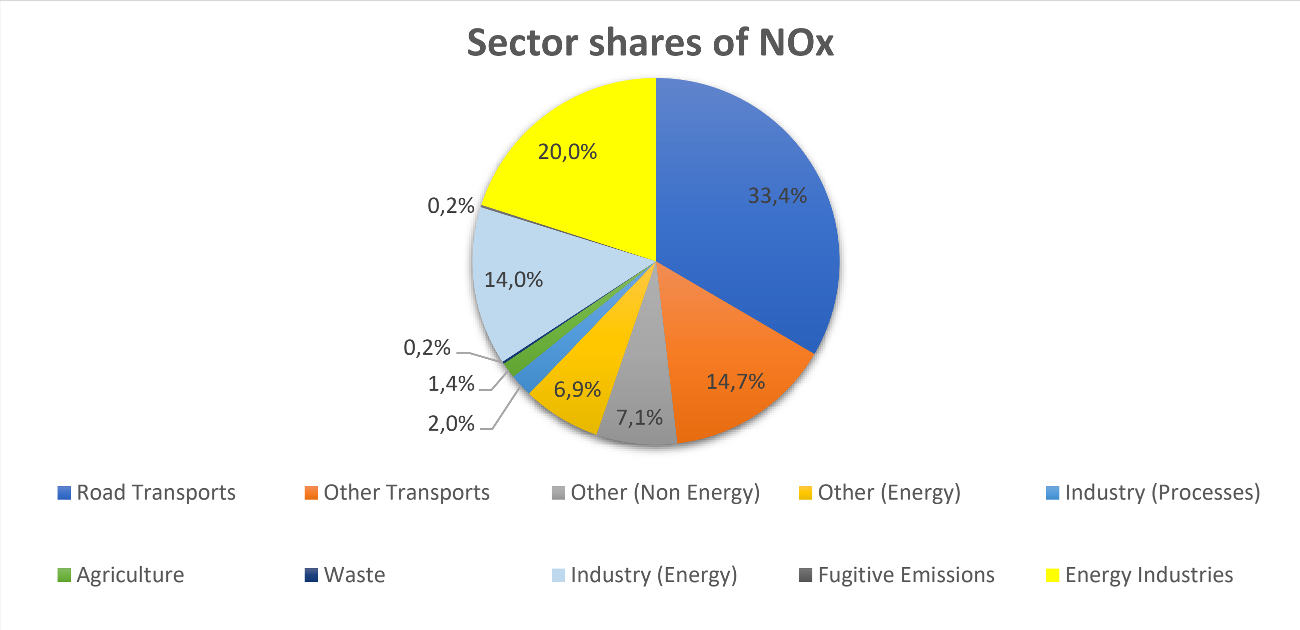

Figure 2: **Sector share of nitrogen oxides emissions (EEA member countries)** [4]

Despite actions have already been taken from 90s in automotive sector (e.g., European emissions standards, now with the incoming EURO 7 normative), further steps had to be taken. Given that all noxious compounds under indictment are by-products of gasoline or Diesel combustion, it was evident that the technological evolution should move in the direction of a combustion-free propulsion. This is the reason of the making of the first hybrid and electric vehicles that are now slowly but unrelentingly gaining shares on the market. On the other hand, hydrogen powered vehicles have always continued to be developed and, even if intended to a niche market, globally commercialized by some brands. Since 2015, Toyota Mirai represents a milestone in the sector and, alongside with Hyundai NEXO from 2018, intends to lead the way of an innovative mobility. To these BMW and Mercedes-Benz have recently been joined with Hydrogen NEXT and GLC F-Cell, respectively.

At this point it becomes clear that the way we intend transports and mobility is fated to drastically change. By 2030, the efforts against climate change will take shape and this will be reflected in first instance by road transport.

1.2 Fuel Cell/Battery Hybrid Electric Vehicles

Hydrogen powered vehicles, or more properly called Fuel Cell Electric Vehicles (FCEV), use an e-motor fed by electricity to propel itself. In contrast with all the other electric vehicles, part of the energy is produced on-board even during the motion, rather than being entirely drawn from a battery pack previously charged. The task of energy (and power) production is entrusted to the Fuel Cell system that can generate electric energy from electrochemical reactions between hydrogen and oxygen. That would mean the possibility to cut down to zero the CO2 at pipeline.

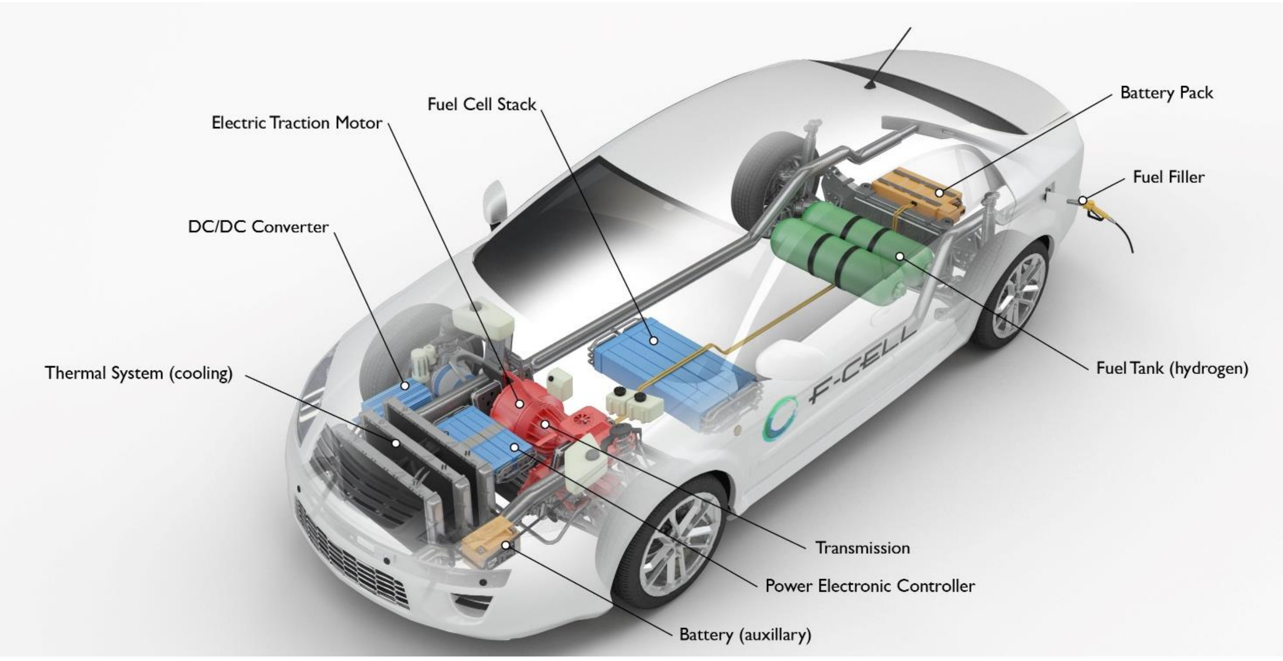

Figure 3: **FCEV architecture and main powertrain components** [5]

FCEV are quite complex vehicles that possess a multitude of different components. Looking at the above picture Figure 3, it is possible to identify:

- **Fuel Cell Stack**: assembly of single polymeric electrode membranes (PEM). It uses hydrogen from on-board tanks and oxygen from air to produce electricity. Further details will be given in a dedicated chapter.
- **Battery Pack**: often directly taken by OEMs from already in production Battery or Hybrid Electric Vehicles (BEV or HEV), it is an assembly of single battery cells. The battery cells are variously connected in series and/or parallel to achieve the desired level of power and energy starting from voltage, current and capacity characteristics of the cell. It also enables a regenerative braking capability, since it can be recharged with the energy recovered during braking maneuvers.

The Pack always incorporates a sophisticated Battery Management System (BMS) that controls Battery parameters such as overvoltage, overcurrent, and thermal conditions to avoid breakdown.

- **DC/DC Converter**: it acts as a three-way voltage mediator between two energy sources (Fuel Cell and Battery Pack) with different voltage levels and the Inverter/E-Motor system. Battery Pack voltage is in the order of several hundreds of Volts, while Fuel Cell voltage is no higher than 100-200 V at rest and can drop up to some tenths of Volts at full power. For this reason, FC voltage must be boosted to higher levels by the DC/DC Converter to match the Battery and Inverter voltage levels. In addition, it can decouple the Fuel Cell during "only battery" driving conditions: it can be useful to preserve the membranes from stresses that arise during peak power requests.
- **Thermal System (cooling)**: like conventional combustion vehicles, it is made by radiators, pumps, sensors, and pipes. It must guarantee the correct operating temperature for Fuel Cell, power electronics, electric motor and all the other components.
- **Battery (auxiliary)**: standard 12 V lead-acid battery, it provides electricity to vehicle accessories. It can also start the vehicle before the traction battery is switched on.
- **Power Electronics Controller**: it performs the DC to AC electrical conversion. It manages the flow of electrical energy delivered by the FC system and the main traction battery, controlling the speed of the electric traction motor and the torque it produces by means of voltage and current control techniques.
- **Electric Traction Motor**: electric machine that can work as a motor to provide traction to the vehicle, or as a generator during regenerative braking phase. It is usually of Synchronous Interior Permanent-Magnet type, only exception is the Asynchronous type adopted by Tesla.
- **Transmission**: one or two speed automatic transmission.
- **Fuel Tank(s)**: one or more carbon fiber, high pressure tanks that contain the pressurized hydrogen. They must be extremely resistant to be safe in case of collisions or impacts, since the hydrogen is stored at about 700 bars so that the on-board quantity could be enough to guarantee a reasonable driving range.
- **Fuel Filler**.
- **Battery Charger** (not shown in Figure 3): electric socket to charge the vehicle battery. It is always present in case of high-capacity batteries, while for batteries of few kWh it may even not be present. In the latter case, battery charging is done exclusively by regenerative braking and/or by the Fuel Cell (if present).

1.3 First design phase problem: powertrain components size choice

During the early phases of the vehicle development, well before any technical consideration about specific components technical characteristics, OEMs must choose the correct size of the adopted powertrain. To create such a complex product and to consider predefined boundary conditions, a flexible development and production process is necessary.

Figure 4: **Principal stages in a state-of-the-art vehicle development process** [6]

Within the first definition phase, all requirements on the concept are collected. This includes all boundary conditions targeting legislative, consumer and, not least, company related factors. Additional considerations of production technologies, dimensions, and functional requirements are investigated. Since the cost of corrective actions in the definition and concept phases is virtually zero (project is still in an embryonic stage and no physical model has been manufactured yet), analysts and engineers must lay the foundation of the work.
Summarizing, the choice must consider:

- **Feasibility** of the project.
- **Performance achievement** by the vehicle.
- **Cost and price competitivity** on the market.

1.3.1 Project feasibility

First target to be assessed is the feasibility of vehicle realization. This task is multidisciplinary and involves all technical and logistic departments. It must be investigated whether the firm possesses all the knowhow necessary to the project, or instead external partners and resources should be recruited. The technology used should be mature and reliable to guarantee performance and product quality. Furthermore, additional industrial constraints are represented by the impossibility of a totally free choice of components properties and dimensions since they are manufactured in predetermined characteristics or sizes. For this reason, it results always in the search of the best compromise between the optimal solution, on one side, and the most suitable one, on the other side.

1.3.2 Performance achievement

Before being put on the real roads, new vehicles must meet strict standards in terms of performances. These targets can be either internal to the company or from legislative regulations. Many of these concern proper vehicles performances such as acceleration, full load gradeability, maximum payload and towing capability. Others, instead, they are related to fuel consumption and noxious emission limits.

1.3.3 Company's costs and market competitiveness

Even if here presented as last parameter to be considered, the cost of the chosen solution is undoubtedly of primary interest to the company. The cost paid by the company is not represented only by product manufacturing, but also by many other factors such as logistic, marketing and after-sale costs, since during the warranty period any repair costs are sustained by the manufacturer. Part of these costs are fixed and unavoidable, parts are instead variable and linked to the number of units sold leading to highly volatile profit margins. For all these reasons, setting the right price is all but straightforward: it must be fixed above OEMs product cost and below the customers perceived value, resulting at the same time competitive towards other competitor's products present in the same market segment.

1.4 Thesis objective: development of a discrete variable optimization algorithm

Aim of the thesis investigation will be the development of an algorithm capable of finding, in an intelligent way, the optimized sizes of vehicle Fuel Cell system and the Battery Pack. Given that these parameters cannot be treated as continuous variables for the above-mentioned problems of manufacturability and availability on market, the algorithm must perform the search between sizes pre-established by the user. What it is going to be minimized is both the cost of the vehicle production for the manufacturer, and the operating cost that will be paid by the final customer for hydrogen and electricity purchase. All this will be done keeping in mind performance constraints for the vehicle, and specific configurations will be identified for each different mission (urban, rural, highway scenarios), using as test case a generic mid-van LCV. Lastly, a configuration for an average and mixed scenario will be investigated.

The computation of the results is based on a FCEV model previously developed by Dott. Michele Settembrino for his thesis work. The model will be resumed, improved, and made more flexible to be adapted to this type of work.

CHAPTER 2: OPTIMIZATION METHODS AND GENETIC ALGORITHM

2.1 Main optimization techniques and their peculiarities

Made these premises, it is necessary to focus on the main optimization methods that are now part of the computer-aided activities. The algorithms, during the project design optimization, have the objective to maximize performances and efficiency while minimizing production cost. For this first part of the chapter, we will refer to papers [7], [8], [9].

In practice, and especially in a manufacturing context, optimization problems that arise are practically always so complex that it is not feasible to come up with a solution in an analytical way. In first instance, the complexity is determined by the number of variables and constraints, which define the “space” dimension of the problem, and then by the possible presence of non-linear functions between the relations. The analytic solution is possible only in the case of a few variables, not conflicting constraints, and extremely simple functions.

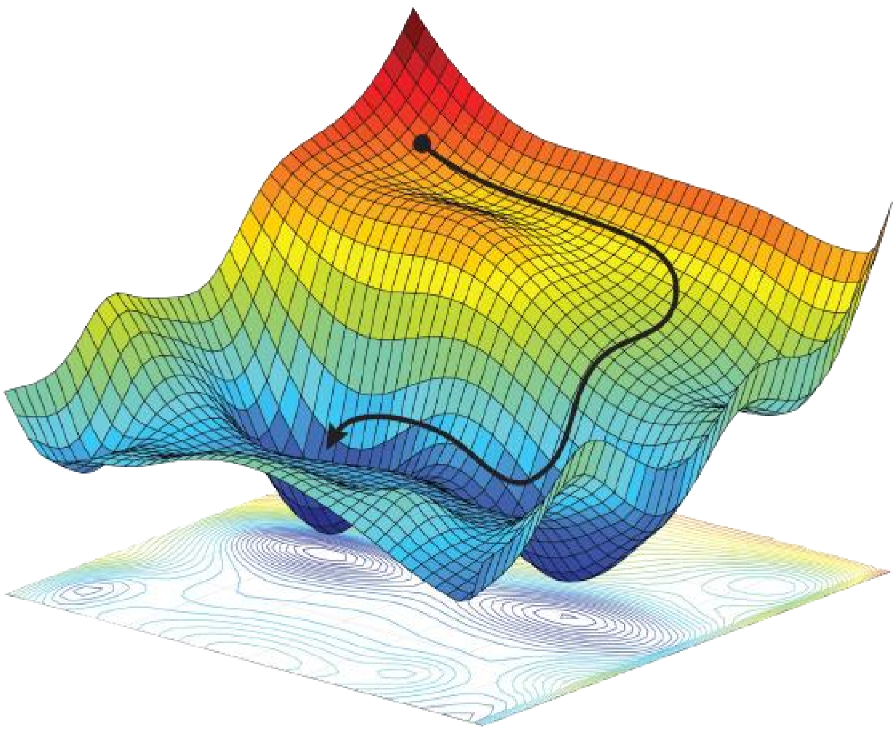

Figure 5: **Example of optimization algorithm path during minimum point search** [10]

Anyway, if conditions permit, there are computational methods that offer the guarantee, at least in theory, to solve the optimization problem in an “exact” way. However, as said before, the deployment of Exact methods is seldom and it is linked to two concomitant factors: the intrinsic complexity of the problem, that must be known very deeply in all its mechanisms, and the computational time. Since all Exact methods are based on the development of a mathematical model, the problem to be optimized should be accurately formulated, devoid of simplifications and perfectly understood. At this point, it becomes clear that the lack of speed is related to this complexity, that could make the problem practically impossible to converge at a precise and manageable solution in a reasonable amount of time. Moreover, the required execution time grows exponentially with the size of the problem resulting to be unapplicable even to simple problems if they involve large number of dependent variables.

Two typologies of Exact methods are present: iterative and enumerative. The former requires only one initial guess to start and executes steps in iterations, finding successive approximations in sequence to reach a solution. The latter has in the simplicity itself its basis: to find the optimum value in a problem space (which is finite), the algorithm looks at the function values at every point in the space. Here the problem is obviously its scarce efficiency. For very large problem spaces, the computational task is massive, if not intractably.

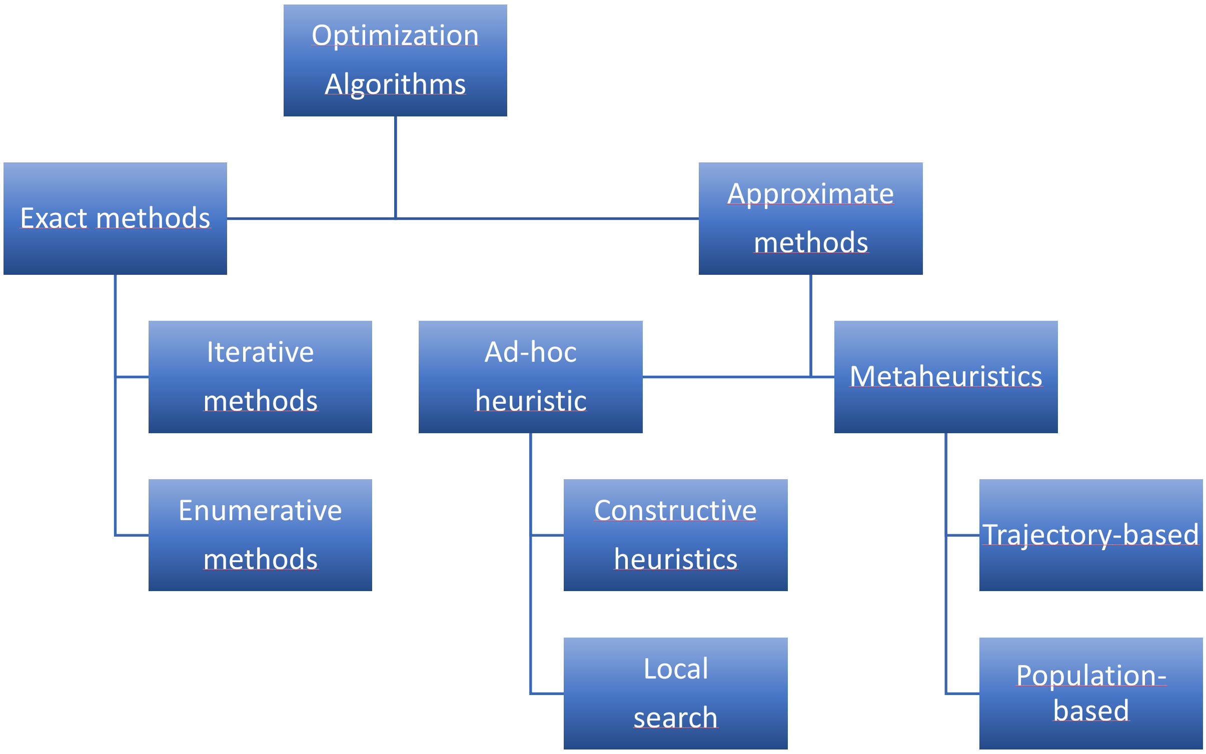

Figure 6: **Optimization algorithms classification** [11]

When the problem and/or the context of the solution does not make it possible to apply Exact solution techniques, it becomes necessary to provide good feasible solutions in reasonable computation times. Note that, typically, the determination of good approximate solutions is what is sufficient in real applications. These aspects explain why, in real applications, is so widespread the use of methods that allow to find good solutions without guaranteeing their optimality, but a relatively short computation time: these methods are called Heuristic methods. The term “heuristic” (from Ancient Greek: εὑρίσκω, heurískō, 'I find, discover') refers to a problem-solving approach that does not follow a clear path, but that relies on intuition and the temporary state of circumstances in order to generate new knowledge and an approximate solution to the problem. Approximative algorithms are said to be “performance guaranteed” because is possible to formally demonstrate that the solution found is not worse than the optimal one, even if unknown, by a certain percentage. Anyway, the percentage can be quite high, and therefore particular attention needs to be paid that the solution is still acceptable in practice. These techniques are historically divided in two categories that, thought similar, are intrinsically very different: Ad-hoc heuristic and Metaheuristic methods.

Ad-hoc heuristics: for most combinatorial optimization problems it is possible to design specific heuristics that exploit the properties of the problem under investigation and the specific knowledge that derives from the experience of it. Obviously, the quality of the solutions obtained depends on the level of experience that is transmitted into the algorithm: if this level is high, the solutions will be of good quality; if the level is low or, at the limit, null, as it can happen if the algorithm developer has no knowledge about the specific problem, the method risks being limited in the quality and even in the correctness of the solutions found. They can be further subdivided in “construction methods” and “local search techniques”.

Constructive heuristics are usually the quickest algorithms to return a result. They determine and actually “construct” a solution from scratch. Starting only from the input data of the problem under examination a complete and mature solution is obtained by iteratively incorporating new components and adding new elements. This mechanism takes the name of “expansion criterion” and is at the base of method functioning. When the satisfaction criteria are met or maximum computational time is reached, the heuristic returns the solution as output. A common feature is the absence (or strong limitation) of backtracking: nothing of what is discarded by the algorithm remains in its procedural memory and any knowledge of the past is not retained. Finding some Constructive algorithm can be not too complex in many cases, but the obtained solutions are often low quality. In fact, designing a method that comes up with high quality solutions is a nontrivial task: the results, being strictly linked to the problem itself, requires an understanding of it as happens for Ad-hoc methods. Furthermore, in problems in which many constraints coexist, it could happen that many partial solutions do not lead to a unique feasible solution.

Among the various types of constructive heuristics, it is worth mentioning the “greedy algorithms”.

The second subcategory of Ad-hoc methods is the Local Search Algorithms. These heuristics are suitable to perform the optimization of generic scalar functions. More details about their peculiarities will be given later, when it will be presented the most known and utilized algorithm among these: the “hill-climbing approach”.

2.1.1 Metaheuristic methods

In recent years, interest (both academic and applicative) has turned to approaches that embrace more general type heuristics. Performances demonstrated on the field by these general methods almost always dominates those of specific heuristic techniques. The literature on Metaheuristic methods is extensive and expandable, with the only limitation represented by the imagination of researchers. In fact, they have been proposed the most varied and suggestive techniques.
The fundamental properties which characterize the set of Metaheuristic algorithms are the following ones [12]:

- Metaheuristics are higher level strategies that guide the search process.
- The goal is to efficiently explore the search space to find (quasi-)optimal solutions.
- Metaheuristic algorithms are approximate and generally non-deterministic.
- The basic concepts of Metaheuristics permit an abstract level of description.
- Metaheuristics are not problem specific.
- Metaheuristics may make use of domain-specific knowledge in the form of heuristics that are controlled by the upper-level strategy.

Recently more advanced metaheuristics are implementing memory features. That would mean that previous search experience would be exploited to guide further attempts.
Metaheuristic algorithms can be categorized into two classes: Trajectory-based and Population-based methods that are distinguished by a remarkable difference. The difference lies in the fact that in Trajectory-based algorithms a single point tracing out a single path is used and the (quasi-)optimal solution is reached through iterations recreating, if represented in the problem space, something similar to Figure 5. In Population-based algorithms, instead, multiple points tracing out multiple paths in the space are used, and each point represents a solution to the problem. As it can be seen in Figure 7, multiple points coexist at the same time, hugely increasing the amount of information acquired at each iteration and reducing the calculating time. Otherwise, by looking at their search ability, algorithms can be categorized in other two classes: -local and Global search algorithms. The former lead to local optimum points and often do not have any capability to escape from them and get stuck. For this reason, it is necessary to resort to Global search algorithms to get to the global optimum. Example of Trajectory-based algorithm is the so-called Simulated Annealing (SA), while the most

used Population-based method family of techniques are the Evolutionary Algorithms, of which the most known is Genetic Algorithm (GA).

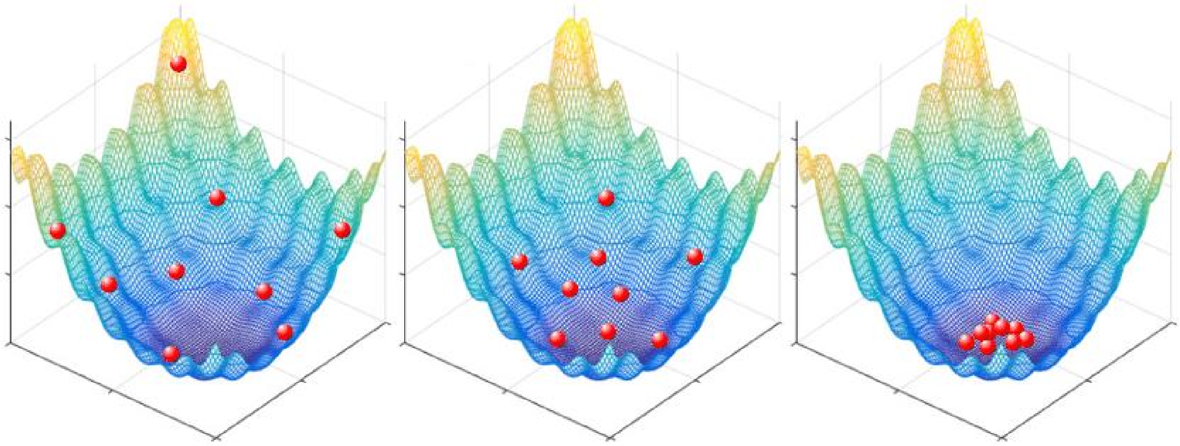

Figure 7: **Population-based optimization algorithm** [13]

In the following pages three algorithms are treated, to show pros and cons of them and give a motivation of the choice of one among them for the thesis work. The three optimization methods are:

- Hill Climbing (Ad-hoc Local search method).
- Simulated Annealing (Metaheuristic Trajectory-based method).
- Genetic Algorithm (Metaheuristic Population-based method).

2.1.2 Hill Climbing Algorithm

The Hill Climbing search is a Local search algorithm based on a search cycle for nodes. The term “hill climbing” indicates the ability of the algorithm to "climb" the nodes towards those with higher values.

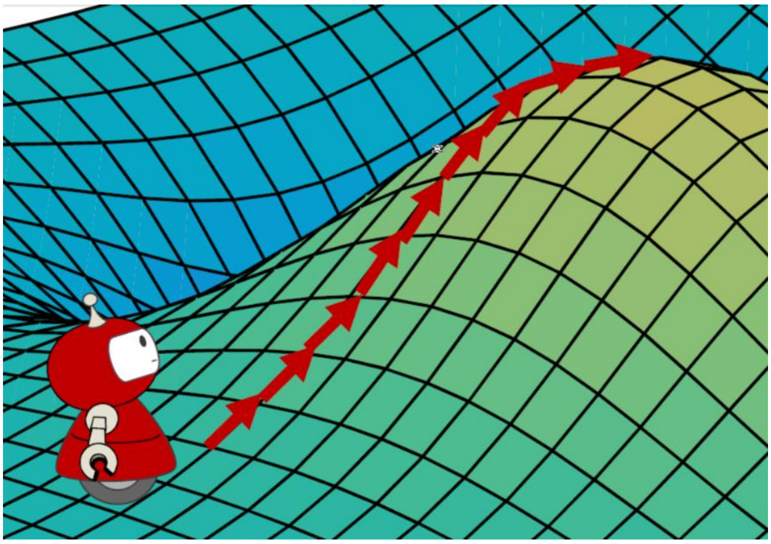

Figure 8: **Hill Climbing Algorithm representation** [14]

The search space of Hill Climbing algorithm is limited only to nodes close to the current one. When a neighboring node is better than the reference node (current node), the latter is replaced with the new node. The processing cycle of the Hill Climbing algorithm ends when the node with the highest value ("peak") is reached, i.e., when no nearby node has a value higher than the reference one. Considering the set of "neighboring" states, it is therefore necessary to define a criterion to choose the next state: the best, that is, the one that improves the function the most (steepest ascend Hill climbing), one randomly chosen among those that improve (Stochastic Hill Climbing), or the first found (Hill Climbing with first choice). Finally, to avoid that the algorithm takes too long in the case of large spaces, it is necessary to define some stopping criteria: Maximum number of iterations, Minor improvements (we end when none of the neighboring states improves the function by a quantity greater than a fixed value) or locally optimal solution (No solution in the neighborhood improves the current one, so we are in a local maximum).

The advantages of the algorithm are its intrinsic simplicity (it requires much less conditions than other search techniques), the possibility to be used for continuous as well discrete domains (nodes can be points of a continuous space or just separated values in a domain) and the fact that always returns a solution according to the objective function, even if the algorithm is stopped in advance. Disadvantages are instead all linked to the presence of local maxima: local peaks, ridges, alleys, and plateau (flat zones in the search space) prevent the HC to reach the optimum, absolute, point getting stuck before.

To avoid these drawbacks, some improvements can be made to the algorithm. Stochastic Hill Climbing: does not examine all neighboring nodes before deciding how to move. Rather, it selects a neighbor at random, and decides (based on the amount of improvement in that point) whether to move to that node or to examine another. It converges more slowly but sometimes finds better solutions. Hill-Climbing with random restart: iterative Hill Climbing algorithm in which several local search attempts are made before returning the processing result to the output. At each loop (iteration) the algorithm explores the search space starting from a different starting node. The selection of the initial node can be determined by a heuristic function or by a stochastic function.

2.1.3 Simulated Annealing Algorithm

In order to find global minimum when many local minima are present in the Search space, Simulated Annealing is highly suitable for any non-convex optimization problem. Problems solved by SA are formulated by an objective function of many variables and it is often used when the Search space is discrete. For problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time, Simulated Annealing may be preferable to Exact algorithms.

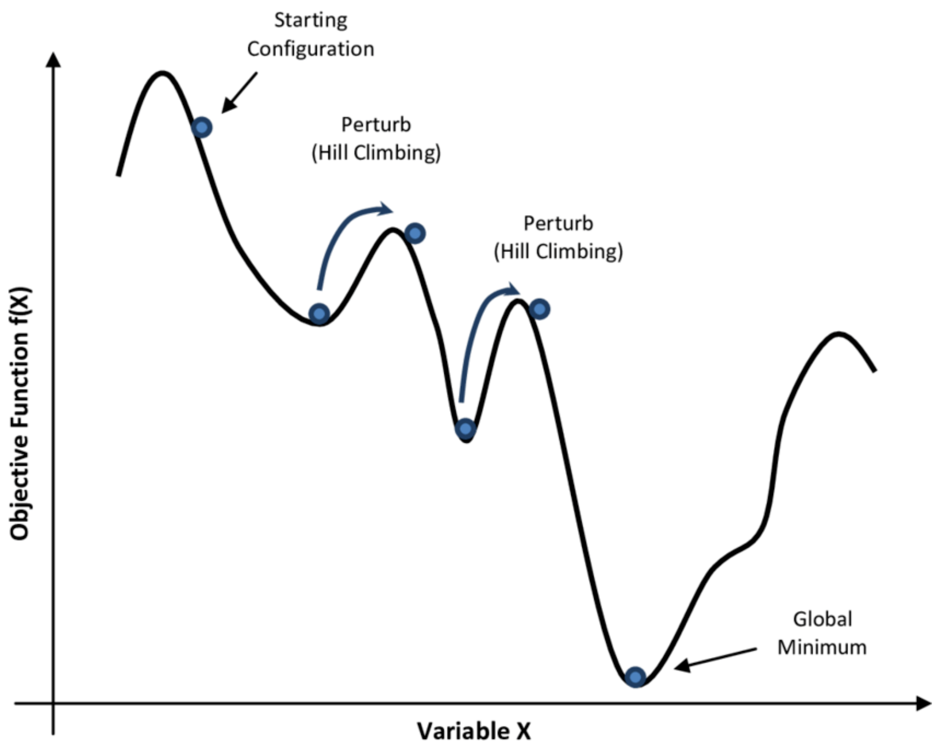

Figure 9: **Simulated Annealing of a one-dimensional objective function** [15]

The name of the algorithm comes from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. Size and defects depend on thermodynamic free energy of the system. At high temperatures, the atoms in the system are in a highly disordered state and therefore the energy of the system is high. To bring such atoms into an (statistically) ordered crystalline configuration, the temperature of the system must be lowered. The analogy with cooling implemented in the SA algorithm is interpreted as a slow decrease in the probability of accepting worse solutions, and so "jumping out" local optima as the Solution space is explored to find the global optimum solution in general. The temperature is the "dummy" parameter used by the algorithm and progressively decreases from an initial positive value to zero.

Simulated Annealing algorithms work as follows. The method begins with an assigned initial configuration with energy E0. Subsequent configurations are then generated with small random perturbations of the current configuration. It is decided whether to accept or reject the new configuration based on the difference between the energy of the current configuration and that of the candidate configuration. The algorithm always accepts a candidate solution whose energy is lower than that of the current configuration. On the other hand, if the energy of the candidate configuration is greater than that of the current configuration, then the candidate is accepted with a probability function of exponential type. At high temperatures, the SA algorithm can traverse almost all the State space since bad solutions are easily accepted. Subsequently, by lowering the value of the control parameter, the algorithm is confined to narrower regions of the State space since it collapses to increasingly lower acceptance probabilities. Therefore, at high temperatures, the algorithm behaves like a Random search: the search jumps from one point to another in the Solution space, identifying the directions or areas in which it is more likely to find the global optimum. At low temperatures, the SA is similar to Steepest-descent methods: solutions are localized in the most promising point in the proximity area. [16]

Said this, Simulated Annealing advantages are easy to be identified: it is flexible, capable to deal with many kinds of problems and cost functions; it guarantees (at least in theory) to find optimal solutions or quasi-optimal ones in less time than conventional algorithms; it is relatively simple, since it can be applied to optimization problems to whom the analyst has no deep knowledge. This makes this technique perfect when problem-specific algorithms are not available.

On the other hand, SA presents some disadvantages: it becomes slow when the cost function is complex and computationally heavy; for problems with smooth Search space, or if few local minima are present, simpler method like Steepest-descend Local search methods are faster and provide same results; the algorithm is not able to tell if the solution found is the optimum, leading to think that further improvements can be done even if this is not true.

2.2 Genetic Algorithm: description and working principles

Evolutionary algorithms (EA) are a subset of evolutionary computation (subfield of artificial intelligence and soft computing). They are generic Population-based metaheuristic optimization methods for solving both constrained and unconstrained problems based on a natural selection process that mimics biological evolution [17]. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the quality of the solutions. An initial set of candidate solutions is generated and iteratively updated. Each new generation is produced by stochastically removing less desired solutions and introducing small random changes. As a result, the population will gradually evolve to increase in fitness, in this case the chosen fitness function of the algorithm.

Evolutionary computation techniques can produce highly optimized solutions in a wide range of problem settings, making them popular in computer science. Evolutionary algorithms often perform well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness landscape. Many variants and extensions exist, suited to more specific families of problems and data structures.

Genetic Algorithm– the most popular type of EA– seeks the solution of a problem in the form of strings of numbers, by applying operators such as recombination and mutation. The space of all feasible solutions (the set of solutions among which the desired solution resides) is called search space and each point in the search space represents one possible solution. Therefore, each possible solution can be "marked" by its fitness value, from least to fittest.

The following paragraphs have been written taking as reference the book "Introduction to Genetic Algorithms" by S.N. Sivanandam · S.N. Deepa, edited by Springer.

2.1.1 Similitude with Nature

The Genetic Algorithm (GA), developed by John Holland and his collaborators in the 1960s and 1970s, is a model or abstraction of biological evolution based on Charles Darwin's theory of natural selection. The inspiration and motivation of Genetic Algorithms comes from looking at the world around us and seeing a staggering diversity of life. Millions of species, each with its own unique behavioral patterns and characteristics, abound. Yet, all these plants and creatures have evolved, and continue evolving, over millions of years. Each species has developed physical features and normal habits that are in a sense optimal in a constantly shifting and changing environment in order to survive.

Those weaker members of a species tend to die, leaving the stronger and fitter to mate, create offspring and ensure the continuing survival of the species. Their lives are dictated by the laws of natural selection and Darwinian evolution. And it is upon these ideas that Genetic Algorithms are based.

In Nature, all the genetic information gets stored in the chromosomes. The chromosomes are divided into several parts called genes. A gene encodes a specific feature of the individual and its characteristics. The possibilities of the genes for one property are called allele and a gene can take different alleles. For example, there is a gene for eye color, and all the different possible alleles are black, brown, blue, and green. The set of all possible alleles present in a particular population forms a gene pool. This gene pool can determine all the different possible variations for the future generations. The size of the gene pool helps in determining the diversity of the individuals in the population. For a particular individual, the entire combination of genes is called genotype. The phenotype describes the physical aspect of decoding a genotype to produce the phenotype.

Table 1: **Parallelism between natural evolution and genetic algorithm terminology** [18]

Natural Evolution	Genetic Algorithm
Chromosome	String
Gene	Feature or character
Allele	Feature or character value
Genotype	Coded structure or string
Phenotype	Decoded structure or string

2.1.2 Genetic Algorithm introduction

Genetic Algorithm raises an important feature: it is a stochastic algorithm, randomness as an essential role in genetic algorithms. Both selection and reproduction need random procedures. For this reason, a primary distinction that may be made between the various operators is whether they introduce any new information into the population. Crossover, for example, does not while mutation does. When two individuals mate, both parents pass their chromosomes onto their offspring. So, the chromosomes undergo a crossover of genetic material, which leads to a unique new individual with characteristics that were previously owned by his parents. In addition, genetic material can undergo mutations, resulting from imperfect crossovers or other external stimuli generating a brand-new character. Although mutation is rare, it leads to a greater diversification of the gene pool of the population. It must be noted however, that too much of mutation is in fact harmful and can destroy good genetic code, so the rate of mutation must be low to prevent severe degradation of the genetic pool.

The Genetic Algorithm iteratively creates new populations from the old by ranking the strings and interbreeding the fittest to create new individuals. So, in each generation, the GA creates a set of strings from the bits and pieces of the previous strings, occasionally adding random new data to keep the population from stagnating. The fitness function takes a string and assigns a relative fitness value to the string. The method by which it does this and the nature of the fitness value does not matter. The only thing that the fitness function must do is to rank the strings in some way by producing the fitness value. These values are then used to select the fittest strings. The concept of a fitness function is, in fact, a particular instance of a more general Artificial Intelligence concept, the objective function.

Populations and Fitness

A population is a collection of individuals being tested with their phenotype The two important aspects of population used in Genetic Algorithms are:

1. The initial population generation.
2. The population size.

For each problem, the population size will depend on the complexity of the problem. Often a random initialization of the population is carried but there may be instances where it is carried out with some knowledge. Sometimes a kind of heuristic can be used to seed the initial population. Thus, the mean fitness of the population is already high, and it may help the Genetic Algorithm to find good solutions faster. But for doing this one should be sure that the gene pool is still large enough. Ideally, the first population should have a gene pool as large as possible in order to be able to explore the whole Search space and all the different possible alleles of each should be present in the population. Otherwise, if the population badly lacks diversity, the algorithm will just explore a small part of the Search space and never find global optimal solutions. The size of the population raises few problems too. The larger the population is, the easier it is to explore the search space. But it has established that it requires much more computational cost, memory, and time. We say that the population has converged when all the individuals are very much alike and further improvement may only be possibly by mutation. GA efficiency to reach global optimum instead of local ones is largely determined by the size of the population.

The fitness of an individual in a Genetic Algorithm is the value of an objective function for its phenotype. For calculating fitness, the chromosome must be first decoded and then the objective function must be evaluated. The fitness not only indicates how good the solution is, but also corresponds to how close the chromosome is to the optimal one.

In the case of multicriteria optimization, the fitness function is definitely more difficult to be determined. In multicriteria optimization problems, there is often a dilemma as how to determine if one solution is better than another. If sometimes a fitness function obtained by a simple combination of the different criteria can give good result, it supposes that criterions can be combined in a consistent way.

2.2.3 Genetic Algorithm steps

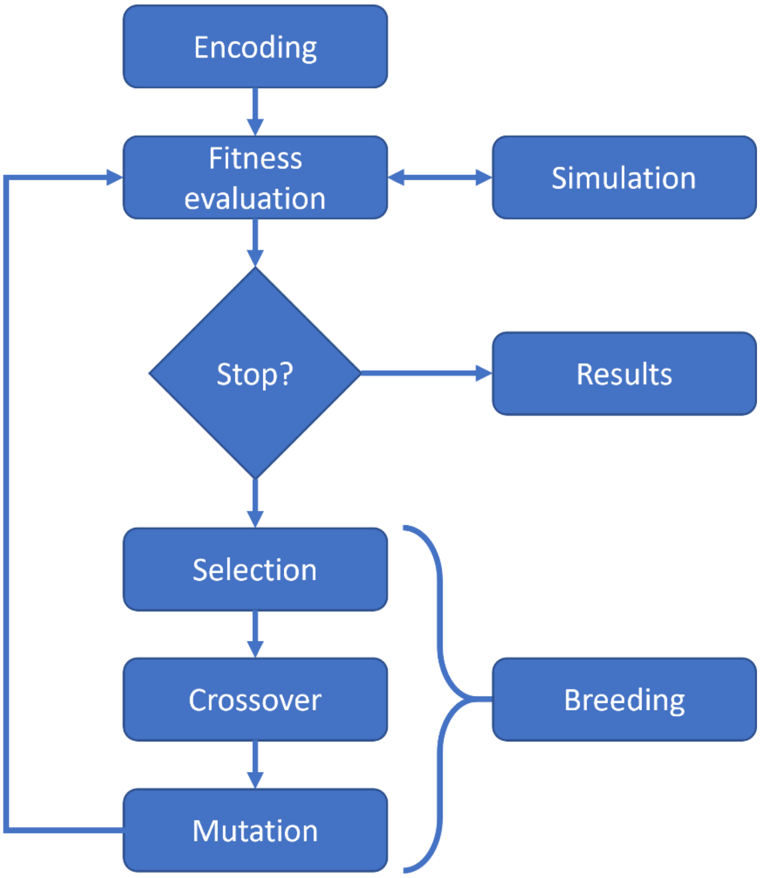

Figure 10: **Flow chart of a Genetic Algorithm operation** [19]

Encoding

The first step in a GA is to find a suitable encoding of the parameters of the fitness function. This is usually done using a population of strings, each representing a possible solution to the problem. Coding all the possible solutions into a chromosome is the first part, but certainly not the most straightforward one of a Genetic Algorithm. A set of reproduction operators must be determined, too. Appropriate representation and reproduction operators are really something determinant, as the behavior of the GA is extremely dependent on it. Frequently, it can be extremely difficult to find a representation, which respects the structure of the search space and reproduction operators, which are coherent and relevant according to the properties of the problems.

Simulation, fitness evaluation and stopping criteria

At this point, the Genetic Algorithm enters the computation loop. Each individual, each with its own gene pool, is simulated in its behavioral aspect in order to identify the solution it represents. The results are ranked by the fitness function and a decision must be taken whether to stop the cycle. The decision is subjected to stopping criteria that can be various: maximum computation time or number of generations reached are usual criteria taken into consideration. Otherwise, often the computation is stopped when the best individual fitness value falls below an acceptable threshold or the improvement between successive generations is no more remarkable.

Breeding

The breeding process is the heart of the Genetic Algorithm. It is in this process, the search process creates new and hopefully fitter individuals, replacing old individuals in the population with the new ones.

The breeding cycle consists of three steps:

a. Selecting parents.

b. Crossing the parents to create new offspring.

c. Introducing mutation in the population genome.

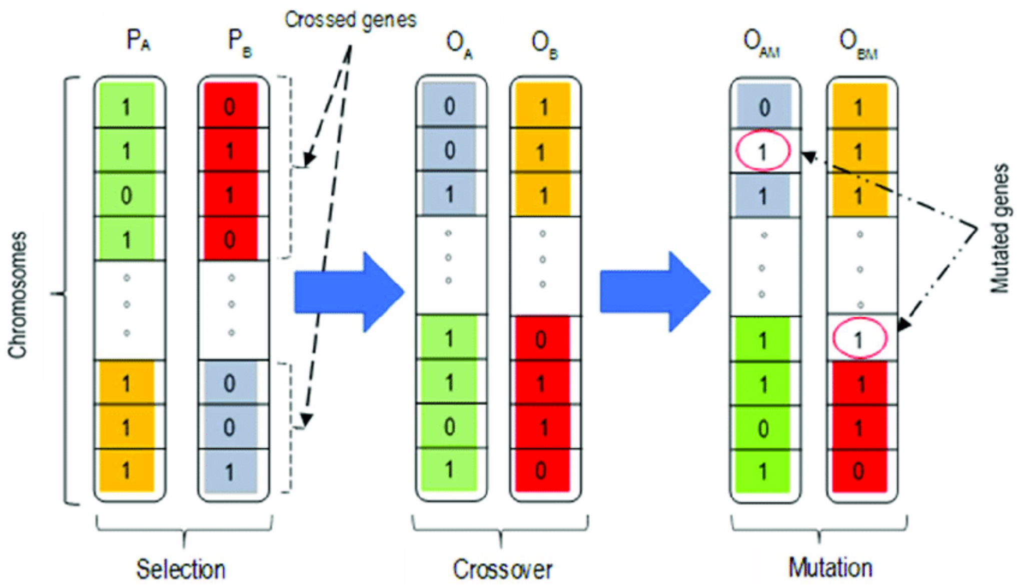

Figure 11: **Representation of selection, crossover, and mutation mechanisms** [20]

Selection

Selection is done by using again the fitness function. This selection is done randomly with a probability depending on the relative fitness of the individuals: fittest ones have higher shares and so the reproduction probabilities of these individuals increase, while weakest ones tend to die and not survive to the next generation.

Crossover

In the second step, offspring are bred by the selected individuals. Two genotypes are taken and produce a new genotype by mixing the genes found in the originals. In biology, the most common form of recombination is crossover: two chromosomes are cut at one point and the halves are spliced to create new chromosomes. The effect of recombination is very important because it allows characteristics from two different parents to be assorted. If the starting individuals possess different good qualities, we would expect that all the good qualities will be passed into the child. Thus, the offspring, just by combining all the good features from its parents, may surpass its ancestors. The same procedure is done to the strings of our solutions, and this is one of the most powerful features of Genetic Algorithms.

Mutation

Mutation is the other way to get new genomes. Mutation consists in changing the value of genes. In natural evolution, mutation mostly engenders non-viable genomes. Actually, mutation is not a very frequent operator in natural evolution. Nevertheless, in optimization environment, a few random changes can be a good way to explore the Search space quickly.

2.3 Pros and cons of GA adoption

2.3.1 Advantages

GA can be even faster in finding global maxima than conventional methods, in particular when derivatives provide misleading information. The enormous potential of GA lies in optimization of non-differentiable or even discontinuous functions, so discrete variables optimization. It has been claimed that via the operations of selection, crossover, and mutation the GA will converge over successive generations towards the global (or near global) optimum. This simple operation should produce a fast, useful and robust technique largely because of the fact that GA combine direction and chance in the search in an effective and efficient manner. Since population implicitly contain much more information than simply the individual fitness scores, GA combines the good information hidden in a solution with good information from another solution to produce new solutions with good

information inherited from both parents, leading towards optimality. The ability of the algorithm to explore and exploit simultaneously huge number of solutions strengthens the conclusion that GAs are a powerful, robust optimization technique. A second very important point is that Genetic Algorithms always consider a population of solutions. Keeping in memory more than a single solution at each iteration offers a lot of advantages. The algorithm can recombine different solutions to get better ones and so, it can use the benefits of assortment. A Population-based algorithm is also very amenable for parallelization. The robustness of the algorithm should also be mentioned as something essential for the algorithm success. Robustness refers to the ability to perform consistently well on a broad range of problem types. There is no requirement on the problem before using GAs, so it can be applied to resolve any problem. All those features make GA a powerful optimization tool.
To resume, the advantages of Genetic Algorithm include:

- Can be employed for a wide variety of optimization problems, performing very well for large-scale optimization problems.
- Discontinuities present on the response surface have little effect on overall optimization performance.
- They require no knowledge or gradient information about the Search space, resulting particularly suited when the fitness landscape is complex or wide.
- Only uses function evaluations.
- The problem has multi-objective function.
- Handles noisy functions well, robust to difficulties in the evaluation of the objective function are resistant to becoming trapped in local optima, easily discovering global optimum.
- Parallelism capability.

2.3.2 Disadvantages

It is also important to mention in this introduction GA limits. Like most stochastic methods, GAs are not guaranteed to find the global optimum solution to a problem, they are satisfied with finding “acceptably good” solutions to the problem. GAs are extremely general too, and so specific techniques for solving particular problems are likely to out-perform GAs. In most cases where conventional methods can be applied, GAs are much slower because they do not take auxiliary information like derivatives into account, affecting both speed and accuracy of the result. GAs are something worth trying when everything else as failed or when we know absolutely nothing of the search space. Nevertheless, even when such specialized techniques exist, it often interesting to hybridize them with a GA to possibly gain some improvements.

To resume, the disadvantages of Genetic Algorithm include:

- Cannot easily incorporate problem specific information.
- The problem of identifying fitness function.
- The problem of choosing the various parameters like the size of the population, mutation rate, crossover rate, selection method and stopping criteria.
- Have trouble finding the exact global optimum
- Cannot use gradients
- Premature convergence occurs
- Require large number of response (fitness) function evaluations.

2.4 Justification of Genetic Algorithm use for the Thesis

Seen the characteristics of GA optimization method, the choice of its adoption has been dictated by some motivations. First, the simplicity of the algorithm and its capability of providing excellent results have been determining. Second, the choice of a vehicle powertrain sizing involves many aspects that are interdependent and not fully understandable in their interaction. This was possible to be overcome thanks to the GA flexibility and its necessity of a fitness function only. In addition, the problem to be solved was based on a constrained and discrete optimization, since for manufacturing reasons the investigation cannot be exploited in a continuous domain.

For these reasons the choice of a Genetic Algorithm has been considered the best and therefore employed in the following chapters.

CHAPTER 3: MODEL IMPROVEMENT WITH EXPERIMENTAL DATA

3.1 Introduction to the FCEV model and need for improvement

Since the goal of the job and the way it would be done was now clear, it became necessary to use a model of a Fuel Cell/ Battery Electric vehicle to be coupled to the Genetic Algorithm. The model taken as reference was developed by Dott. Michele Settembrino, for his previous thesis project "**Analysis of Fuel Cell System for Automotive and Modelling of a Range Extender FCV based on PEMFC**". The modeling concerned a small Class A/B vehicle with a Battery Pack and a Fuel Cell with low output power, used as a Range Extender to increase the distance that the car can travel with a single charge.

Table 2: **Basic parameters of the starting model** [21]

Parameter	Value [unit]
Kerb weight	1300 kg
Test load	200 kg
Battery Max Energy	6.2 kWh
Fuel Cell Max Power	33 kWh
E-Motor Power	93 kW

The model, developed in MATLAB/SIMULINK environment, was composed by 4 main parts:

- Driver Command, in which the drive-cycle profile is generated, and a driver simulator provides brake and accelerator positions to follow the cycle-imposed velocity. The Driver basically acts as a controller, using as inputs the desired and actual (given as a feedback) velocities.
- Driveline, that reproduces the vehicle behavior. It includes the entire driveline, modeling the gearbox and differential, and the tires.
- FCV Electrical Subsystem, it's the main part of the model, and the one on which we will focus. Under this subsystem, they are modeled all the parts that compose the powertrain: Battery Pack, Fuel Cell system with its auxiliaries, DC-DC Converter, Inverter, E-Motor.

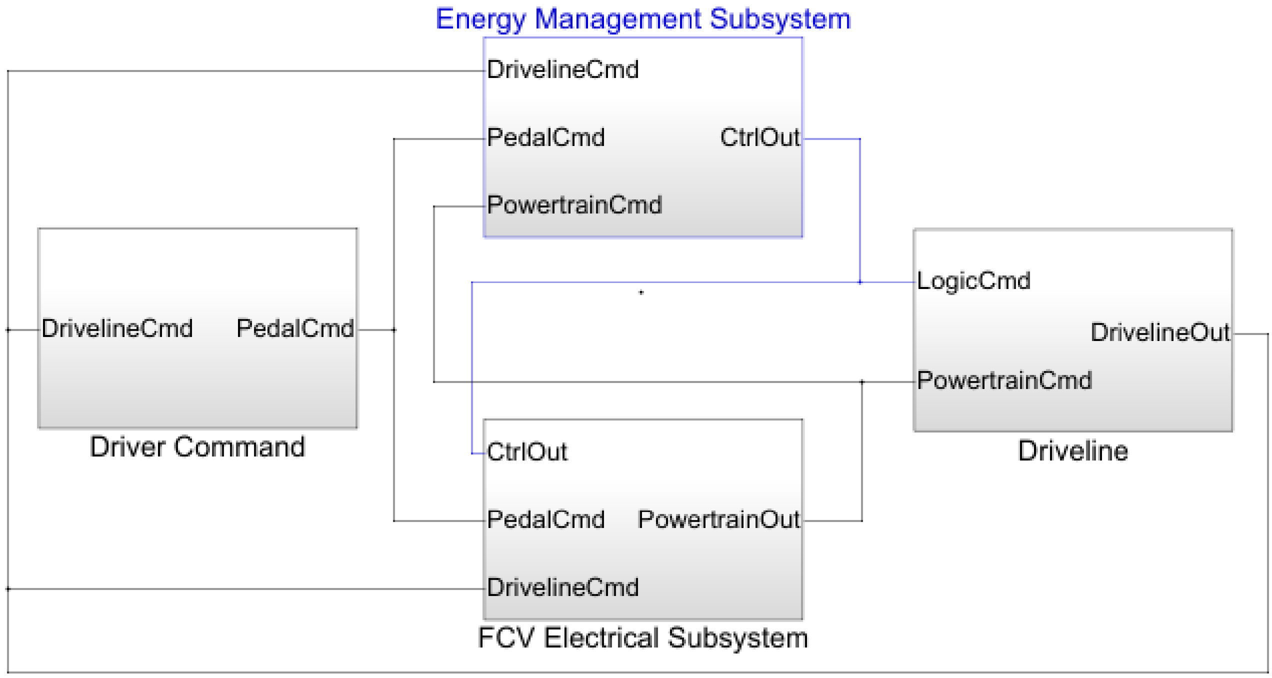

Figure 12: **FCEV modeling subsystems** [21]

- Energy Management Subsystem, containing the "Logic" that drives the operation of the vehicle. Using the information of buses coming from powertrain, driveline, and driver (such as power and torque required) choses the best strategy for the vehicle. The Control Logic mainly regulates the power flows from the Fuel Cell and from/to the battery, to guarantee performances and range, keeping at the same time the working temperature of each part in its best operating window.

The starting model, although excellent for a rough simulation of the vehicle, had limitations that could invalidate the accuracy of derived results. Indeed, previous work was focused more on the development of the Energy Management and "Driving Modes", which were very sophisticated and brilliantly refined. However, more attention could be paid on the modeling of the Fuel Cell System, using experimental data to approach a representation of the phenomena more adherent to reality.

The performance of a PEMFC can be affected by many factors. Load current, temperature, relative humidity, management of water inside the cell, membrane thickness, membrane-active area, electrode active area, corrosion, pressure, and concentration of hydrogen fuel, are just some of them. In particular, the baseline model did not take into consideration the influence of dynamics on the behavior expressed by the Fuel Cell: many parameters were considered as constants or slightly changing, leading to a quasi-static representation of the phenomena. This has repercussion on the power produced and on reagents consumption. As their effects could not be neglected, a critical review of the involved parts was necessary before coupling the model to the Genetic Algorithm for the configuration comparison. In addition, it has been investigated and implemented a more complex cooling of the components, which comprises also the DC/DC Converter and the Inverter/E-Motor assembly. This part was not faced in the previous work, but it was deemed relevant for vehicle energy balances.

In summary, the identified points for improvement are:

- Behavior of the Fuel Cell under the influence of its temperature and the environment:
    - Warm-up phase modeling.
    - Influence of temperature on output power, efficiency, and consumption.
- Powertrain thermal management:
    - FC alternative cooling strategies.
    - DC/DC Converter, Inverter/E-Motor cooling, and implications on energy balance.
- Refinement of Fuel Cell reagents supply with experimental data:
    - Anode and Cathode pressure modeling.
    - Excess Ratios of reagents.

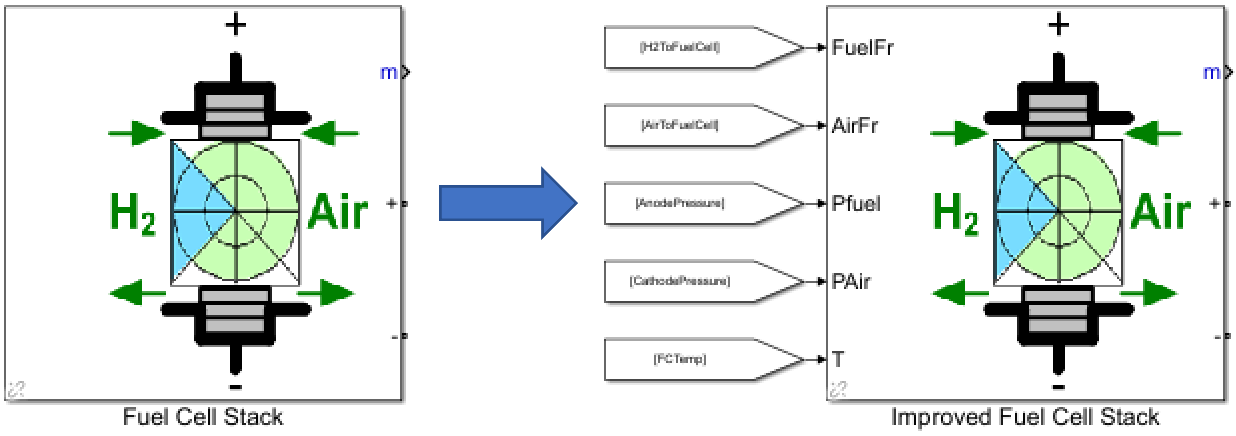

Figure 13: **Comparison between baseline and improved Fuel Cell Stack blocks**

3.2 Warm-Up phase and influence of temperature on FC

The first thing done was to provide to the Fuel Cell Stack block the value of its temperature. The model already had implemented the calculation and control of the FC temperature by the Cooling System, but the data were not returned to FC block: the Fuel Cell was supposed to be at a constant temperature equal to 75 °C. The phenomena that characterize the production of voltage, and therefore of power, by the cell are of electrochemical nature and therefore intimately linked to the temperature factor. Electrochemical reactions of hydrogen and oxygen molecules, electronic/ionic transport, and heat/mass transfer, govern the operation of the Fuel Cell. Without going into details (for the mathematical expressions of the phenomena it can be referred to [22]), the influence of thermal conditions on the polarization curve that defines the relationship between current required and voltage across the plates must not to be neglected, as can be seen in Figure 14.

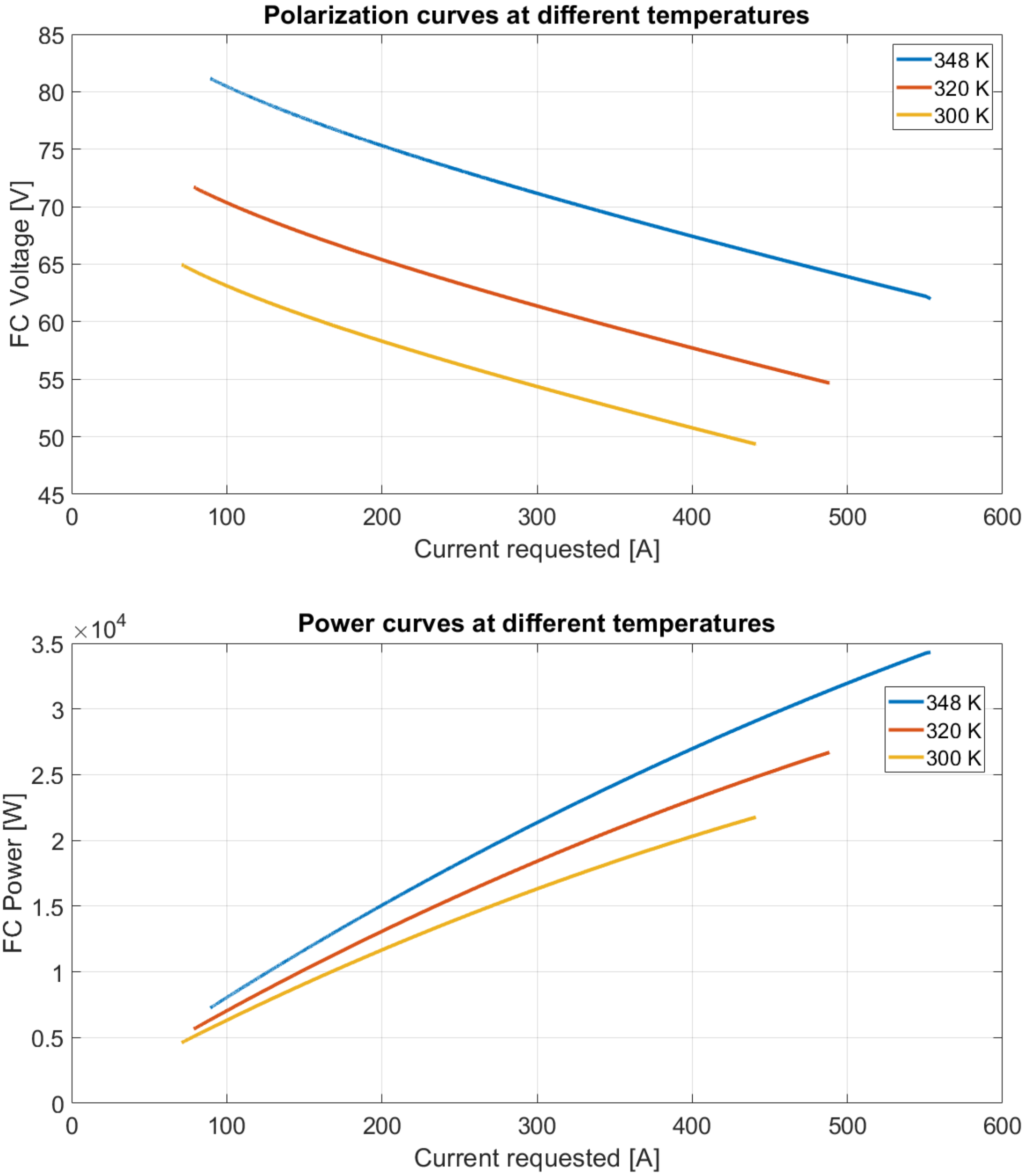

Figure 14: **Influence of temperature on polarization and power curves**

At lower temperatures not only the generated voltage is lower, but also the maximum current that can be required from the Fuel Cell is not the one reported by the manufacturer, but significantly limited. The cause can be traced back to oxidation/reduction reactions of the reagents, lower capability of platinum catalyst to increase chemicals reactivity and inhibited transportation phenomena at lower temperatures. All this has repercussions on the output power produced and that can be used for traction and battery charging.

3.2.1 Warm-Up phase

Warm-Up represents an extremely delicate phase during the operation of the Fuel Cell. The cold startup is of critical importance for optimal PEMFC performance and durability. This is especially true at sub-zero temperatures, when the water produced at the cathode through the electrochemical reaction could freeze and lead to ice formation under subfreezing temperatures. The ice that is formed can affect the performance leading to an irreversible decay, damage the cell components, block the gas passage, coat the catalyst and lead to cold start failure. If the severity of the phenomena increases, physical breakdown of the membranes can occur. Alongside this, OEMs had to implement different strategies with the aim of satisfying targets of cold start performances set by several countries and organizations. This is the case of the United States, where from 2020 the Department of Energy (DOE) has established as target a rapid startup of a Fuel Cell to 50% rated power in less than 30 seconds, to be achieved at a temperature of -20°C. [23]

Besides studies about purge systems and anti-freezing materials, the research has focused on two different Warm-Up solutions: External and Internal. External heating uses heat generated from an external heating source and delivers it into the stack through a heat transfer medium, while internal heating uses heat generated within the stack to warm itself up. The latter is the one employed in the analyzed Fuel Cell, and for this reason it has been the object of the investigation. Fuel Cells are designed with more than one internal electrical resistance that can change with temperature. Such resistances allow a thermal management and control of the FC, with rapid heat up from low temperature to the operating one, which is optimal for water management and power production [24].

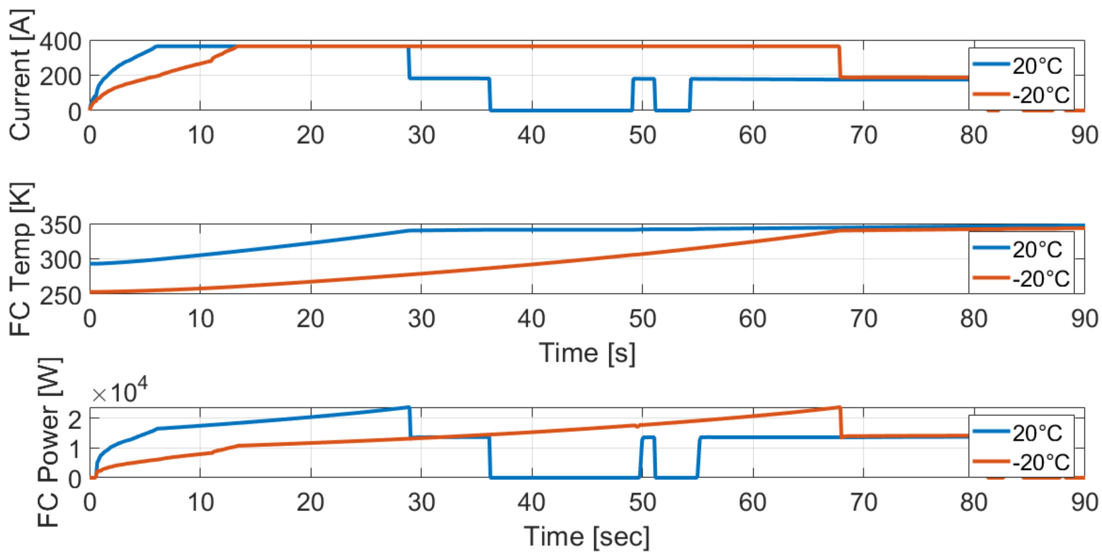

Figure 15: **Fuel Cell parameters during warm (20°C) and cold (-20°C) start-up**

The original model presented just one, very "rough" Warm-Up procedure. During this, no distinction was done about the environment conditions and the status in which the cell could be: the modeling did not take care to whether it was at room temperature or below zero, with all the ensuing consequences. In addition, at time zero a sudden current step is required from the cell, rising instantaneously the current drawn from rest to the nominal one (384 A): a similar operation can cause damage if ice prevents a homogeneous distribution of reagents on the membrane, leading to an imbalance of electrical charges on its surface.

First, a distinction between a start-up procedure performed in warm condition, equal to 20°C, and one in cold condition, equal to -20°C, has been done. The choice of two such different temperatures was made not only to demonstrate the influence of thermal conditions on the refined model under operating conditions, but also and above all in the heating phase trend.

Therefore, to prevent damages linked to a too fast current request, the current demand until the nominal value is done in a smoother and slower way. No step rise is present anymore: 6.2 seconds are taken at ambient temperature to reach the nominal value, allowing in this way a gradual awakening of the Fuel Cell. Secondly, greater attention is paid when temperatures are subzero: as showed in Figure 15.1, at temperature below 5°C, the current reaches the nominal value in 13.5 seconds, more than twice the time of previous case. As a result, these facts are mirrored by the total time spent to reach the fully warmed condition, in our case set at 340 K, and represented in Figure 15.2: just 29 second are required to perform a warm start, while 67.8 seconds are spent to bridge the almost 90°C of difference when starting from an extremely cold environment.

Finally, some words need to be said about the above stated legislative limits. According to our improved model, 50% of Fuel Cell nominal power output (12.5 kW) is reached in 26.5 seconds, perfectly compliant with the American normative.

3.2.2 Influence of temperature on FC power, efficiency, and consumption

Inappropriate thermal energy will decrease the performance of the Proton Exchange Membrane. Since several factors are connected to the operating temperature and have vital effects on the performance of hydrogen Fuel Cell, in this paper we will discuss the effects of temperature elaborately.

Table 3: **Effects of temperature on FC** [25]

Parameter	Value [unit]
Humidity	Optimum temperature maintains the required humidity
Voltage	Increases with the increase in temperature
Leakage Current	Increases with the increase in temperature
Catalyst tolerance	Increases with the increase in temperature
Mass crossover	Decreases with the increase in temperature
Durability	Decreases with the increase in temperature
Power production and efficiency	Increases with the increase in temperature

Humidity

The ion exchange permeability of the membrane in both electrodes depends on its humidity: the presence of water maintains the optimum humid condition. Wet Proton Exchange Membrane is very essential for proton exchange from anode to cathode. The electrochemical reaction would rapidly rise with the increase in temperature and would produce enough water. Adequate water is required for the membrane to be hydrated and the rest of the water needs to come out of the Fuel Cell for better performance. Otherwise, the extra water will create additional complications inside the Fuel Cell. At the same time, the temperature rise is one of the reasons for water loss in the membrane**.** When membrane becomes dehydrated less amount of proton can pass through the anode to the cathode side which will reduce the electron flow and efficiency of the PEMFC. In high temperature and high humidity, membrane crossover of the hydrogen gas rises. After the exchange of protons through the membrane with electrochemical reaction, water is produced. Excess water production will make the membrane wet by the diffusion process. Without optimum humid conditions in the membrane, the resistance of the membrane to hydrogen ion will rise. As a result, this rise in resistance will increase the temperature.

The performance and durability of the membrane directly depend on the humid condition. If the humidity in the proton exchange membrane is too high, it can lead to catalyst flooding. Besides, in less humidity, the polymer electrolyte membrane turns into more brittle form and degrades faster, particularly the acid group of the membrane degrades, and the catalyst is washed away from the surface of the membrane.

Voltage

According to the Nernst equation, the temperature is proportional to the output voltage. Higher temperature leads to faster kinetics and as a result, the voltage is also increased. However, this increase in voltage can be surpassed by the voltage loss from the negative thermodynamic factors. Thus, particular attention must be paid to the correlation between the open-circuit voltage and temperature.

Leakage Current

The membrane of PEMFC cannot be considered as hydrogen impermeable and electrically insulated. During the electrochemical reaction in the Fuel Cell hydrogen gas and electrons diffuse through the proton exchange membrane. The leakage current is generated by this diffusion process of hydrogen gas and electrons through the proton exchange membrane. With the rise in temperature, the leakage current also increases with negative effects on power production.

Catalyst Tolerance

The efficiency of catalyst decay over time depends on the hydrogen oxidation reaction, oxygen reduction reaction and pH environment. Platinum catalyst plays a vital role in the performance of Fuel Cells. The oxygen reduction reaction in the cathode is a slow reaction process. To overcome the slowness, an effective catalyst can accelerate the oxygen reaction rate in the cathode which will improve the PEMFC efficiency rapidly. If the hydrogen is not pure then carbon monoxide will be produced and associates with the surface of the catalyst. The tolerance level of the catalyst to the contaminants in the membrane will rise significantly with temperature. When PEMFC operates at low temperature, CO covers the catalyst layer. As a result, the electrochemical reaction process becomes slower. The CO accumulation in the catalyst surface reduces the 50% lifetime of the Fuel Cell. To ameliorate the bad effect of CO, a certain type of catalyst should be selected which has no reactive mechanism.

Mass Cross-Over and Concentration Over-Potential

Mass cross-over and concentration over-potential are also related to the temperature of the PEMFC. If the temperature rises, the mass cross-over falls and concentration over-potential rises leading to a higher current density on the FC membrane.

Durability

Despite the uninterrupted evolution of Proton Exchange Membranes, longevity is still a concern. The durability of the catalyst, electrode plates, gas diffusion layers, and gaskets is directly related to the longevity of the proton exchange membrane. Electrochemical erosion, component erosion, and thermal effects are the leading factors for the longevity of the Proton Exchange Membrane. The Proton Exchange Membrane loses its water and becomes dehydrated with the rise of the temperature. As a result, the hydrogen gas crossing the dehydrated membrane will reach on the cathode side. Hydrogen in the cathode side will then damage the catalyst, bipolar plates, and gaskets. If it continues to operate at high temperatures, then the durability of the PEMFC will decrease over time.

Power production and efficiency

All the above phenomena affect the power output of the Fuel Cell. As the stack temperature increases, an increase of cell power production is associated. In a Proton Exchange Membrane Fuel Cell, the density of power production rises up to 20% when operational temperature rises from 50 ℃ to 80 ℃. Since the improved model is now capable to show the effects of temperature, a close look can be taken on Figure 16. Again, the result is particularly relevant during the Warm-Up phase, when temperatures are still far from operating ones. Subsequently, system reaches the thermal stability oscillating around the nominal temperature, equal to 75 °C. At this point, the influence becomes less pronounced since the oscillation amplitude is limited.

Same behavior is assumed by the cell efficiency. The value of dissipated power is reduced, and the initiated over-potential become less due to the rising temperature which results in increased power production efficiency. The overall stack efficiency calculated by the original model was around 60%, while considering the temperature effect the value becomes lower. During the heating phase, efficiency is below 50% and grows up according to temperature rise. When Fuel Cell thermal condition reaches the optimal value, the efficiency is substantially the same of the original model, and oscillates according to temperature oscillations, as in the power production.

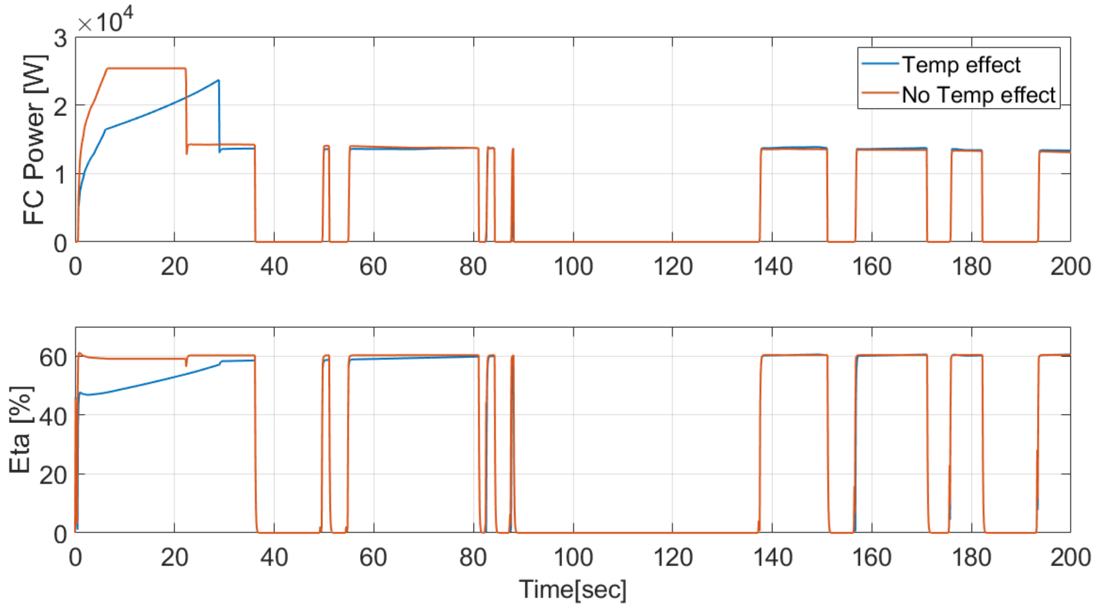

Figure 16: **Effect of temperature on Fuel Cell power and efficiency**

For better efficiency and consistence output, there must be an air or fluid cooling system to dissipate the cell generated heat. As the thermal management is improved, the overall performance like current, current density, voltage, electricity production of a proton exchange membrane Fuel Cell improves. However, it is worth to highlight the values of efficiency reached by Fuel Cells, roughly twice the one of conventional internal combustion engine. Despite the overall efficiency of the system is lower, due to auxiliaries inefficiencies (air compressor, above all) and can range between 40-50%, it sounds clear how promising it is this technology.

Lastly, it is reported the cumulative hydrogen consumption of the cell in the cases that temperature effect is taken or not into account by the model. It is evident that, since the efficiency is lower during cell warm-up, fuel consumption is significantly higher.

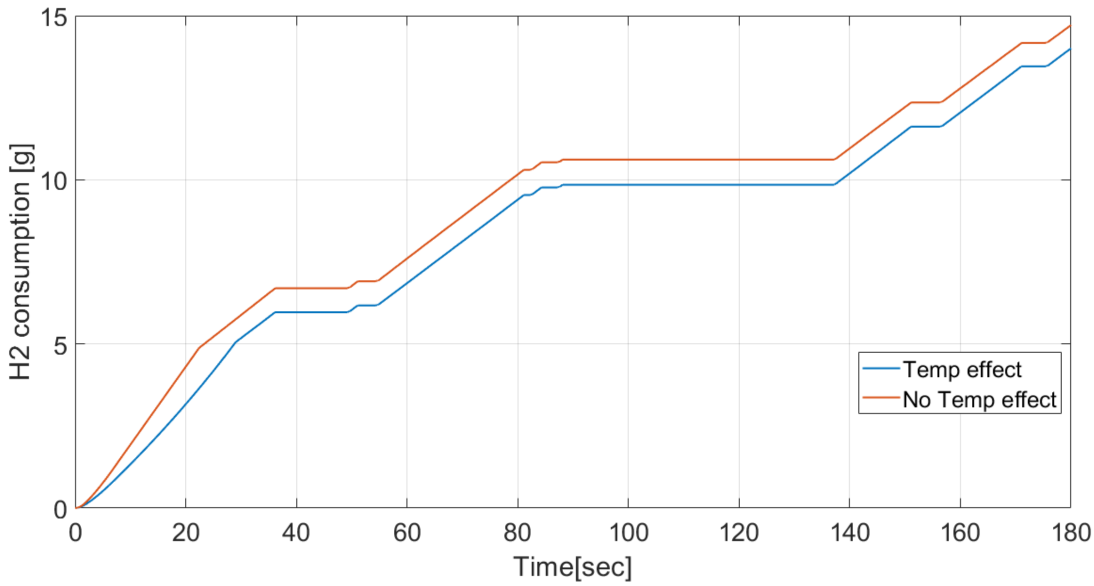

Figure 17: **Effect of temperature on hydrogen consumption**

3.3 Powertrain thermal management

3.3.1 FC alternative cooling strategies

As stated in the previous paragraph, thermal condition of the Fuel Cell is of primary importance for its correct working and durability. Temperature management is performed by a dedicated cooling circuit that uses a water and glycol mixture. The fluid is circulated by an electric pump through pipes, draws heat by the cell and is cooled by the environment air in a heat exchanger placed in front of the vehicle. Fuel Cell temperature is controlled by the pump driving: when the pump is shut off, stack temperature rises due to the electrochemical reactions that take place inside it; when it is switched on, temperature decreases thanks to the heat taken away from coolant convection. In order to manage this thermal status in the correct operating windows, a dedicated Control Logic was developed in the original model. Since effects of temperature on the Fuel Cells are so relevant, a strict strategy was implemented, able to keep stack temperature in a very narrow range of +/- 1 °C than the optimal condition, equal to 75 °C (348 K). The "normal" strategy was really effective in temperature control but required a rapid switch on and off of the electric pump. In Figure 18, FC temperature and power absorbed by the pump trends are represented during a WLTP cycle simulation. The cooling pump is driven tenths of times from rest to a fixed velocity, corresponding to "ON condition" and absorbing around 100 W. These rapid and numerous transitions can hamper pump mechanical resistance and durability.

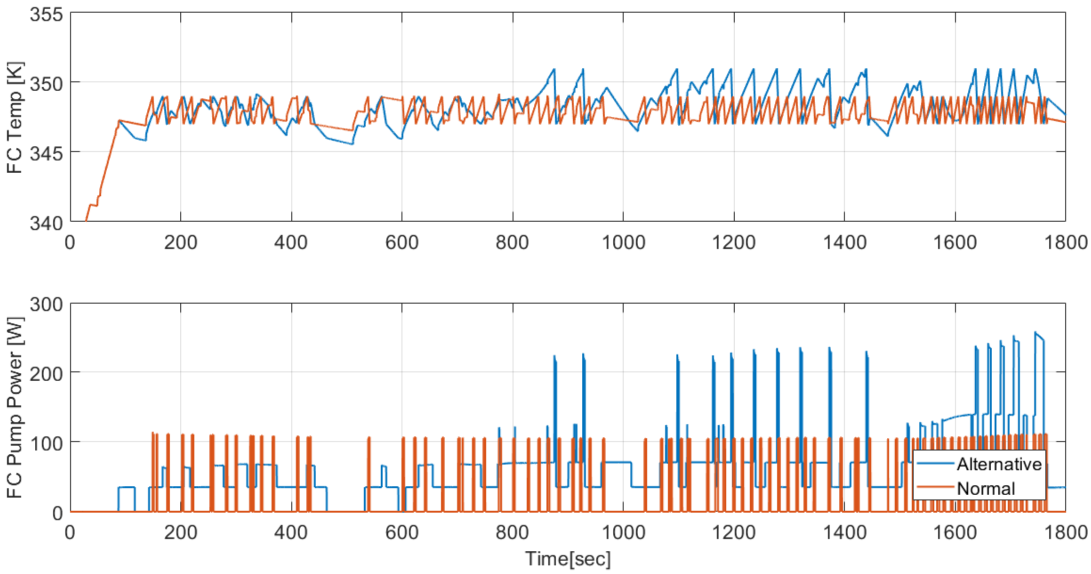

Figure 18: **Comparison between "normal" and "alternative" FC cooling strategies**

For this reason, an alternative strategy was investigated. The primary purpose was to limit the number of pump switching cycles, and to lengthen pump life, while keeping still effective the temperature control. To realize that an idling power equal to 40 W was set to guarantee a minimum fluid circulation in the pipes: this value permitted a smoother FC temperature rise while the pump is operated continuously, avoiding harmful ON/OFF operations. Instead, when heat to be dissipated becomes higher, pump can reach higher power levels. During the design stage, it was discovered that this alternative cooling strategy, to be feasible, required to enlarge the temperature window to 5 °C, ranging 73-78 °C, as can be seen in Figure 18.1. The comparison between the two strategies, both simulated on a WLTP driving cycle, carried out some interesting results. The "normal" strategy was responsible for a total energy expense of 7.34 Wh, while the "alternative" required nearly four times, accounting for 29.65 Wh. Anyway, the latter showed a drastic cut down on switching cycles, passing from some tenths to only 3. Despite this improvement, the advantage of the alternative strategy was not considered relevant enough to choose for his adoption: pump durability can be improved with a right sizing and design, also recurring to more advanced materials. The normal strategy, with its more precise stack thermal management and lower energy requirement, was deemed better for a vehicle which is developed around the concept of Fuel Cell usage and driving range.

3.3.2 DC/DC Converter, Inverter/E-Motor cooling, and implications on energy balance

The original model was devoid of a cooling circuit for the DC/DC Converter and the Inverter/E-Motor. These electric machines are affected by inefficiencies and produce heat that leads to an increase of their temperature. Heat must be taken away from them because, even if they are components not so sensitive to thermal conditions, can incur in overtemperature that can damage them irreparably. For this reason, a second dedicated cooling circuit was developed, to maintain the parts at a temperature around 80 °C, and in any case not above 100 °C to avoid overheating.

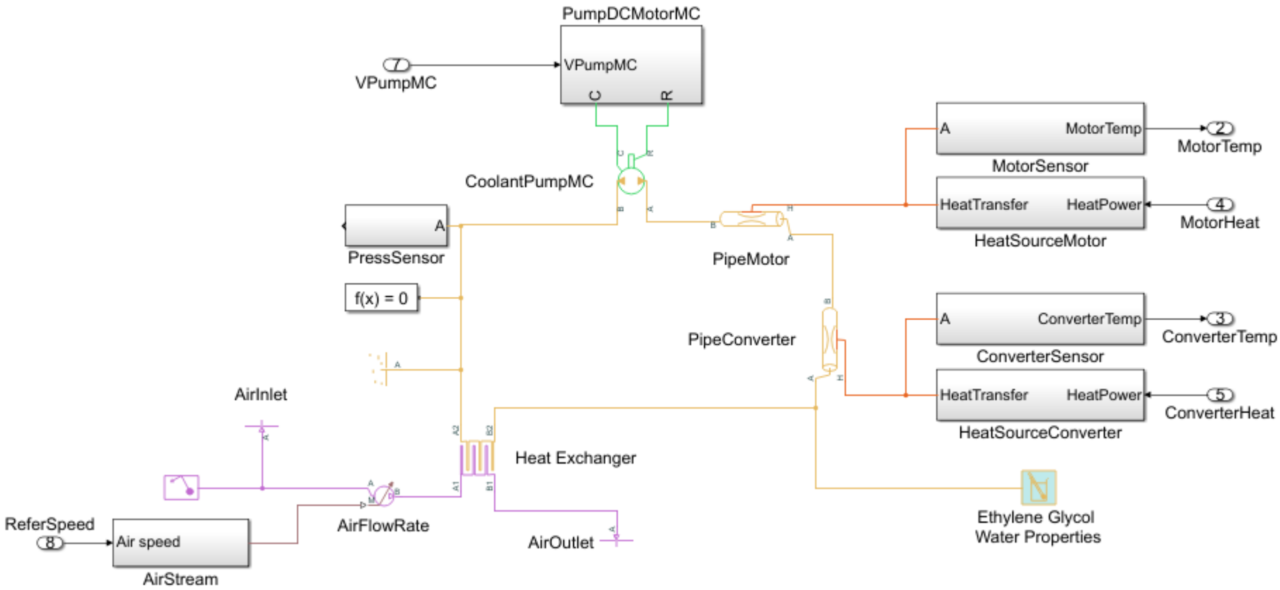

Figure 19: **Representation of DC/DC and E-Motor cooling circuit**

The second cooling system includes:

- a DC pump whose dynamic is regulated by the Control Logic supplied voltage.
- pipes connecting the E-Motor and DC/DC Converter.
- an air/fluid heat exchanger (radiator).

Additional blocks are used to represent temperature and pressure sensors, heat sources, glycol and water refrigerant mixture, and airstream entering and leaving the radiator. The results of a simulation of the vehicle, running on a WLTP cycle, are shown in Figure 20. Temperature trends are substantially different from those of the Fuel Cell: while stack temperature rises rapidly, the other components take longer time due to the higher thermal inertia and mass, and the lower energy dissipated into heat by the electrical machines. Power electronics and electric motors have efficiency in the order of 98%, so the amount of energy converted into heat is far lower than those of the Fuel Cel, even if not negligible. That's the reason why DC/DC Converter cooling starts just at half the cycle, after 700 seconds, while the assembly Inverter/E-Motor does not reach the warning temperature before cycle ending.

In Figure 20.2 it is possible to see the pumps absorbed power. For the total energy balance, the energy spent by the secondary cooling circuit was around 3.65 Wh: this value must be added to the energy adsorbed by the auxiliaries.

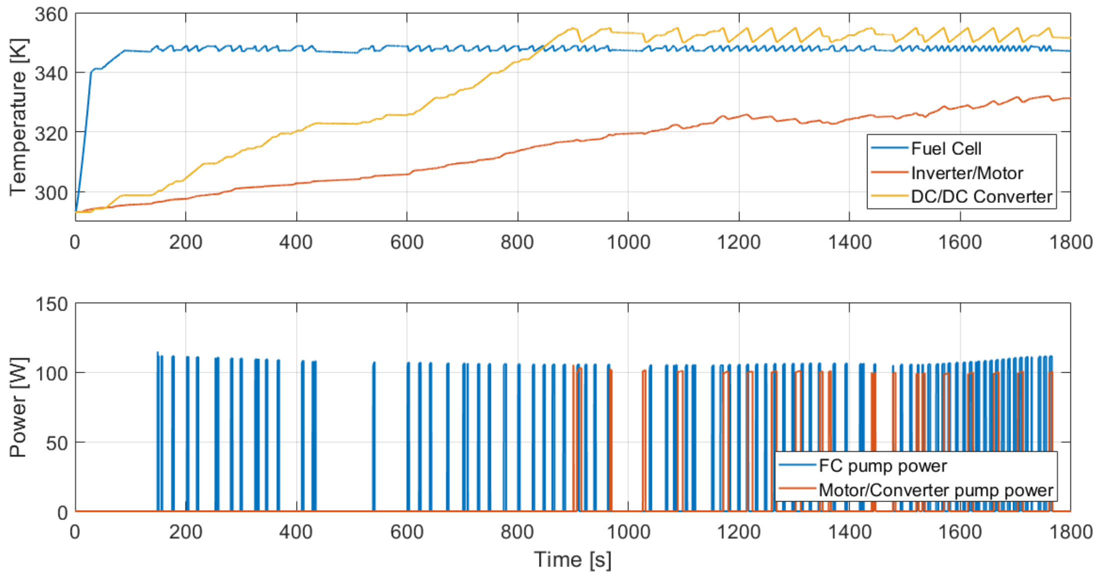

Figure 20: **Components temperature trend and power adsorbed by the cooling pumps**

3.4 Refinement of Fuel Cell reagents supply with experimental data

Other parameters besides the temperature affect the Fuel Cell performances. Between these, the way reagents are supplied to the stack are fundamental. The hydrogen supply system plays a crucial role for the proper operation of the Fuel Cell system, providing fuel to the anode. On the other side, air supply system provides oxygen to the cathode thanks to a compressor, one of the most important auxiliaries for FC balance of performance. The air supply system is crucial for the stable and efficient operation of a Fuel Cell system. Firstly, it influences the humidity level (and humidity removal) of the stack. Secondly, the oxygen in the air influences the stack voltage and therefore the efficiency of the stack. The air compressor can supply air at different air mass flows and air pressure levels to the stack. These operating parameters and the corresponding electric energy consumption influence the stack and system efficiency, accounting to greatest extent to the system power consumption. Reagent pressure improves the stack produced output: higher pressure is linked to higher Nerst open circuit voltages and lower activation losses of the electrochemical reaction. These phenomena lead to a better polarization curve, increasing the corresponding voltage for the same current request and a consequent higher output power. In addition, higher pressures guarantee a uniform and homogeneous reactants distribution on PEM membrane and prevents possible hydrogen and oxygen starvation. The results of effect pressure on the model are reported in Figure 21. As can be noticed, effects are lower in magnitude if compared to temperature, but not negligible at all.

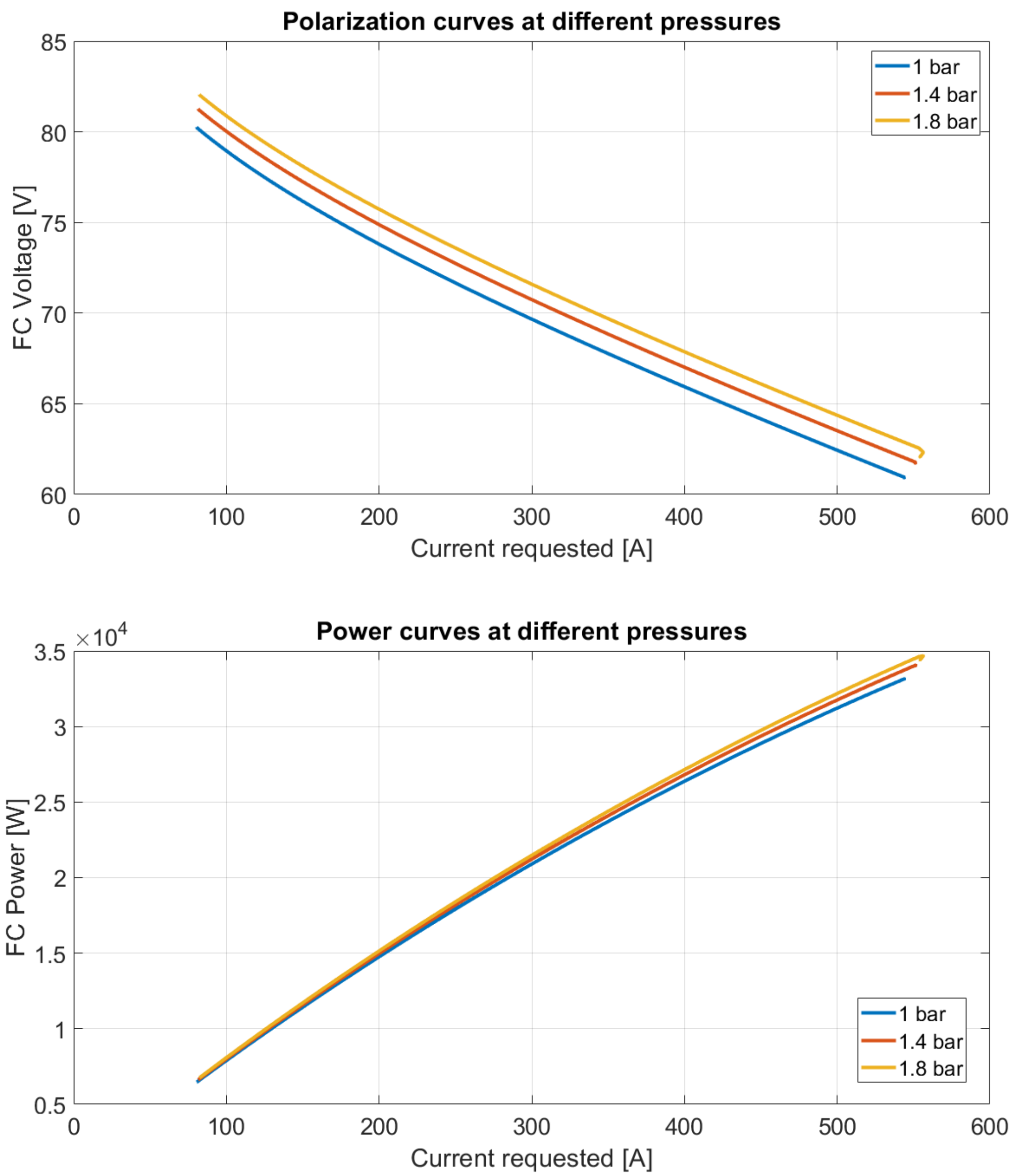

Figure 21: **Influence of pressure on polarization and power curves**

A second parameter that is investigated is reagents flow rate. Generally, a higher air mass flow increases the stack voltage (and stack efficiency). At lower mass flows, the stable operation of the stack cannot be guaranteed due to the higher propensity of water condensation and oxygen starvation. High velocity air is needed to remove the produced water at the cathode side of the stack. At high air mass flows, the oxygen partial pressure is also higher thus increasing the stack voltage. However, after longer operation at high air mass flows the membranes are not humidified enough and drying up can occur [26]. Cathode pressure and air flow rate relations are dictated by compressor characteristic: maximum air inlet pressure of the stack is limited by the surge line of the air compressor while lowest pressure is limited by the pressure drop of the stack and the choke line of the air compressor.

In the following paragraphs, a more accurate modeling of anode and cathode will be explained. This works aims a more correct representation of Fuel Cell behavior, and a calibration of the model was also performed using real experimental data.

3.4.1 Anode pressure modeling

The hydrogen supply system plays a crucial role for the proper operation of the Fuel Cell system. Hydrogen is conserved in high-pressure tanks, and it is delivered to a pressure reducing valve to lower the pressure from the high value (700 bar) to the rail one (around 15 bar) and then to the injector. When the hydrogen gas enters the anode of the stack, an electric pressure control valve guarantees the desired pressure, avoiding overpressure conditions and large pressure differences between anode and cathode sides of the membrane, that can cause cracks. A purge valve is periodically opened to remove water and gas impurities from the anode chamber, which negatively affect the voltage level of the stack. A recirculation pump collects the unused hydrogen and refills the inlet line, since the supplied quantity is never the one required by the electrochemical reactions. The pump speed is controlled depending on the load point, so that the hydrogen flow over the membranes on the anode side guarantees an efficient water removal of the gas diffusion layers. The hydrogen recirculation pump has an electric energy consumption level in the range of the coolant pump, and it usually consumes less power compared to the air supply side, especially at higher loads when compressor provides the maximum flow rate.

An anode model was developed based on Jay Tawee Pukrushpan's works, presented in "Modeling and Control of Fuel Cell Systems and Fuel Processors" [22]. It is basically a mass conservation law for an open system, and is formulated as:

$$\frac{dp_{Anode}}{dt} = \frac{R_{H2}T_{Anode}}{V_{Anode}}\left(W_{In} - W_{React} - W_{Pump}\right)$$

Where:

- p_{Anode}, T_{Anode}, V_{Anode} are anode pressure, temperature, and volume respectively.
- R_{H2} is the hydrogen gas constant, equal to 4125 J/(kg*K).
- W_{In} is the hydrogen mass flow rate at anode inlet.

- W_{React} is the hydrogen mass flow rate spent by the FC for power production.

- W_{Pump} is the hydrogen recirculated by the pump at anode exit.

Finally, model has been calibrated using experimental data from a Nuvera 34 kW Fuel Cell previously used for [21]. Figure 22.1 shows the Anode pressure from zero to full power, comparing the results of the experimental ones and the simulated ones, while Figure 22.2 the pressure trend during a full WLTP cycle simulation.

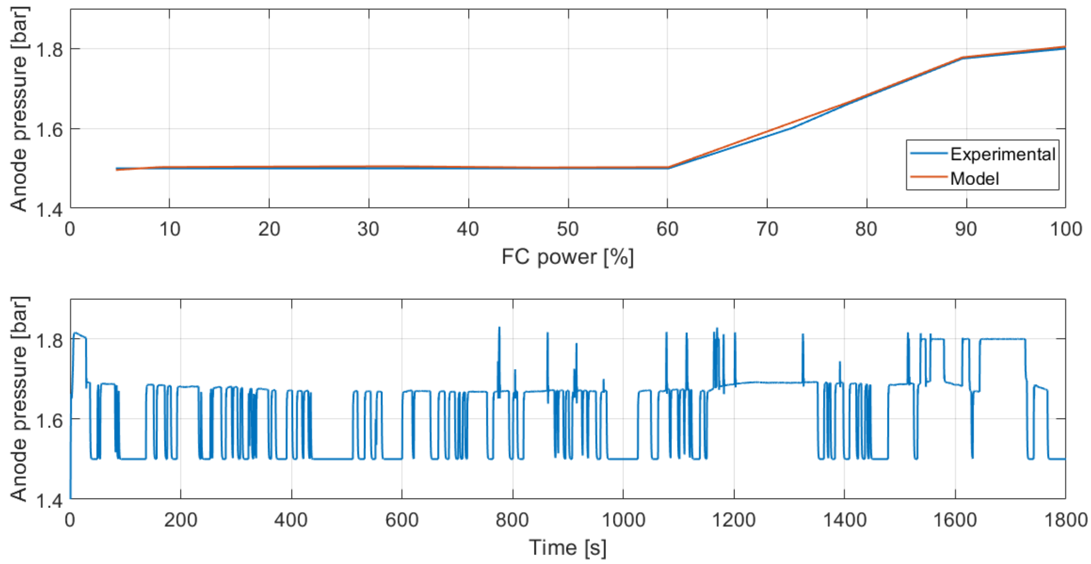

Figure 22: **Anode pressure trends for a power ramp and during a WLTP cycle**

The original model set the Anode pressure to constant, assuming a value of 1.6 bar. This approximation, even if not completely far from reality, was not correct. As can be seen in the picture above, Anode pressure of the real stack is kept at 1.5 bar from rest to around 60% of maximum power. Then it ramps up to 1.8 bar at full power, when a higher pressure is needed to increase the available and avoid reagents starvation in the membrane. A relief valve was modeled and set to 1.85 bar, in order to limit pressure that could lead to cracks.

It is remarkable the fine tuning of the model, that is very close to the real data, and thus capable of producing correct and reliable results.

3.4.2 Cathode pressure modeling

Cathode supply system is composed mainly by the air compressor, which provides the required mass flow rate to the Cathode. Cathode side modeling requires the knowledge of the behavior of more than one chemical species: while Anode is fed by practically pure hydrogen (99.996%), Cathode receives air, mixture of nitrogen, oxygen, and water vapor. The equation proposed by [22] defined cathode total pressure as the sum of partial pressures:

$$p_{Cathode} = p_{N2} + p_{O2} + p_V$$

The above equation was quite complex to be known accurately because it was dependent on various parameters such as air composition, humidity, thermodynamic state and mass flow rates in and out the cathode. Since there was no need of collecting back the excess of air provided to the stack (that is dispersed directly in the environment), a different approach was used. Cathode pressure is regulated by a control valve, which is governed to match as much as possible the experimental data.

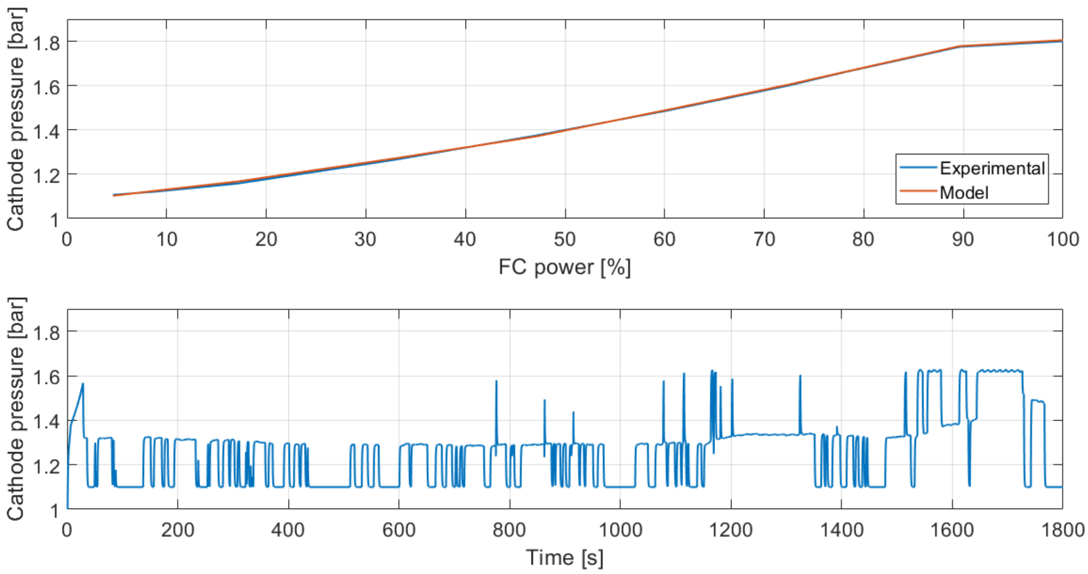

Figure 23: **Cathode pressure trends for a power ramp and during a WLTP cycle**

The old model assumed again a constant pressure equal to 1.6, but in this case the assumption was further from the experimental evidence: Cathode pressure shows a more flexible behavior along the power range, increasing almost linearly from 1.1 bar at rest to 1.8 bar at maximum power, when higher flow rates are required. In Figure 23.2, cathode pressure history during a WLTP cycle simulation is represented.

Again, it should be highlighted the correspondence of experimental data with the model ones, result of an accurate calibration work.

3.4.3 Reagents Excess Ratios

As previously mentioned, reagents are not provided in the quantities that would be spent by the Fuel Cell to produce voltage and power. They are not supplied according to the electrochemical reaction laws, but in excess, to be sure that enough reagents are present in the diffusion layer in order that reaction could take place. Reactions are quite slow, and mass transportation phenomena even more, so that to avoid starvation a simple but effective way to solve the issue is this one. The definition of Excess Ratio is:

$$XER = \frac{W_{X,In}}{W_{X,React}}$$

Where "X" could be hydrogen or air, $W_{X,In}$ is the supplied mass flow rate while $W_{X,React}$ is defined:

$$W_{H2,React} = \frac{60 * I_{Req} * n_{Cell} * M_{molH2}}{2 * F * \rho_{H2}}$$

$$W_{Air,React} = SR * \frac{60 * I_{Req} * n_{Cell} * M_{molAir}}{4 * F * \rho_{Air}}$$

I_{Req} is the requested current to the Cell, n_{Cell} the number of elementary cells, M_{mol} the molar mass of the considered specie, F the Faraday Constant (96484 C/mol), ρ the density and SR the stoichiometric ratio, which displays the ratio between the mass flow rate of air and the mass flow rate of Hydrogen. To simplify the analysis, the SR is kept constant and in the specific case it is equal to 1.8.

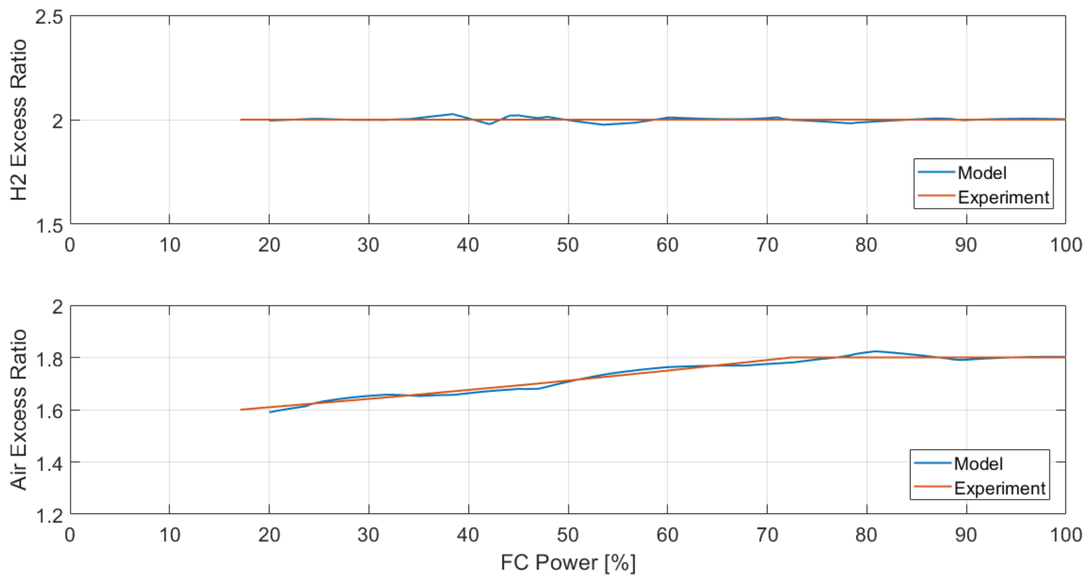

Figure 24: **FC Excess ratios comparison**

As shown in Figure 24, experimental Excess Ratios are now respected by the improved model. Anode supply system respect a constant ratio of 2, meaning that at any required power it is provided to the FC twice the hydrogen required. It is evident at this point the need of a recirculation pump to send back the reagent in excess. Instead, Air Excess Ratio is not constant, but starts with a value around 1.6, approaching 1.8 when the power requested is above 70%.

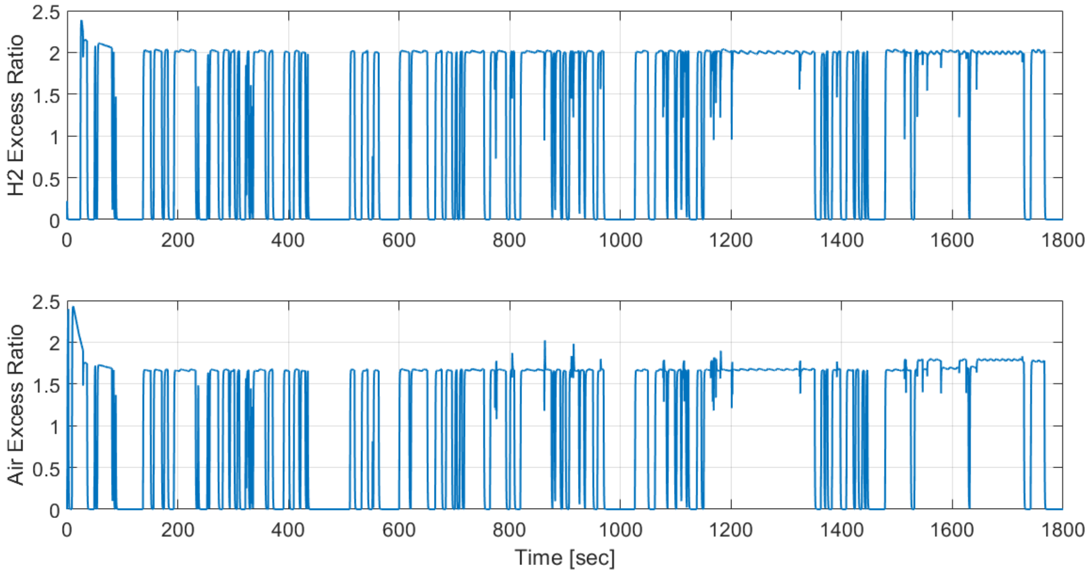

Figure 25: **FC Excess Ratios during a WLTP cycle simulation**

In Figure 25, it is reported the trend of Excess Ratios in a WLTP cycle simulation. It is interesting to highlight that during the Warm-Up phase the values are higher than the one expected: this fact happens because the FC is not capable of using the reagents in the estimated quantity due to the lower temperature. In addition, spikes are present because of supply systems dynamics, which are not able to instantaneously recover the objective Excess Ratio.

3.5 Resume of model improvements

With respect to the starting model, numerous improvements have been made in the Fuel Cell characterization and dynamic behavior. The model now dynamically responds in its parameters to transitions of the required power level, undergoing the influence of the temperature and pressure of the reagents, as well as the quantities in which these are supplied to the Fuel Cell. The calibration has required a fine tuning of all Balance of Plant components, from the cooling system to supply systems pumps and parts. The importance of the results is given that they were obtained from a calibration that used real experimental data. This greater accuracy than the base model reflects more reality. The previous model referred only to average energy values and therefore worked in a transition condition between infinite static conditions.

The new, improved model was the starting base for the following works, being coupled to Genetic Algorithm. Their duty was to answer to the question of “best configuration” in different scenarios, and it is what is done in the following chapter.

CHAPTER 4: APPLICATION TO A PRACTICAL CASE. CONSTRAINED OPTIMIZATION OF COMPONENTS SIZE OF AN ELECTRIC POWERTRAIN

4.1 Test vehicle: mid-van Light Commercial Vehicle

At this point of the work, both an approach to the optimization solving method, in our case a Genetic Algorithm, and a reliable and accurate FCEV model were available. Thus, a vehicle to which applicate the methodology was necessary, and for this task it was chosen a generic Light Commercial Duty vehicle.

Figure 26: **Light Commercial Vehicle** [27]

The mission was to provide freedom of mobility with safe, affordable, and sustainable solutions. Fuel Cell showed great promise as zero-emission technology, especially for Light Commercial Duty vehicles. This done fulfilling customer range expectations combined with towing and payload capability.

In LDV applications, not all usage profiles can be covered by battery-electric propulsion. Indeed, customers are asking for:

- Long range in zero emission mode, since a large part of these vehicles operate in suburban scenarios as well as in city centers, where zero emission is essential.

- Short charging times because operational unavailability during recharging cannot be allowed.
- Same payload capability of conventional vehicles since items transportation remains the primary task of LCV.

In order to meet customers' requirements, the following objectives have to be achieved:

- A range of 400 km is assured by combining the advantages of both hydrogen and batteries, in combination with brake energy recovery and plug-in.
- 3 minutes hydrogen refilling time guarantees short stop times.
- To preserve payload capability powertrain components had to be integrated out of cargo space. In addition, the system is integrated to enable a minimum amount of change between the full electric and the hydrogen version.

Different options are possible to define the configuration of a FCEV. The extremes are:

- A full-power FC system, in which a large FC represents the main propulsion source under all operating condition. This requires a large and powerful fuel cell and a small battery.
- A range extender, which is a battery-electric vehicle with a large battery and an additional low-power fuel cell that extends the driving range by providing power to the battery. However, when the battery is empty, the FC is not able to provide enough power to propel the vehicle.

Given customer requirements, it was chosen an intermediate solution. First, it enables a smart packaging compared to the full power system: the whole system can be integrated under the hood. To provide the hydrogen to the Fuel Cell, the traction battery was replaced by a hydrogen storage system consisting of three tanks. The solution has no impact on cargo space or payload. Second, compared to a range-extender, there is no compromise in term of performances. The FC is able to provide enough power for continuous highway speed and, when required, peak power is provided by the battery. Third, the battery also covers power requirements during start-up and first mile. This improves durability, when compared to full-power systems, since the FC can run at optimum operating conditions.

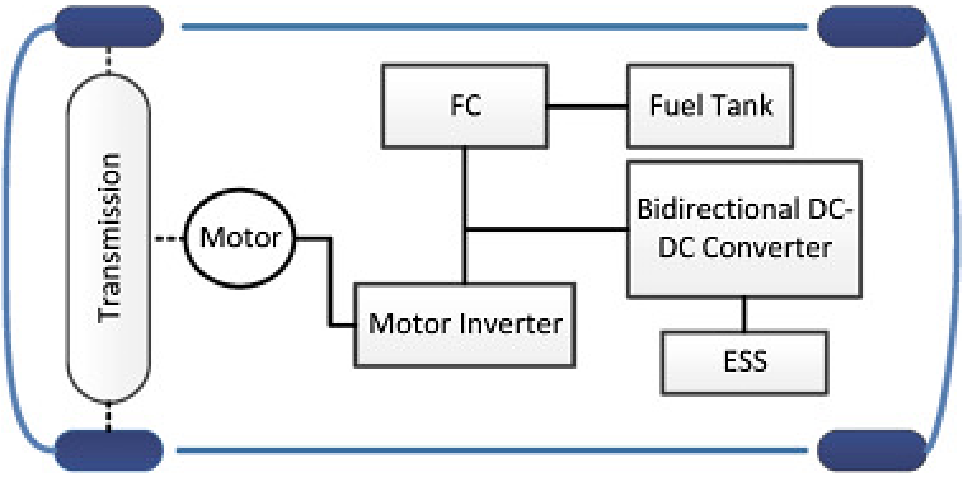

Figure 27: **Vehicle powertrain** [28]

The main subsystems of the Fuel Cell drivetrain to be integrated into the base vehicle are the Fuel Cell system, the hydrogen tank system and the high-voltage battery. The Fuel Cell system is mounted entirely in the engine compartment to which it supplies electricity. The additional battery providing dynamic peak power and regenerative braking has been adapted from already available plug-in electric vehicles. It is placed under the seats of the passenger compartment. The 700 bar hydrogen tanks providing hydrogen to the Fuel Cell are placed underneath the vehicle. The tanks can be filled with hydrogen via a specific filler neck, located at the fuel door normally reserved for diesel applications. Integrating the components of the entire FC propulsion system as described maintains the same cargo space as in the internal combustion version.

Table 4: **Starting generic LCV Technical Data**

System	Parameter	Value [unit]
Vehicle	Lenght	5.3 m
	Height	2 m
	Curb weight	1975 kg
	Payload	1100 kg
	Towing	1000 kg
Fuel Tanks	Pressure	700 bars
	Capacity	4.4 kg
Fuel Cell	Power	45 kW

Battery Pack	Power	90 kW
	Energy content	10.5 kWh
	Charging power	11 kW
E-Motor	Power	100 kW
	Torque	260 Nm

4.2 Definition of components to be optimized and constraints

4.2.1 Components size

Both Battery Pack and Fuel Cell system are perfect for a size investigation of the components due to their intrinsic modularity. This characteristic let us to work in straightforward way, hypothesizing simple relations between size and component performance.

Starting from the battery pack, it can be seen as series and parallel connection of elementary cells, each with the same electrical characteristic.

Table 5: **Battery Single Cell characteristics**

Parameter	Value [unit]
Capacity	15.5 Ah
Max Voltage	2.7 V
Nominal Voltage	2.3 V
Voltage Range	1.5-2.7 V
Max Discharge/Recharge Current @10 sec	240 A
Internal Resistance	1 mΩ @ SOC= 50% and 25 °C
Weight/Energy Density	150 Wh/kg

The elementary single cells are arranged following basic electric laws to achieve the desired capacity. Basically, when a higher energy storage capability is asked to the pack, more cells are put in parallel. In this way 6 different sizes of the traction battery were obtained from low to high capacity, according to different manufacturing and sizing "philosophies".

- The smallest 6.5 kWh Battery Pack is of the same capacity of 1st generation Toyota Mirai one. It is not intended to provide a full-electric driving range, but to compensate power leaks of the Fuel Cell during acceleration and enable regenerative braking.
- The 10.5 kWh Battery is the one used in the real case by the vehicle and represents an intermediate solution between a power buffer and electric driving.
- 20-40 kWh Battery Packs are typical values of Hybrid Electric Vehicles. The relevant energy inside makes the vehicle capable of driving tenths/hundreds of kilometers in full electric mode, or continuously sustaining an ICE/e-motor.
- The biggest sizes, 60 and 75 kWh, are intended to Battery Electric Vehicle. The 75 kWh pack was chosen because is proposed to be representative of full electric vehicles size. In this configuration, it should be capable of 330 km of pure electric driving.

Table 6: **Battery Pack sizes and characteristics**

Philosophy	Parallel Cells [-]	Series Cells [-]	Pack Weight [kg]	Capacity [kWh]
Power Buffer	1	155	44	6.5
Case study	2	125	70	10.5
Plug-in HEV	3	160	134	20
Plug-in HEV	6	160	268	40
BEV	9	160	400	60
BEV	12	150	500	75

A similar argument can be made about the Fuel Cell system: the FC stack can be seen as an assembly of elementary Fuel Cells put together in series. Each cell produces a voltage across its terminals and if a higher total output voltage is desired, it is normally enough to put more and more cells in series. This is what is done, even if it is exposed here in a simplified way, by FC manufacturers to obtain different power levels for the products that they market. Obviously, a proper re-design of FC auxiliaries and cooling circuit components must be done, but the FC stack itself obeys these simple linear laws quite accurately.

Table 7: **FC Single Cell characteristics**

Parameter	Value [unit]
Nominal Voltage	0.674 V
Nominal Current	364 A
Nominal Power	245 W
Minimum Voltage	0.61 V
Maximum Current	550 A
Maximum Power	335.5 W
Power Density	300 W/kg

Thus, several elementary cells are assembled in series to obtain a set of different power levels, from 20 to 100 kW. The enlisted power levels were chosen to cover a range of different possibilities of usage of the FC, so different 'philosophies' of Fuel Cell tasks assigned.

- The smallest, 20 kW FC, is intended to be operated as a range extender. As previously mentioned, a range extender is not designed to directly produce power for motion, but to work as a generator to provide additional energy for battery sustaining.
- Intermediate power levels, comprising the original 45 kW FC adopted by vehicle under study, are usually called "Load followers". Thanks to their higher power output, they are capable both to work as simple generators, as in the case of range extenders, but also to provide power for traction when needed. Their output power is usually designed to be equal to the average power requested by a reference driving cycle (ex. WLTP).
- Lastly, 80 and 100 kW stacks follow "Full performance" sizing philosophy. They are designed as principal traction power providers while in this case the Battery Pack should only compensate lack of FC dynamic during transient.

Table 8: **FC system sizes and characteristics**

Philosophy	Series Cells [-]	FC Weight [kg]	Max Power [kW]
Range extender	60	67	20

Load follower	120	134	40
Case study	135	150	45
Load follower	180	200	60
Full performance	240	268	80
Full performance	300	335	100

4.2.2 Vehicle performance constraints

Vehicle feasibility passes also through crucial performance requirements. Targets must be met before vehicle production starts and checks are done since the first design phases. Performances are crucial to make product competitive in its tasks and appealing to the final customers. For this reason, some basic performance requirements were set when a configuration was investigated: this was done to constrain choices to feasible configurations. Skimming the alternatives is fundamental in the early development phases, avoiding wasting time and money on too many options.

Therefore, 5 basic performance targets were established and set to be investigated by the Genetic Algorithm during its simulations.

- First of all, vehicle was tested to understand if minimum acceleration capabilities are met. 0-100 km/h is a crucial data for a vehicle: it is fundamental for the driving feeling even for LCV, where this kind of performance could not seem of primary interest. Thus, a maximum value was set both for empty and full load (1100 kg) conditions: in the former case, snap from standstill must be achieved in under 20 seconds, in the latter in less than 25 seconds.
- Another important feature for a vehicle in real life is gradeability. Our Light Commercial Vehicle must be able to climb mountain slopes and other obstacles, such as steep garage ramps. About this, gradeability targets were set: the vehicle must be capable of reaching 20 km/h from standstill on 25% slopes when empty, while 15% at full load.
- Finally, a last, crucial constraint was set: the daily driving range. As said before, an issue linked to pure electric vehicles is the driving range, and it is in greater extent for commercial ones, since the time spent for battery charging means unavailability and inoperability. To avoid that, checks need to be made, making sure that the vehicle is able to cover at least a daily mileage before asking for a recharge. Considering the average LCV mission, 200 km were chosen, being more than enough according to customer demand.

During the first release of the process, the identification of not suitable configurations in terms of performances was performed manually. This was done launching performance simulations of "weak configurations" (with low power FC and small batteries), or "heavy" ones (with big and weighty Battery Pack) chosen arbitrarily by the operator. The procedure resulted lengthy and not reliable, because some problematic configuration could escape from the operator preliminary analysis. Therefore, for practicality and effectiveness, it was implemented an automatic performance simulation and assessment before the drive cycle and consumption evaluation.

4.2.3 Model simplifications to speed up simulation

Both the original FCEV model and the improved version were affected by long simulation time. A complete simulation of a WLTP driving cycle required 20-25 minutes to be completed on an Intel Core i5-6198DU CPU @ 2.30 GHz, RAM 12 GB. The amount of time was not an issue when one simulation had to be done: being less than the 30 minutes of cycle duration, it represented a quasi-real time simulation. Instead, it becomes an obstacle when tenths of iterations must be performed, as in the case of a Genetic Algorithm application. Therefore, a substantial speed up of the simulation was necessary, and to achieve this a simplification and streamlining of the model.

Using the optimization tools implemented on MATLAB/SIMULINK, it was possible to identify that most of the slowdown was due to Simscape Library blocks that were used to model some components in the Supply Systems and Cooling Circuit. With a view to cut down on the calculation time, actions were taken always with the care of not affecting the accuracy of the results.

- Since the Fuel Cell temperature is kept by the cooling circuit nearly constant within a window of +/- 1° C, FC thermal dynamics was simplified, alongside with some Cooling system components. The influence on power and H2 consumption is negligible in the considered range according to the results derived in Chapter 3, while the impact of auxiliaries and Cooling circuit on energy balance was maintained with no changes.
- The Warm-Up phase was eliminated. This assumption can be considered valid since it takes few second, and for this reason can be neglected in a simulation that covers hours of consecutive vehicle usage.
- Some Supply System components, like Hydrogen Injectors and Air compressor, were simplified or eliminated, being substituted by more "computation-friendly" Look-Up tables. No modifications were done on parameters such as Anode/Cathode Pressure and Excess Ratios relations with FC power, that remained as they were calibrated using the experimental

data. Again, energy consumed by auxiliaries and its impact on the vehicle energy economy was not modified.

The modifications let to cut the computation time of a WLTP cycle from 20-25 minutes to only 5-6 minutes. This means a reduction of -60/-80% of time spent for cycle simulation.

A simulation was performed to verify the simplified model consumption compared to the data made available during the press presentation of the vehicle. The simulation was completed with data about van frontal area, estimated drag coefficient and applying a test lost, so that it was representative of reality. The last parameter was chosen according to the WLTP procedure [30]. Vehicle weight without Fuel Cell system and Battery Pack was set in a way that, adding the weight of the missing components used in the study case, the complete vehicle matches the 1975 kg. That ensured to simulate a modeled vehicle as close as possible to the real one, at least for the main characteristics.

Table 9: **Additional data for simulation**

Parameter	Value [-]
Frontal area	3.3 m^2
Drag coefficient	0.34
Weight without FC and Battery Pack	1755 kg
Test Load	265 kg (100 kg + 15% of Max Payload)

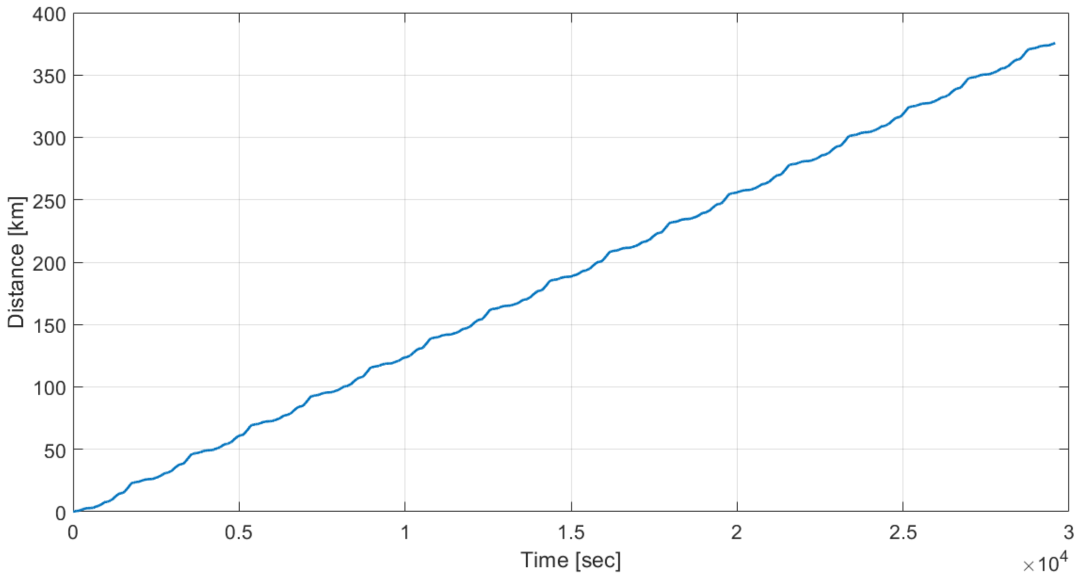

Figure 28: **Distance traveled on a WLTP cycle by the simulated vehicle**

Vehicle autonomy target was set around 400 kilometers on WLTP for the Fuel Cell version. Our vehicle simulation demonstrates a satisfying result: 376 km travelled on the same cycle. These results are obtained consuming 4.2 of 4.4 kg of on-board hydrogen, while half of the battery energy is still available (Figure 28). The choice of not considering the full hydrogen quantity is given to preserve a minimum pressure in the tanks, while preserving a small reserve of fuel to cover few tenth of kilometers.

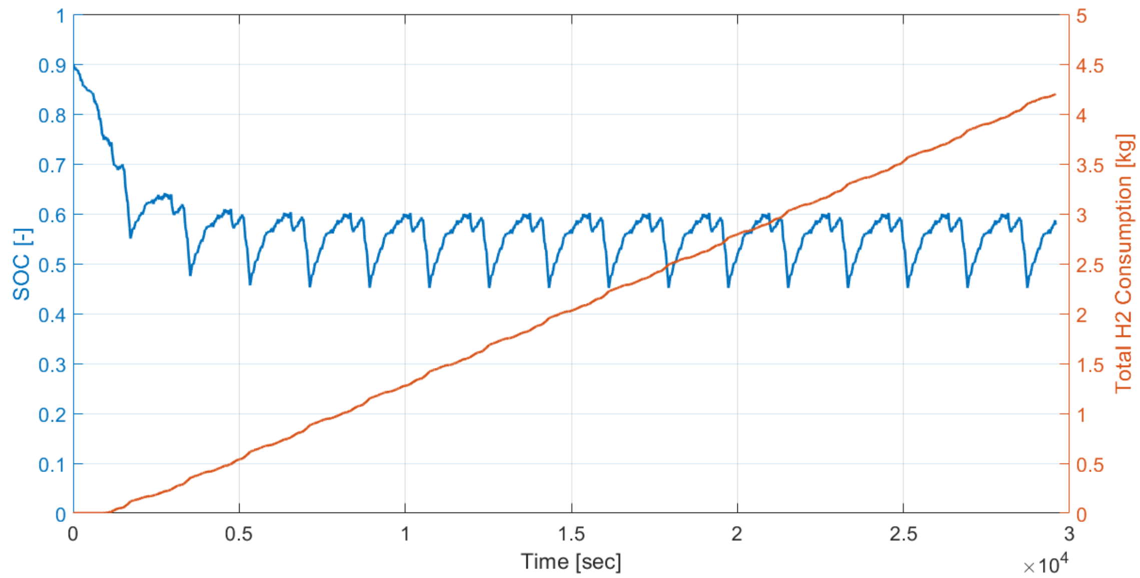

Figure 29: **SOC and H2 consumption during WLTP simulation of vehicle autonomy**

The cycle is completed almost 17 times and takes place for about 8.5 hours. During this, hydrogen consumption is nearly constant, while SOC trend is different and peculiar. After an initial phase during which the FC is shut down, when SOC reaches 75% battery level stops falling and it is maintained steadily between 45 and 60% by the power and energy produced by the Fuel Cell system. Thus, the Fuel Cell operates to sustain power requested to the battery, providing a fraction of the traction power and avoiding that the battery is completely discharged.

CHAPTER 5: DEFINITION OF COST FUNCTION AND OPTIMIZATION RESULTS. SIMULATION OF DIFFERENT MISSIONS AND SCENARIOS

Now that a reliable and accurate model is in our possession, it must be coupled with the Genetic Algorithm to deliver the results we are looking for. Then, to be suitable for our objective, some parameters must be appropriately set and, most importantly, a significant Fitness Function must be formulated to drive the GA to the optimal solution. Finally, optimization through configuration simulations takes place: each Individual is analyzed through a process involving a preliminary performance assessment and, for those able to pass it, a subsequent drive cycle simulation. A last evaluation is done to understand if the vehicle is capable of fulfilling a minimum daily driving range, but more details will be given.

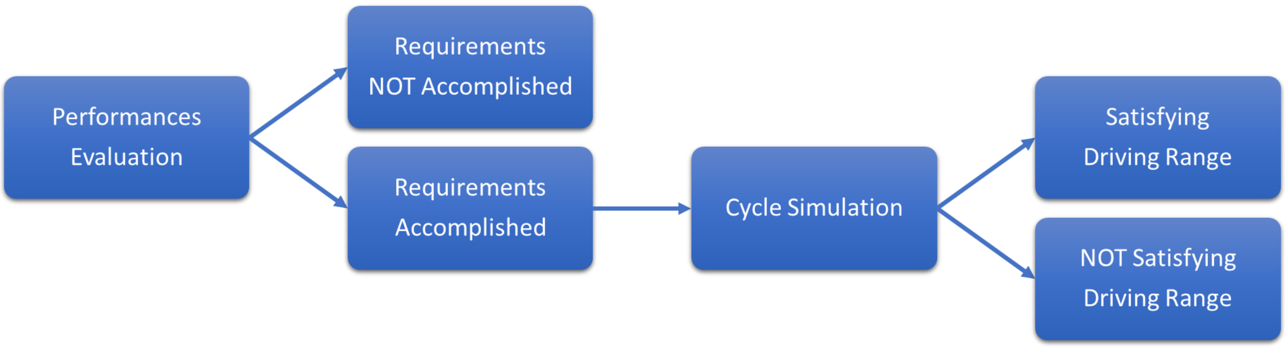

Figure 30: **Genetic Algorithm cost evaluation flowchart**

5.1 Genetic Algorithm calibration: Population and Genetic Operators definition

Genetic Algorithm is already implemented in MATLAB environment, as part of Global Optimization Toolbox [31]. First step during Genetic Algorithm configuration is represented by the choice of the simulated Population and the Genetic Operators that will act on this. Our problem consists in a 2 variables optimization, in which the parameters to be optimized are:

- Fuel Cell system power.
- Battery Pack energy stored.

Each of them is characterized by 6 different values that can be assumed, representing the possible component sizes. Therefore, it can be classified as a 2 variables discrete problem, in which the state space is composed in total by $6^2 = 36$ possible combinations.

The Population, set of all individuals each one encoding a solution, should be defined according to the problem size. After some trials and errors, a Population of 7 Individuals for each Generation was chosen, representing a good compromise between solution quality and computation speed. Finding a good tradeoff is crucial during Genetic Algorithm design: if few Individuals are considered the solution found can lack of reliability, leading to results that are local minima on the problem surface or still far from the optimal solution. Instead, if too many points are investigated, the amount of time drastically increases, and approaching a Full-space resolution makes the application of the Genetic Algorithm useless. Between these 7 Individuals, another trial-and-error campaign identified a composition subdivided in:

- 1 "Elite Child", setting the "EliteCount" optimization option equal to 1. Elite Individuals are the best within the current generation, having the lowest value of the function to be optimized. They are not affected by Genetic Operators but pass unaltered to the next Generation. This is done to preserve good genetic information, avoiding that it is not passed through Generations and improving final solution quality.
- 5 "Crossover Children", giving value 0.7 to the "CrossoverFraction" setting. In this way, 70% of next Generation Population is composed by crossover of previous Individuals. It is crucial in the Genetic Algorithm operation and gives to the optimization method the capability of reaching the optimal solution.
- 1, last, "Mutation Child" to complete the Population set. The mutated Individual has the role of adding fresh, random values (within the permissible ones) to the encoded individual. The aim of Mutation is to avoid early convergence and local minima.

To ensure a reasonable and thorough investigation of the Search space, and to allow the Algorithm to evolve through time and Generations, 4 Generations were set. The choice was taken after observing the Population and the quality of the solution: when 3 or less Generations were used, the Algorithm had no chance to evolve enough, experimenting new combinations and crossing the best Individuals' genes to the offspring. Instead, when more Generations are allowed to proliferate, the quality of the solution does not improve, since last pools are composed by Individuals very similar to each other, making the crossover and GA continuation practically useless and a waste of time. Considering these settings, around 14-16 different configurations were tested during a complete algorithm simulation between the 7*4= 28 iterations.

In addition, to speed up Algorithm computation, the Genetic Algorithm was provided with a sort of "memory" of Individuals already tested. The fitness value of a simulated solution is saved after its calculation, and when the same Individual is considered again the simulation is not performed, but it is returned to the algorithm the fitness value previously saved. This happens, for example, when the individual is an elite child, so passes unaltered to the next generation, or when a crossover child has the same values of an already computed progenitor). If, as said, between the 28 considered individuals on average only 14-16 are "different", the implementation of this feature allows to save up to 50% of computational time. Time that can be reinvested increasing the number of Individuals and Generations, if the problem requires it.

The Figure below represents the evolution of the program: from the initial version which investigated just 10 Individuals in 4.5 hours, to the last one, that implementing the simplified model, the memory feature, and the automatic performance evaluation, is able to simulate both consumption and performance of 28 Individuals in 1.25 hours.

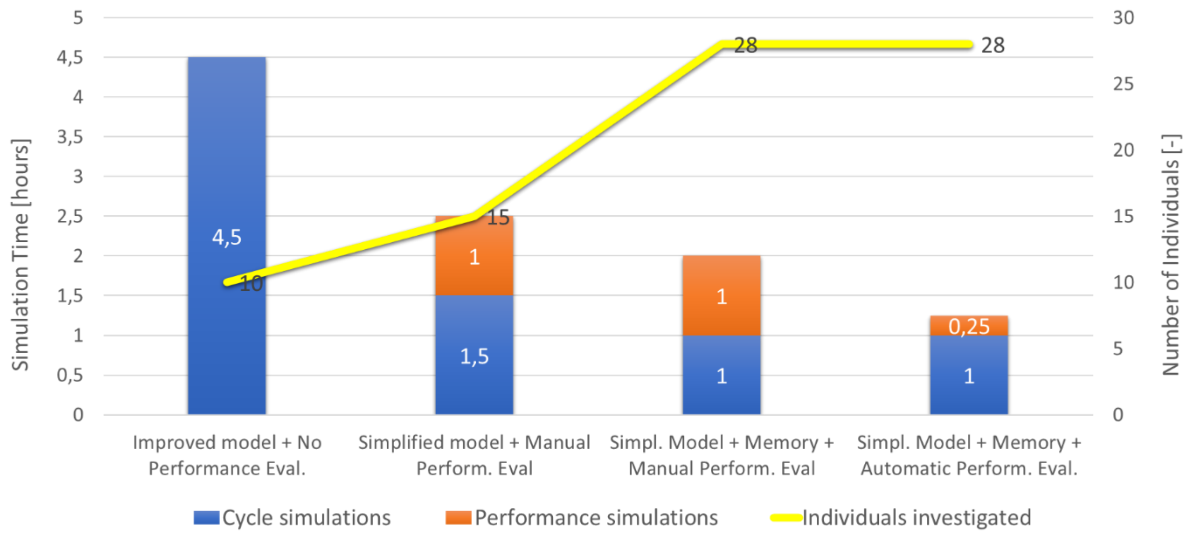

Figure 31: **Simulation time and individuals investigated comparison**

5.2 Cost Function definition

The Fitness function represents the core of Genetic Algorithm optimization, and its importance is well described in Chapter 2. Since it represents the discriminant with which the Algorithm labels a solution not only as "good" or "bad", but also ranks them, its formulation is crucial. As sentenced before, being the Genetic Algorithm method not specific but capable of embracing different applications without a specific knowledge of the problem, the Fitness function must be accurately defined.

The economic nature of the optimization problem makes the fitness function to be often called "Cost Function", term that is nowadays catching on also in non-monetary contexts. The Cost Function to be minimized is composed by 2 parts:

$$COST_{TOTAL} = COST_{CONFIG} + COST_{OPER}$$

- The cost, from firm point of view, of vehicle's powertrain production. Costs associated with powertrain components are essential for vehicle feasibility. In first instance, they weight on Company pockets, that has to sustain parts production or purchase from suppliers. Secondly, expensive solutions have repercussion on the final price that it is in charge of the final customers. In short, high vehicle price tag becomes an obstacle to product marketability and competitivity, even if the vehicle presents attracting and innovative features.
- The operating cost of the vehicle, to be sustained by the customer. It consists of the expenses for hydrogen and electric energy purchase at hydrogen station and charging column. It is calculated on 200000 kilometers, so that it represents the cost of refueling during a normal vehicle lifetime, and it is totally in charge of the customer.

5.2.1 Configuration cost

Configuration cost includes the expense sustained by OEM to produce or acquire from suppliers the vehicle powertrain components. It is the sum of several elements, among which the only one not considered in our analysis is the e-Motor: the reason is that is the same for all vehicle configurations, and it is directly taken from the battery electric version. Since it does not represent a varying component neither between different configurations nor with the full electric vehicle, the e-motor impact on cost is neglected. Thus, the final equation is:

$$COST_{CONFIG} = Batt_{Cost} + FC_{Cost} + Tanks_{Cost} + Charger_{Cost} + PE_{Cost}$$

Where:

- $Batt_{Cost}$ is the cost associated to Battery Pack production. In our discussion the Battery Pack cost was assumed to be directly dependent with the design energy storage capacity. Despite being a simplification, it is not far from the real situation.
- FC_{Cost} is the cost of the Fuel Cell system. It is composed by the cost of PEM Stack and the cost for Fuel Cell auxiliaries, comprising supply systems, compressor, and dedicated cooling circuit. Thus, it is formulated as:

$$FC_{Cost} = FC_{Stack} + FC_{Auxiliaries}$$

FC cost linearly depends on Fuel Cell desired power level, as it can be supposed to be in reality with a reasonable error.

- $Tanks_{Cost}$ is linked to the price of Hydrogen storage tanks, an essential and expensive component. It does not vary through Fuel Cell sizes, because it is assumed that the vehicle always carries a 4.4 kilograms hydrogen storage.
- $Charger_{Cost}$ is the cost of battery charger. It must be highlighted that the 6.5 kWh Battery Pack is not provided with a charger. The reason is given by the small size and energy stored by the pack, that makes unnecessary the adoption of a charger. In this case, the pack is charged by the only Fuel Cell and/or the regenerative braking. For all configurations in which it is present, the charger is sized for 11 kW recharging power, as specified by vehicle technical data.
- PE_{Cost} represents the cost of on-board Power Electronics, so the DC/DC Converter and the e-Motor Inverter. Two cost levels were defined for Power Electronics cost, both linearly increasing with FC system power:
  - For the lowest FC power levels, corresponding to Range Extenders and Load Followers (FC Power <= 45 kW), a higher associated cost was imposed.
  - For Full Load system (60-80 kW), a lower cost per FC kilowatt was defined.

Table 10: **Configuration costs table**

Component	Cost [Unit]
$\boldsymbol{Batt_{Cost}}$	116 €/kWh [32]
$\boldsymbol{FC_{Stack}}$	100 €/kW [33]
$\boldsymbol{FC_{Auxiliaries}}$	50 €/kW [33]
$\boldsymbol{Tanks_{Cost}}$	500 €/kg [33]
$\boldsymbol{Charger_{Cost}}$	550 €/kW [33]
$\boldsymbol{PE_{Cost}}$	5-10 €/kW [33]

5.2.2 Operating cost

Operating costs are linked to vehicle usage and, in our specific case, consist in the money the customer must spend to run 200000 kilometers in terms of hydrogen and electric energy. Thus, it is trivial that it is formulated as:

$$COST_{OPER} = Cost_{H2} + Cost_{Electr}$$

Or, written in a clearer way:

$$COST_{OPER} = H_{2\_PRICE} * m_{H2\_Cons} + Electr_{PRICE} * kWh_{Cons}$$

In which the first terms are hydrogen and electric energy price, while the latter are fuel and kWhs consumed during a cycle simulation.

Table 11: **Operating costs table**

Component	Cost [Unit]
$\boldsymbol{H_{2\_PRICE}}$	5.9 €/kg [34]
$\boldsymbol{Electr_{PRICE}}$	0.15 €/kWh [34]

Before going into details of above equations, a summary of the ways in which the FC is operated is needed, so that to understand the decisions taken. The base model [21], of which the Control Logic was maintained, disposes of three main operating modes. Vehicle operating modes are dependent on battery SOC and lead to different battery usage profiles [35]. Since these three modes have very different impacts on consumption, particular care was paid.

- Charge Depleting (CD), above 90% of battery charge. To avoid running with the battery fully charged, fact that prevents efficient regenerative braking energy recovery and FC operation, the Fuel Cell is shut off. All power for traction is asked to the battery: SOC may fluctuate but on-average decreases while driving.
- Blended Strategy (BS), up to 40% of SOC. It is a Charge Depleting strategy in which the Fuel Cell is used to supplement battery power. This mode avoids that all power is asked to the battery alone, which consequently would drain too quickly. When the power produced by the FC is higher than the one requested by the vehicle for motion, Battery Pack recharges.
- Charge Sustaining (CS), below 40% battery SOC and up to 45%. The battery SOC may fluctuate but on-average is maintained at a certain level while driving by the Fuel Cell. To do this, the Fuel Cell operates continuously at nominal power, in order to maintain the energy content around a threshold. The reason behind is to always dispose of some energy in the event that the vehicle unexpectedly requires relevant amount of power for prolonged time (up-hill or highway driving).

To estimate the consumptions associated to a full drive cycle, a first simulation is performed with a SOC= 60%, thus in Blended Strategy. At this point, a first differentiation is done always looking at the battery SOC at end of cycle simulation:

- If the battery presents a higher energy level than at the beginning of the cycle, it must be considered that there will be a time when the vehicle will enter the Charge Depleting mode as the battery is fully charged: the hydrogen previously used to create excess energy in the battery is therefore deducted from the total value. To account for this, the formula used to correct the amount of hydrogen consumed is:

$$m_{H2\_Corr} = m_{H2\_End} - \frac{\Delta SOC * Cap_{Max}}{\eta_{DC/DC} * P_{FC\_Nom}} * \dot{m}_{H2\_Nom}$$

  Where:
  - m_{H2_End} is the mass of hydrogen consumed during the cycle.
  - ΔSOC is the delta of SOC between beginning and end of simulation.
  - Cap_{Max} is the nominal battery energy capacity in kWh.
  - $\eta_{DC/DC}$ is the DC/DC Converter efficiency.
  - $\dot{m}_{H2\_Nom}$ is the hydrogen mass flow rate at nominal FC power.

  The above formula comes from [21]. Since vehicle SOC is higher at cycle end with respect to the one at the beginning, the 200 km daily range constraint is not an issue, because the vehicle has no need to be stopped to be recharged.

- When the cycle simulation returns a SOC level lower than the initial one (fact that is usual when FC size and, consequently, power are lower) more attention is needed. The reason is that there is the eventuality that the battery, initially fully charged, cannot cover the daily mission without stopping for a recharge.

In this second case, a more accurate analysis of vehicle consumption was performed. From the results of the previous simulation, calculated in Blended Strategy, it was possible to identify if the vehicle is able to run 200 km without entering Charge Sustaining. Thus, given that the available SOC during Charge Depleting is full SOC minus Charge Sustaining SOC, so 90 - 40 = 50%, and knowing the per cycle SOC depletion, it is possible to calculate the distance the vehicle can travel.

Example 1: on a WLTP cycle (23.25 km), the vehicle shows a ΔSOC = 5.23%, with a certain H2 and electric energy total consumption. Therefore, before entering the Charge Sustaining mode the LCDV is able to run:

$$\frac{50}{5.23} * 23.25 = 222.28\ km > 200\ km$$

This means that all the distance is statistically covered in Blended Strategy. At this point, consumptions are normalized on 200 km and the total cost for 200k kilometers is evaluated, according to Eq. 1.

Example 2: on a WLTP cycle (23.25 km), the vehicle shows a ΔSOC = 11.09% (due to a smaller battery pack or Fuel Cell), with a certain H2 and electric energy total consumption. Therefore, before entering the Fast-charging mode the LCDV is able to run:

$$\frac{50}{11.09} * 23.25 = 104.82\ km < 200\ km$$

So, the vehicle is forced to enter in Charge Sustaining mode to complete the daily mission. The data about travelled distance, H2 and electric energy consumed are stored as $Dist_{CS}$, $H_{2,CS}$, kWh_{CS} . Since the consumptions are different during this operation, another simulation is performed with 40% of initial SOC. The results obtained can lead to 2 scenarios:

- The ΔSOC of the second simulation is small enough to let the vehicle cover the remaining kilometers of the 200 estimated. The available SOC range is the initial threshold minus the lower battery limit, so 40 - 10 = 30%. To be clear of the procedure, lets continue Example 2: to complete the daily mission, 200 - 104.82 = 95.18 km remain. The second simulation returns a ΔSOC= 6.31%, always considering a WLTP cycle. Thus,
$$\frac{30}{6.31} * 23.25 = 110.53\ km > 95.18\ km$$
The vehicle is able to drive the last kilometers in Charge Sustaining mode, without having to be stopped for a recharge. At the end fuel and energy consumptions are the sum of consumptions during each mode, each weighted for its respective distance travelled.
$$H_{2,200KM} = \left(\left| H_{2,CS} \right|_{110.53} + \left| H_{2,FC} \right|_{95.18} \right) * H_{2\_PRICE}$$
$$Electr_{200KM} = \left(\left| kWh_{,CS} \right|_{110.53} + \left| kWh_{,FC} \right|_{95.18} \right) * Electr_{PRICE}$$
- The ΔSOC of the second simulation is high and the vehicle is not able to cover the remaining kilometers without being stopped and plugged to the charging column. As example, lets continue where we left Example 2, but in this powertrain configuration the simulation returned a value ΔSOC= 13.77%,

$$\frac{30}{13.77} * 23.25 = 50.65\ km < 95.18\ km$$

The vehicle range is not enough for the daily mission. The configuration must be discarded.

5.2.3 Constraints not achieved

As said before, during the simulations some performance and driving range constraints are investigated. When one or more of these is not met, the corresponding configuration must be discarded. To be understandable by the Genetic Algorithm, a proper value must be given to the Fitness Function. In this case, the value assigned is infinite so that the probability of the gene to be inherited by the next Generation is infinitesimal.

$$COST_{TOTAL} = \infty$$

To resume the fundamental and quite complex decisional flow for the Operating costs calculation, it is represented in Figure 29.

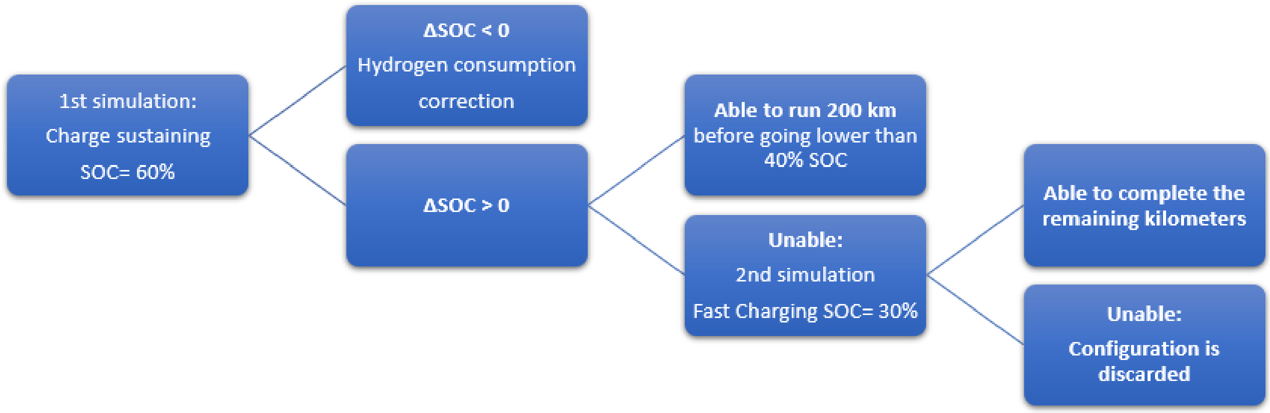

Figure 32: **Decisional flow of consumption calculation**

5.3 ARTEMIS Urban Cycle

First cycle simulated is the ARTEMIS Urban Cycle, which represents a mission on a city route (for more information, look at Appendix). The results obtained with the Genetic Algorithm were compared to those of a Full-space investigation. This was done to identify whether of not the GA could find the best configuration among all possible.

Tables report (in Euros) Total Cost, Configuration Cost and Operating Cost. Being the Configuration Cost not changing varying the tested cycle, it will not be shown again further in the discussion.

In black, the configurations tested by the Genetic Algorithm. In red the one not investigated.

Table 12: **Urban Cycle costs**

Total €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	11745	18416	19739	23292	28177	32819
10,5	12716	19509	20915	24752	29800	35006
20	15131	20821	22264	26415	32066	Inf
40	18047	23383	24863	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Config €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	6173	9394	10199	12312	15433	18553
10,5	7185	10405	11210	13324	16444	19564
20	8301	11522	12327	14441	17561	Inf
40	10631	13852	14657	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Fuel €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	5572	9022	9540	10980	12744	14266
10,5	5531	9104	9705	11428	13356	15442
20	6830	9299	9937	11974	14505	Inf
40	7416	9531	10206	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

In first instance, it must be highlighted that the algorithm was able to identify the configuration having the global minimum cost. In second instance, much information can be derived from the above data:

- The best configuration for a vehicle with a totally urban mission is the smallest one: 20 kW Fuel Cell and 6.5 kWh. It corresponds to the lightest powertrain, and it ensures the daily driving range without any issue. The approximative total cost is around 12000 Euros, fairly evenly divided between Configuration and Operating Costs.
- Many configurations are discarded for not having achieved the minimum performance objectives. The main problem was connected to gradeability, which becomes unfeasible for big and heavy FC systems and Battery Packs. This happens for the 60 and 75 kWh packs,

which weight 400 and 500 kg respectively and the situation is aggravated when the most powerful FC Stack and the relative auxiliaries.

- The powertrain sizes having the lowest total and operating costs practically coincide. Thus, both OEM and customer interests are respected at the same time.

Table 13: **Resume of Urban Cycle results**

Solutions	FC kW	Batt kWh	Total Cost €	Fuel Cost €
Best	20	6,5	11745	5572
Lowest Fuel Cons	20	10,5	12716	5531

5.4 ARTEMIS Rural Cycle

Second scenario analyzed is the ARTEMIS Rural cycle, scheduling the vehicle to run on an extra urban road. Extra urban routes are typical to connect cities or, in our hypothesis, the logistic hub from which the delivery van starts in the morning and returns at the end of the day. As can be seen in the Appendix, the cycle is characterized by higher average speed and also stops are less frequent.

Table 14: **Rural Cycle costs**

Total €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	16847	21777	24514	28497	32100
10,5	Inf	21670	22678	25673	29968	34040
20	37561	22875	23938	27250	31974	Inf
40	29580	25440	26534	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Fuel €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	7453	11578	12201	13064	13547
10,5	Inf	11264	11468	12349	13524	14475
20	29260	11353	11611	12809	14413	Inf
40	18948	11588	11877	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Looking at the Tables above, some relevant information can be derived, starting from the fact that again the Genetic Algorithm was able to identify the configuration having the lowest Total Cost. In addition:

- The best powertrain sizes were found to be 40 kW Fuel Cell system and 6.5 kWh Battery Pack, thus a Load Follower FC in which the Battery is designed just as power buffer given its small capacity. This configuration guarantees a low production cost since components are few modules and cells, while at the same time being light, they contribute to hydrogen and electric energy saving.
- Total cost increased from 12000 to nearly 17000 € to run the same 200000 kilometers: this is linked both to an increase in powertrain cost and energy consumption given the higher average speed of the cycle.
- The configurations showing the "globally" lowest cost and fuel consumption are the same. This is good news because design can focus on just one powertrain, without damaging one actor between manufacturer and customer.

Table 15: **Resume of Rural Cycle results**

Solutions	FC kW	Batt kWh	Total Cost €	Fuel Cost €
Best	40	10,5	16847	7453
Lowest Fuel Cons	40	10,5	16847	7453

5.5 ARTEMIS Motorway 130 km/h Cycle

Last of the ARTEMIS cycles object of our analysis was the Motorway schedule. This scenario is used to simulate vehicles facing a Highway route: since our vehicle is electronically limited to 130 km/h, the variant under study is the "Motorway 130 km/h". The considered mission is quite far from real vehicle use since LCV are in general not supposed to pass most of their time on the motorway. Nevertheless, to see the results and also to prove the goodness of our model and algorithm, a simulation of this scenario was performed.

Table 16: **Motorway 130 km/h Cycle costs**

Total €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	Inf	Inf	28514	33824	38126
10,5	Inf	Inf	Inf	28710	32079	38888
20	Inf	Inf	Inf	29874	31674	Inf
40	Inf	Inf	71572	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Fuel €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	Inf	Inf	16201	18391	19573
10,5	Inf	Inf	Inf	15385	15635	19323
20	Inf	Inf	Inf	15433	14114	Inf
40	Inf	Inf	56915	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Again, the Genetic Algorithm was able to identify the configuration with the associated lowest cost. This time, results were quite different from the previous and need to be explained.

- First, the components size further increased, especially from the Fuel Cell power point of view. The selected size is 60 kW FC aided by a 6.5 (or 10.5 since results are close) kWh Battery Pack. Thus, now the Fuel Cell is in charge to provide most of requested tractive power while the batteries cover the peaks. The constructive philosophy is moving toward Full Load sizing when from urban scenarios we moved gradually to journeys characterized to higher average speeds, less frequent stops and "more static" Fuel Cell operation.
- The difference between cheapest global solution and least fuel consuming is in this case more relevant: while costing 3000 € more, a configuration with 80 kW and 20 kWh leads to save nearly 2000 € on the operating costs. Therefore, a choice between company and customer must be taken. In brief, to save hydrogen and electric energy, in this scenario it is better to choose for a Full Load design of the Fuel Cell and becomes more advantageous the more the kilometers to be travelled.
- Some words cold be said about the 45 kW and 40 kWh powertrain, characterized by a huge operating cost. Looking at the data provided by the vehicle model, the reason of this result is given by the fact that the Fuel Cell is practically always operated in Fast charging mode. That leads to a lower efficiency and very high hydrogen consumption which has repercussions on travelling costs.

Table 17: **Resume of Motorway 130 km/h Cycle results**

Solutions	FC kW	Batt kWh	Total Cost €	Fuel Cost €
Best	60	6,5	28514	16201
Lowest Fuel Cons	80	20	31674	14114

5.6 WLTP Cycle

Until now, cycles used for vehicle simulation were representing very specific scenarios: a full urban mission, an extra urban route, and a motorway travel. Thus, the cycles gave information about the best configuration and powertrain components size for determinate cases. The fact that sizes, passing from a scenario to a totally opposite one, are completely different it is a proof of this.

It was necessary at this point a cycle representing various scenarios within one simulation in order to identify a configuration representing a trade-off between all possible situations. To achieve it, it was chosen the WLTP cycle: scheduling a low (urban), a medium, a high (rural) and very high (motorway) speed parts it was perfect for our purpose. For more information, look at the Appendix while the results of simulations are proposed in the tables below.

Table 18: **WLTP Cycle costs**

Total €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	25252	20910	25421	28833	31662
10,5	Inf	21289	20474	26591	30519	33853
20	Inf	22042	25336	28237	32652	Inf
40	50654	26903	28035	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Fuel €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	15858	10711	13108	13400	13109
10,5	Inf	10884	9264	13267	14075	14289
20	Inf	10520	13009	13796	15091	Inf
40	40023	13051	13378	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Firstly, it must be highlighted that, for the fourth time out of four, the Genetic Algorithm managed to find the global minimum of the Fitness function. Thus, the optimization using this method turned out to be reliable and fast. Instead, looking at the raw matrix results:

- The best powertrain sizing was revealed to be a 45 kW Fuel Cell system coupled with a 10.5 kW Battery pack. What is astonishing is that these are the same components used by our starting generic LCV.

- Globally cheapest and least consuming configurations coincide once again. The powertrain cost is assessed to be around 11000 €, while cost for hydrogen and electric energy accounts for a total Operating Cost of 9200 € to drive 200000 kilometers. As expected, these values are in the middle between those of the Urban Cycle, which were lower since the distance is travelled at low speed when dissipating forces are lower, and a purely Motorway Cyle.
- The identified powertrain reflects the “mixed” characteristics of WLTP Cycle too. The configuration is halfway between the Range Extender philosophy adopted in urban scenarios and the Full Load in the highways: the Fuel Cell is designed to directly provide power at low speed, when the magnitude requested is lower. Instead, when cruising at high speed, the Fuel Cell is not able to provide the total power asked by the vehicle (thus compensated by the Battery Pack) and works more statically to sustain battery SOC.

Table 19: **Resume of WLTP Cycle results**

Solutions	FC kW	Batt kWh	Total Cost €	Fuel Cost €
Best	45	10,5	20474	9264
Lowest Fuel Cons	45	10,5	20474	9264

5.7 Forecast 2030: WLTP cost simulation

A last analysis was undertaken, considering this time not a different drive cycle, but a forecast of 2030 economic scenario. The investigation had the purpose of finding (if exist) differences between the results obtained with current data with respect to projections of components and energy vectors in a decade. The values used for Algorithm computation were modified and substituted by those suggested by reliable sources.

Table 20: **Configuration costs table 2030**

Component	Cost [Unit]
$\boldsymbol{Batt_{Cost}}$	49 €/kWh [32]
$\boldsymbol{FC_{Stack}}$	45 €/kW [33]
$\boldsymbol{FC_{Auxiliaries}}$	40 €/kW [33]
$\boldsymbol{Tanks_{Cost}}$	300 €/kg [33]
$\boldsymbol{Charger_{Cost}}$	275 €/kW [33]

PE_{Cost}	2-2.5 €/kW [33]

It is immediately evident that forecasts hypothesize a drastic decrease in components costs. Starting from Battery Pack, its price is intended to fall from more than 110 €/kWh today to less than 50 €/kWh in 2030, according to BloombergNEF. The reason is linked to battery technology progress and above all to mass production and the economy of scale that will be reached in the next years. In parallel, also Power Electronics and other electrical components such as on-board chargers would cut half of actual cost. If instead we focus on Fuel Cell system, a similar argument can be done: Fuel Cell technology has still large limits of improvement and the sales number far from a relevant share on the market. OEMs are thus confident to drop costs for Stack production in a decade by one half, while auxiliaries decrease will be lower, because are mainly related to compressor and cooling circuit purchase (consolidated technologies).

Table 21: **Operating costs table 2030**

Component	Cost [Unit]
H_{2_PRICE}	2.4 €/kg [34]
$Electr_{PRICE}$	0.18 €/kWh [36]

Same was done with the operating costs, considering hydrogen and electric energy price evolution through time. Deloitte and Ballard, two of the most important Fuel Cell producers, suggest a relevant fall of hydrogen cost at the filling station. The cut will be caused by the decrease of hydrogen production cost thanks to Green and Blue Hydrogen production at good price and to the enhanced demand. On the other side, electric energy price is probable to have a completely different trend: while all other components and fuel are expected to be cheaper, electricity will be more likely slightly more expensive than today. Always considering price in Europe, French Environment Ministry forecast an electricity price going up in the following decade, due to the increasing demand linked to Electric Mobility.

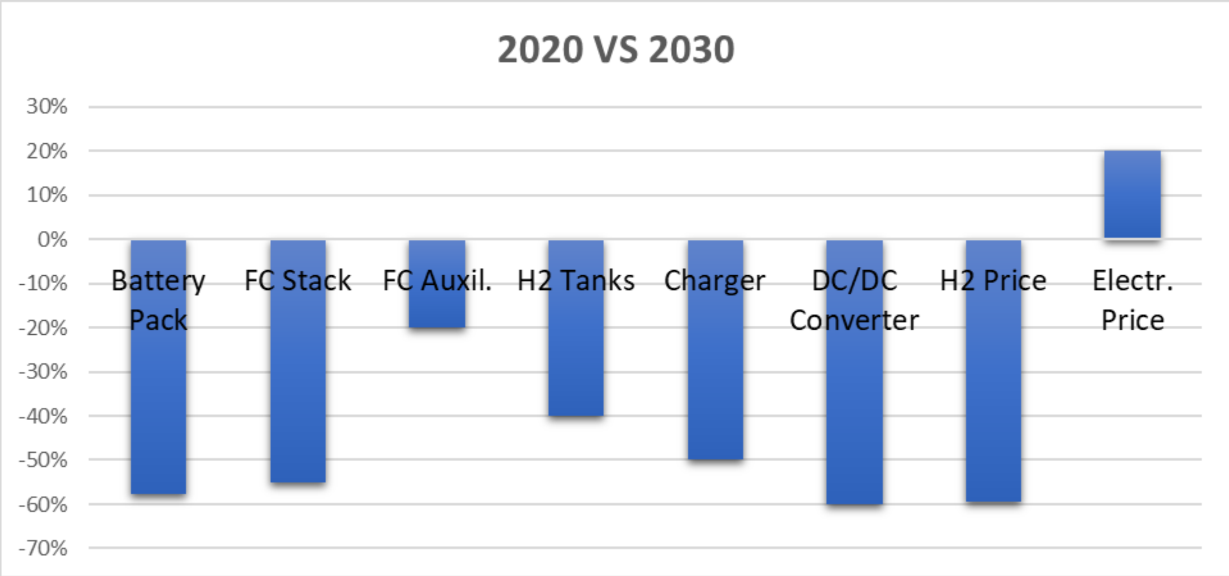

Figure 33: **2020 versus 2030 cost comparison**

Then, with the new forecasted data, a simulation of the Genetic Algorithm was performed leading to the following results.

Table 22: **WLTP Cycle costs 2030**

Total €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	14137	11220	12454	14045	15626
10,5	Inf	11475	11805	12777	14602	16369
20	Inf	12419	12740	13323	15220	Inf
40	47175	13899	13960	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Config €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	3379	5140	5580	6871	8623	10374
10,5	3849	5610	6050	7341	9092	10844
20	4320	6082	6522	7813	9564	Inf
40	5305	7066	7506	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

Fuel €	FC kW 20	40	45	60	80	100
Batt kWh 6,5	Inf	8996	5638	5583	5422	5251
10,5	Inf	5864	5734	5436	5509	5525
20	Inf	6336	6217	5510	5655	Inf
40	41870	6833	6454	Inf	Inf	Inf
60	Inf	Inf	Inf	Inf	Inf	Inf
75	Inf	Inf	Inf	Inf	Inf	Inf

The Algorithm optimization returned the best configuration between those feasible. The best sizing of powertrain components was identified in 45 kW Fuel Cell and 6.5 kWh Battery Pack, practically the same of 2020 WLTP case. Beside this, some other considerations can be done:

- The powertrain costs fall from 11000 € to less than 6000 €. This means that FC/Battery powertrain will become more appealing though time when the technologies of both Fuel Cell and batteries becomes mature and the market shares grow.
- Operating costs for hydrogen and electricity purchase decrease from more than 9000 € to 5600 € to travel 200000 kilometers. If compared with a diesel vehicle version that would require on average of 20000 € for the same distance, the drastic cut of cost of using is evident.
- Combining the above-mentioned trends, final cost is around 11200 €. In addition, best and least consuming configurations coincide with the clear advantage of both OEM and customer.

Table 23: **Resume of WLTP Cycle 2030 results**

Solutions	FC kW	Batt kWh	Total Cost €	Fuel Cost €
Best	45	6,5	11220	5638
Lowest Fuel Cons	45	6,5	11220	5638

CHAPTER 6: RESULT OUTCOMES AND CONCLUSIONS

6.1 Final comment on obtained results by Genetic Algorithm application on FCEV model

Thesis objective was to develop a methodology to determine the most suitable sizing of a Fuel Cell/Battery vehicle powertrain components. The task required a flexible and powerful optimization method able to identify the optimum in a two variables problem with discrete values, represented by FC power and Battery Pack energy capacity. The complexity and characteristics of the studied situation made necessary the adoption of a non-conventional, metaheuristic optimization technique: the Genetic Algorithm. Then, the procedure had to be coupled to a vehicle model. For the purpose, it was taken an already developed model and improved in its powertrain and FC model: being a crucial element in the simulation, Fuel Cell behavior was calibrated according to experimental data. The acquired information let to consider a modeling in which temperature, pressure and reagents supply was dependent on FC power generation and dynamics. At that point, the model was made adaptable to simulate different powertrain components sizes, while the Control Logic was left unaltered. After implementing some features and simplifications to speed simulation time, technical data of a mid-size LCV were applied. Results on test case vehicle simulations showed a good accuracy and prediction of performances and consumption, making it reliable for the analysis.

Simulations were performed on extremely various driving scenarios and involved both a vehicle performance evaluation and a cost analysis. The latter task relied on a powertrain manufacturing cost and operating cost study of the configurations. The main consideration derived were:

- Genetic Algorithm method resulted highly reliable for project optimization. The Algorithm managed to find the best configuration according to its Fitness function in all trials. Its utilization let to cut simulation time from several hours to a few.
- Vehicle performances and range are affected mainly by components weight: large and heavy Battery Packs, although guaranteeing a reassuring pure electric range, affect performance and compel to always bring around hundreds of kilos of batteries. This is even more useless when an on-board energy generator (engine or Fuel Cell) is present, and it is the reason why none of the suggested configuration had a Battery Pack larger than some kWh.

- Fuel Cell system sizing was highly dependent on the imposed mission, as expected. FC output power naturally converged to cycle average requested power, thus leading to Range Extender in Urban cycle up to Full Performance dimensioning in Motorway driving scenarios.
- Simulating a mixed-conditions driving cycle like WLTP, the Genetic Algorithm returned a mid-power FC sizing similar to the one used by the test case. This fact confirms that the choice of powertrain dimensioning should mirror average cycle conditions.
- Costs analysis evidenced a higher cost of powertrain components with respect to a conventional powertrain, while the operating cost for hydrogen and electricity purchase are significantly lower than the conventional Diesel version. The competitiveness on this aspect is even more evident in 2030 context forecasts, when hydrogen price will probably decrease in parallel with Fuel Cell and batteries cost, as consequence of a natural technology evolution and market shares gain.

6.2 Potentialities of the work and possible improvements

Genetic Algorithm application on this kind of problems was evident. Therefore, the methodology has the potentialities to be applied to an optimization involving more variables than the two used for our work. The only limit is represented by computational time, but the issue can be easily overcome using more PCs in parallel and coupled models simplified by not relevant parts that can slow simulation. In addition, the Fitness Function can be formulated according to the desired objectives to be investigated: the more accurate the data possessed about costs and other parameters, the more precise and reliable the results obtained.

In light of these considerations, further improvements can be done. More analysis should be done on the Fitness Function and the data used for the simulation since they affect the results. Lastly, the vehicle model is still far from being perfect, and although being good, can be perfected.

APPENDIX: Driving Cycles

Common Artemis Driving Cycles

Common Artemis Driving Cycles (CADC) consist in a set of dynamometer procedures designed by a European collaboration work called European Artemis (Assessment and Reliability of Transport Emission Models and Inventory Systems). Their design is based on statistical extrapolation of wide samples of data of European real world driving patterns. The cycles represent three different driving scenarios: Urban, Rural and Motorway. The Motorway cycle is further divided in two versions: the first characterized by a maximum speed of 130 km/h, the second by a part that reaches 150 km/h.

Vehicle speed profiles of the three Artemis cycles are represented in the figures below. The procedure also defines gear changing profiles during the cycles that must be followed by the vehicle under approval test [37].

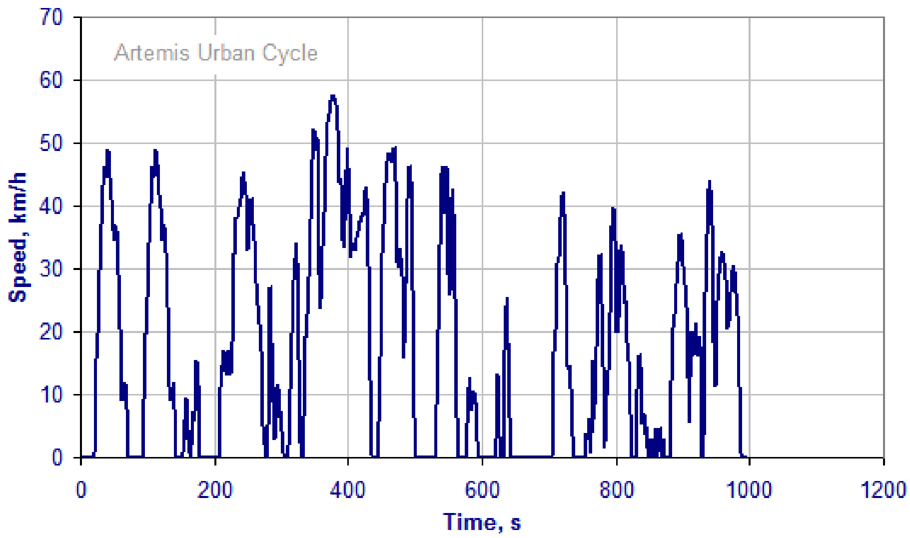

Figure 34: **ARTEMIS Urban Cycle**

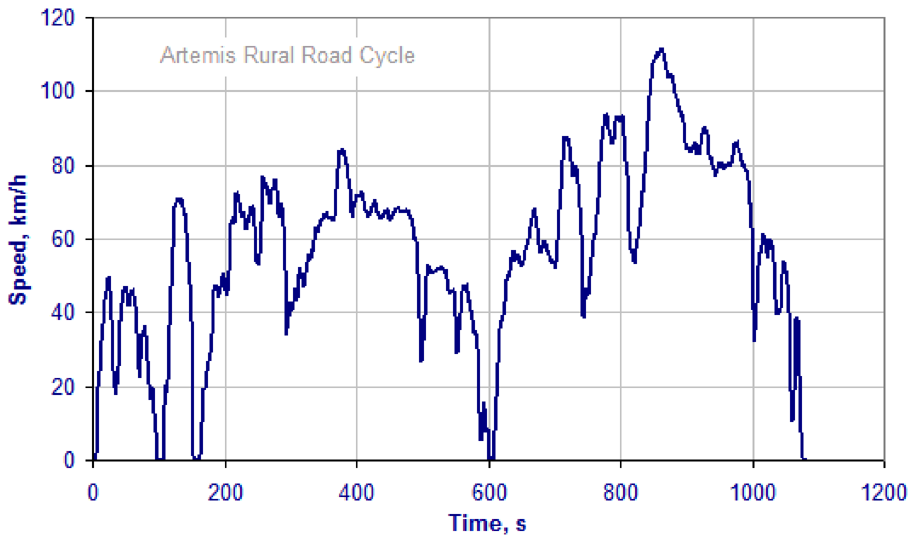

Figure 35: **ARTEMIS Rural Road Cycle**

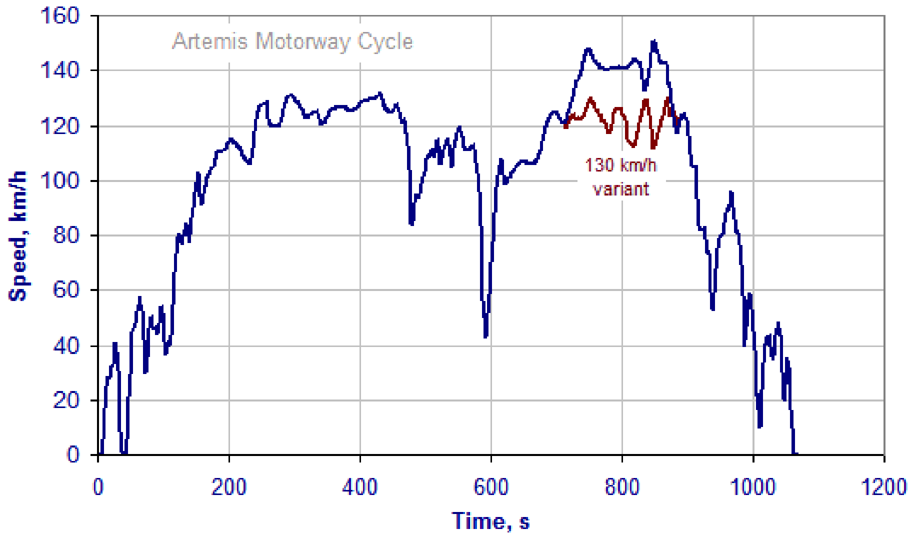

Figure 36: **ARTEMIS Motorway Cycle**

Characteristic	Urban	Rural Road	Motorway 130	Motorway 150
Duration, s	993	1082	1068	1068
Distance, km	4.874	17.275	28.737	29.547
Average speed (trip), km/h	17.7	57.5	96.9	99.6
Maximum speed, km/h	57.3	111.1	131.4	150.4
Speed distribution, %				
- Idle (S = 0 km/h)	21	2	1	1
- Low speed (0 < S ≤ 50)	77	32	15	14
- Medium speed (50 < S ≤ 90)	2	59	14	14
- High speed (S > 90)	0	7	70	71

Figure 37: **ARTEMIS Cycles data**

Worldwide harmonized Light vehicles Test Cycles

The Worldwide harmonized Light vehicles Test Cycles (WLTC) are chassis dynamometer tests used to measure emissions and fuel consumption for light-duty and light-commercial vehicles with the aim of being more representative of real driving conditions. The tests have been developed by the United Nations Economic Commission for Europe (UNECE) from 1998, and its final version was released in 2015. The WLTC cycles are part of the Worldwide harmonized Light vehicles Test Procedures (WLTP), published in Addenda 15 of UNECE Global technical regulation. While the acronyms WLTP and WLTC are often incorrectly used one instead of the other, the WLTP procedures define the whole type-approval procedures, while the WLTC are just the test cycles that are used to type-approve the vehicle.

From 1 September 2019, WLTP replaces the European NEDC with all vehicles registered in EU countries that must comply to the standard, with the transition from NEDC to WLTP occurring over 2017-2019. In addition to the European Union, the WLTP is accepted by China, Japan, India, South Korea, and the United States.

The WLTP procedure provides strict regulations regarding the conditions of dynamometer tests and motion resistance, gear shifting profiles, car weight also including optional equipment, passengers and luggage, environment conditions, and equipped tires. In addition, procedures include several WLTC test cycles applied to different vehicle class defined by power-to-mass (PMR) ratio in W/kg. The PMR parameter is defined as the ratio of rated power (W) divided by curb mass (kg). The curb mass also referred elsewhere as “unladen mass” (not including the driver) is defined in ECE R83. Lastly, cycle definitions also consider the maximum speed (v_max) which the vehicle is able to reach, as it is declared by the OEM (ECE R68) [38].

Category	PMR, W/kg	v_max, km/h	Speed Phase Sequence
Class 3b	PMR > 34	v_max ≥ 120	Low 3 + Medium 3-2 + High 3-2 + Extra High 3
Class 3a		v_max < 120	Low 3 + Medium 3-1 + High 3-1 + Extra High 3
Class 2	34 ≥ PMR > 22	-	Low 2 + Medium 2 + High 2 + Extra High 2
Class 1	PMR ≤ 22	-	Low 1 + Medium 1 + Low 1

Figure 38: **WLTP Cycles classes**

Class 3 includes the vehicles with the highest PMR, and it is representative of passenger cars and Light Commercial Vehicles driven in Europe and Japan. Class 3 vehicles are subdivided into 2 classes: Class 3a with v_max < 120 km/h and Class 3b with v_max ≥ 120 km/h. Characteristics of Class 3b cycles are presented in Table 39.

Phase	Duration	Stop Duration	Distance	p_stop	v_max	v_ave w/o stops	v_ave w/ stops	a_min	a_max
	s	*s*	*m*		*km/h*	*km/h*	*km/h*	*m/s²*	*m/s²*
Class 3b (v_max ≥ 120 km/h)									
Low 3	589	156	3095	26.5%	56.5	25.7	18.9	-1.47	1.47
Medium 3-2	433	48	4756	11.1%	76.6	44.5	39.5	-1.49	1.57
High 3-2	455	31	7162	6.8%	97.4	60.8	56.7	-1.49	1.58
Extra-High 3	323	7	8254	2.2%	131.3	94.0	92.0	-1.21	1.03
Total	**1800**	**242**	**23266**						

Figure 39: **WLTP Class 3b data**

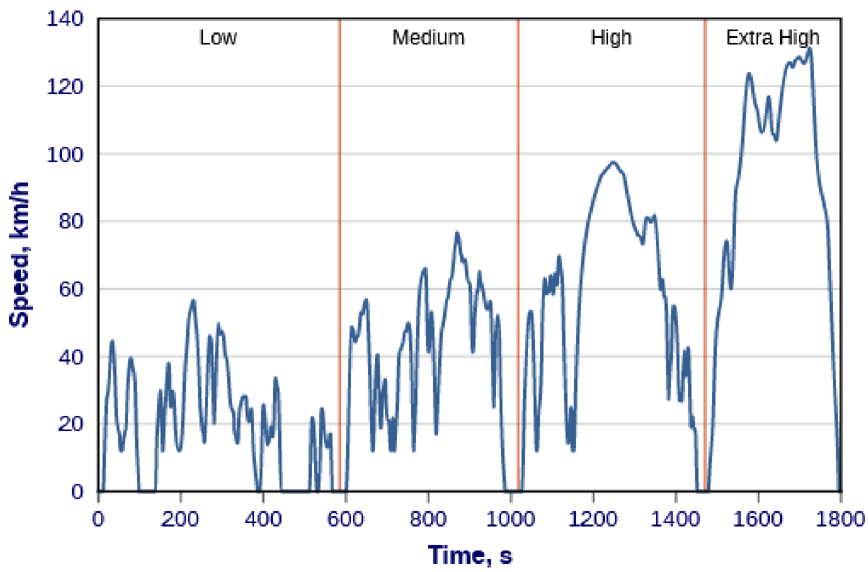

Figure 40: **WLTP Cycle**

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