Bachelor's thesis

Bachelor degree in Industrial Technologies Engineering

Using deep-learning methods to predict driving profiles

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Abstract

Due to high number of vehicles, the greenhouse gases in the atmosphere have reached the highest level. If it is compared a Fuel Cell Hybrid Electric Vehicle (FCHEV) to conventional Internal Combustion Engine (ICE) vehicles or Hybrid Electric Vehicles (HEVs), the first group has zero greenhouse gas emissions, and for that reason is a better alternative. Regarding All Electric Vehicles (AEVs) the charging time is longer which is a negative point. A fully charged battery from an AEV for example gives less range if it is compared to a FCHEV with a full hydrogen tank. So basically, the main advantages of FCHEV compared to AEV are: a quicker filing in of the tank and more autonomy. The most common used fuel cell (FC) is the Proton Electron Membrane Fuel Cell (PEMFC). The main problem of this type of FC is the slow current dynamics which leads for not being suitable for the sole power source in a vehicle. Therefore, the FCHEV is the best option, and by upgrading the power management system (PMS) in the proper way, the car’s performance can be improved.

This bachelor’s thesis studies the integration of a neural network (NN) to a FCHEV. The objective is to analyze the effect of integrating NN on the PMS of FCHEV and try to improve its efficiency by predicting the driving profiles.

A model to simulate the physical behavior of FCHEV has been looked for in MathWorks webpage by using MATLAB/Simulink software as a tool for simulation. All the parts of the model have been studied for better comprehension on how it works and for future modifications in order to implement the NN.

Results shows that by implementing NN using the Time Series app from MATLAB, a driving profile can be predicted with an acceptable error, which means that after get prepared the NN by training with lot of data, the power economy can be improved by modifying the controller parameters. Moreover, this solution let to increase the life of the battery.

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1. Abbreviations

FCHEV	Fuel Cell Hybrid Electric Vehicle
ICE	Internal Combustion Engine
HEV	Hybrid Electric Vehicle
AEV	All electric Vehicle
FC	Fuel Cell
PEMFC	Proton Electron Membrane Fuel Cell
PMS	Power Management System
NN	Neural Network
PHEV	Plug in Hybrid Electric Vehicle
FCV	Fuel Cell Vehicle
DOE	Department of Energy
ESS	Energy Storage System
DOH	Degree Of Hybridization
SOC	State of Charge
EF	Equivalent Factor
EMS	Energy Management Subsystem
IGBT	Insulated Gate Bipolar Transistor
PMSM	Permanent Magnet Synchronous Machine
RBF	Radial Basis Function
NARX	Nonlinear autoregressive network with exogenous inputs

2. Background

Lately, rapid advances and developments in the auto industry have occurred. The increasing use of electric motors and the advances in their efficiency and capacity of high voltage energy storage devices has opened new frontiers. Although these latest improvements in the electric powertrain components, greenhouse gases' levels have reached an alarming level. Therefore, the automotive industry is looking for other solutions by doing research and development in AEVs, HEVs and Plug in Hybrid Electric Vehicles (PHEVs). But the research is not limited only for those types. Alternatively, FCHEV seem to have a promising future as they have the advantage of going longer range in one complete hydrogen tank compared to AEVs which go lesser range, and moreover, with a very heavy battery pack. The tank refiling time for the hydrogen gas is about 3-5 minutes, while for AEVs can take hours to get the necessary amount of energy for doing the same route. On the other hand, HEVs still use gasoline and so have greenhouses gases coming out of the exhaust pipes.

In the current scenario of environmental crisis and stringent environmental laws and capping of greenhouse gases, the advances in FCHEV vehicle research has made some people think that FCHEV can be a viable substitute to ICE and a better alternative to AEVs if the advancement and infrastructure reaches a level that it becomes convenient to have a FCHEV.

Although the FC has shown promising capabilities as a main power source in a vehicle, it has some inherent characteristics that need to be taken care of in the power management strategy. In order to make FCHEVs a commercial success, some obstacles that it faces need to be discussed.

2.1. Impediments in the commercialization of Fuel Cell Vehicles (FCV)

In order to make successful the FC commercialization, it is required a solid infrastructure: hydrogen refueling stations, affordable price of Hydrogen gas, etc. Some of the main barriers are discussed below.

2.2. Hydrogen: availability, cost and quality

Social acceptance and economy viability of the FC technology go hand in hand in order to success this kind of technology. One of the most important factors is the hydrogen fueling stations availability. The map shows the locations of the hydrogen fueling stations across Spain. According to the data provided by netinform.net [1], there are just 6 hydrogen gas fueling stations in operation which are shown in the map in Figure 1. Three of them are in Aragón, one in Albacete, one in Sevilla and the last one in Castilla La Mancha.

Figure 1. Hydrogen fueling stations in Spain

 In operation

 Planned

 Old projects

2.3. Commercial features of the FCHEV

As explained above, lot of research and development is being done by the automotive companies to bring the cost down. According to a report from the Department of Energy (DOE), the goal on 2025 is to have a cost of FC system around 40 €/kW at 500,000 units produced per year [2]. This cost will only be possible with high volume production. Another institution, The International Energy Agency, also considers the possibility of FCVs as a solution to a cleaner transportation. An economic analysis done in [3], shows that by 2030, the cost of fuel cell stacks produced would be 32 – 68 €/kW of FC. According to another study done in [4] shows an expected technology learning curve between 0.78 – 0.85. This will bring down the cost from 22% to 15% which will make FC technology more economical. As seen below, Table 1 includes powertrain cost prediction for 2030:

Table 1. Cost summary of the powertrains for 2030 [3]

Powertrain Cost	Minimum [€]	Maximum [€]	Average [€]
Fuel Cell €/kW	35	70	50
Battery €/kW	180	270	225
Electric drive train	1,085	1,835	1,460
Hydrogen Storage	810	1,805	1,310
Conventional (ICE)	2,165	2,285	2,225

The running cost is also an important factor which leads to make any technology viable. Basically, the running cost would be the cost of the fuel. Table 2 below includes fuel cost prediction for 2030:

Table 2. Cost prediction of fuel for 2030 [3]

Fuel cost	Minimum [€]	Maximum [€]	Average [€]	Distance [km]
Gasoline	17	34	25.5	550
Hydrogen	13	51	32	1,100
Electric	24	41	32.5	2,200

The ambition of the auto makers is to make FCHEV technology reach a similar level compared to gasoline vehicles in terms of durability, safety, performance, etc. In order for doing that, it is needed that the costs discussed above (powertrain cost and the fuel cost) decrease as much as possible until make this kind of cars the main used. This will promote more production of FCHEVs, which consequently will bring down cost even further.

2.4. Motivation for developing a PMS with NN

Regarding the scarcity of hydrogen refueling stations and the production cost of a FC stack, by increasing the autonomy of the vehicle through controlling in an optimal way the power demanded, will improve the reliability and the performance of this type of vehicles. The combination of electric power provided by the battery and the energy provided by the FC, let to have a one degree of freedom, giving flexibility to operate with the FC in its most optimum region as well as with the battery. This bachelor’s thesis investigates how to design a PMS that distributes the necessary power among the two sources in an optimal way. Along with satisfying the power demand while accelerating efficiently, taking profit from the regenerative power efficiently with an added degree of freedom would be also an ambitious challenge on designing an efficient PMS. Nevertheless, because the time and the complexity, it has been decided to work only with one degree of freedom.

The effect of using NN is to make sure that the FC and the battery work in the most efficient region.

3. FCV: powertrain technology

During the last years, lot of researches have focused on the development of towards non-conventional powertrain vehicles. Cars like GM Volt and companies like Tesla have changed the automotive industries' point of view. At the same time, with a lot of research regarding FCs, have emerged as an alternative to the ICEs. FCVs have almost no one real environmental concern. The fuel used is hydrogen H_2 gas which undertakes a reaction with oxygen O_2 and produces electricity, heat and water making all together a very environment friendly.

Regarding the advantages, the FCHEVs have quite simple structure compared to ICE vehicles. In the FCHEV there are no moving parts, being that most of it is electronics are solid state devices. As a consequence, there are no vibration or noise issues with FCHEVs. Moreover, as no moving parts contemplated, the maintenance cost comes down and no parts require lubrication, which means no oil changes and no lubrication change in transmissions and other parts.

The major automotive companies are investing for developing FCHEVs. Some of the reasons are that the environmental laws are becoming stricter and at the same time FCHEVs offers all the benefits discussed above. Nowadays, can be find commercially available some FCHEVs: Hyundai Tucson uses a 100kW FC stack with a range of 427 Km on a 0,95kWh battery. The Toyota Mirai has a 114kW FC stack with a 1.6kWh battery and with a range of 502 Km.

Apart from improving the FC stack technology and efficiency, the type of components used for the energy storage system (ESS), which is another name to call the battery, and the powertrain types used in hybridization of the FCV play a tremendous role in its performance and range. So, different types of configurations have been investigated at the moment. In Table 3 below there is a list of projects from automotive companies trying to reach best configuration for FCHEV:

Table 3. FCHEV projects from Car Manufacturers [5]

Company	System configuration
Daimler Chrysler	Straight fuel cell – Fuel cell-battery hybrid

Ford	Straight fuel cell
General Motors (GM)	Fuel cell-battery hybrid
Honda	Fuel cell – ultra capacitor hybrid
Mazda	Fuel cell – ultra capacitor hybrid
Nissan	Fuel cell-battery hybrid
Renault	Fuel cell-battery hybrid
Toyota	Fuel cell-battery hybrid
Volkswagen	Straight fuel cell – Fuel cell-battery hybrid
ZeTech	Fuel cell-battery hybrid

3.1. The FC

A FC is similar to a battery in that it generates electricity from an electrochemical reaction. Both, batteries and FCs convert chemical energy into electrical energy and also, as a by-product of this process into heat. However, a battery holds a closed store of energy within it and once this is consumed the battery must be thrown away or recharged by using an external supply of electricity to drive the electrochemical reaction in the reverse direction.

On the other hand, a FC can run indefinitely as long as it is supplied with a source of hydrogen fuel (hence the name) and is similar to an ICE in that it oxidizes fuel in order to create energy. But rather than using combustion, a FC oxidizes H_2 electrochemically in a very efficient way. During the reaction, hydrogen ions react with oxygen atoms to form water. In the process electrons are released and flow through an external circuit as an electric current. The only exhaust is water steam.

The FC type used in automotive industry is the PEMFC, a low-temperature, hydrogen fueled cell containing a platinum catalyst. It is the most common type of FC and allows for variable electrical output, ideal for vehicle use. The PEMFC is made up of two electrodes with a membrane acting as an insulator between the two electrodes. The electrodes along with the membrane from the membrane electrode assembly. The chemical reaction which takes place in this membrane is shown below [6]:

Anode: $$H_2(g) \rightleftharpoons 2H^+ + 2e^- \quad (1)$$

Cathode: $$\frac{1}{2}O_2(g) + 2H^+ + 2e^- \rightleftharpoons H_2O(g) \quad (2)$$

Global reaction: $$\frac{1}{2}O_2(g) + H_2(g) \rightleftharpoons H_2O(g) \quad (3)$$

Figure 2 represents the structure of a membrane electrode assembly:

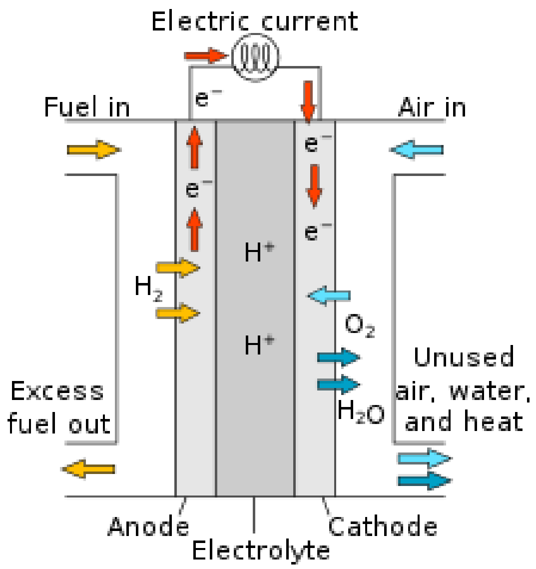

Figure 2. Membrane's structure [7]

Another phenomenon which occurs in FCs, which is the biggest concern, is the starvation. Parallelly to the cathode's reaction represented in the (2), there is another reaction which take place (4):

$$C + 2H_2O \rightleftharpoons CO_2 + 4H^+ + 4e^- \tag{4}$$

Starvation is negligible under normal conditions, but the problem appears when large power is drawn from a FC stack under transient conditions: as a start/stop or rapid acceleration. A FC produces insufficient power for make the vehicle works only with that, hence hybridization becomes inevitable. The Figure 3 below shows the structure of PEMFC cell stack.

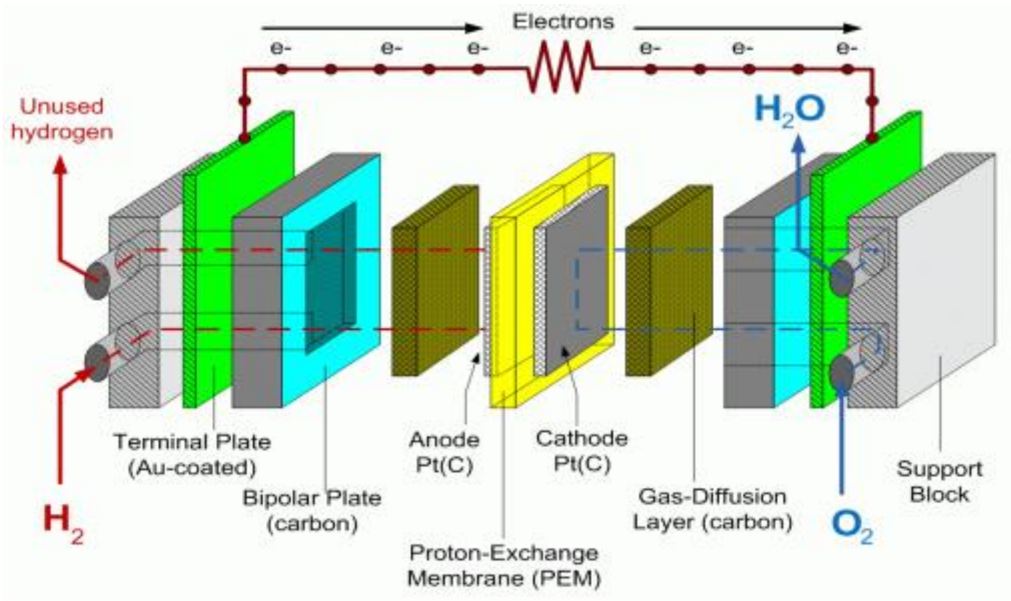

Figure 3. PEMFC structure [8]

One of the most important factors which affects the operating conditions of a FC is the temperature. With a proper operating temperature, the oxygen reduction reaction is enhanced which avoids major voltage loss. When the FC works at 1 atm pressure and 100 ºC, water is in vapor state, so it is transported through the membrane, catalyst and diffusion layer is easier. Nevertheless, by working with temperatures above 100 ºC, water will be completely vaporized. As a consequence, that will trigger to a deficiency of water and dehydration of the membrane, which reduces the proton conductivity in the membrane. Regarding the broad range of cells, the operating temperature of PEMFCs is between 60-100 ºC. That is the reason why the PEMFC are the most preferred type of fuel cell for automotive industry.

Although PEMFC are better compared to other FCs, still needs a PMS in order to assure that the PEMFC remains in a good range of temperature for working and appropriate amount of current is drawn. That only can be achieved through the PMS. When high current is extracted from the FC, the CO_2 liberated regarding to (4) can provoke permanent loss of carbon, and therefore, reduces MEA membrane durability [9]. In order to avoid reaction (4) from becoming intense, an efficient PMS is needed for having a better performance. For the PMS it has to take into account the energy storage devices, which are used in the powertrain of FCVs to facilitate and supply power in cases of high-power transient demand.

Another factor that prevents FC for being used as the only source of power in vehicles is starvation. As said before, when a large amount of current is extracted from the FC in a vehicle while driving, the membrane can easily be damaged. Hence, another device is needed to complement the FC stack, and for this reason the existence of FCHEVs instead of FCVs. In that case, battery packs are the preferred as ESSs in auto industry, which are widely used in HEVs, PHEVs and AEVs. Some car models of nowadays could be for example the Toyota Mirai or the Hyundai Tucson. There are still several challenges to face for developing and implementing a hydrogen-fueling infrastructure. One of the most important is the fact of reducing CO_2 emissions while producing hydrogen. The industry and the government are still working on these issues trying to solve them as soon as possible.

As seen in the reaction shown in (3), oxygen is one of the two important parts of the reaction. As long as more current is extracted from the fuel cell it means that the reaction must be done at a faster rate. So, it is necessary to be refilled very quickly the O_2 used in the reaction in the FC. If that does not happen, the partial pressure of O_2 drops at the cathode which provokes that the voltage of the FC stack drops drastically damaging the membrane. This phenomenon is the FC starvation explained in more detail. This will in turn lead to reduce the power response of the FC stack. Apart from the FC's inability to stand sudden variations in power demand, the cooling requirements and water balance of the FC are critical in maintaining the stability and performance of the FC stack. These factors affect directly on the lifetime of the FC stack as well. If FC was the only power source in a car, it would not be any alternative for controlling the power demand. Nevertheless, when the ESSs as batteries are included, from one hand, lets the system to have one degree of freedom provoking an improvement in the dynamic behavior of the vehicle, and on the other hand, it prevents the extract of energy from the FC during sudden variations in power demand. A powertrain configuration having both devices, can be used to the best of their capabilities to make a system quite efficient. Hence, creating an intelligent PMS for this kind of powertrains is the objective of this bachelor’s thesis.

4. Hybridization of FCHEV and PMS

4.1. Powertrain topologies

Depending on the number of power sources, the powertrain topologies can be divided in full power source with Battery, full power source with UC and Triple Hybrid power source. Figure 4, Figure 5 and Figure 6 shows a block diagram of the different topologies of power source:

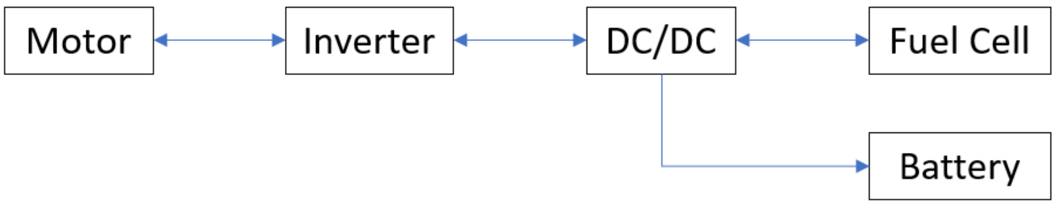

Figure 4. Full power source battery

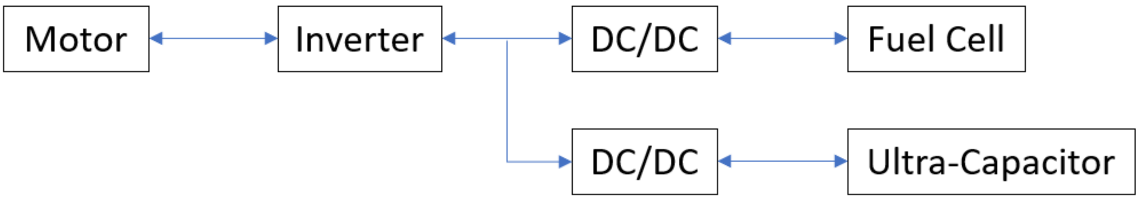

Figure 5. Full power source with UC

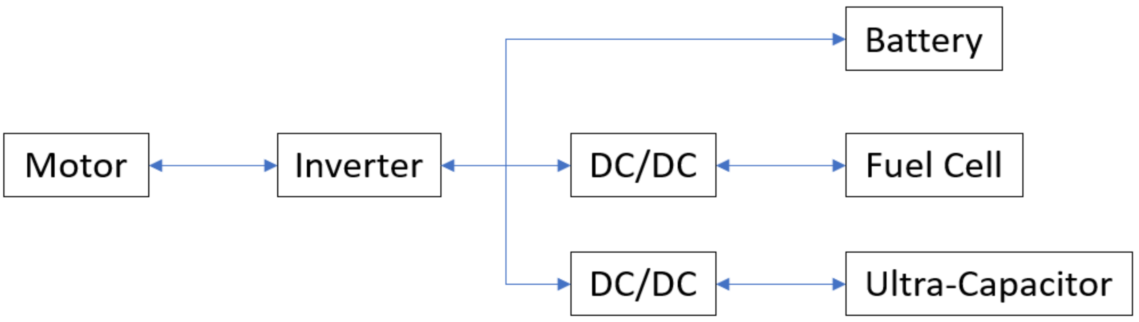

Figure 6. Triple hybrid power source

Hybridization with various power resources makes more complex the control strategy for the system by adding more degrees of freedom, but at the same time, it creates an opportunity for optimizing the control strategy. Find below (5) which calculates the degree of Hybridization (DOH):

$$DOH = \frac{P_{EM}}{P_{EM} + P_{EC}} \tag{5}$$

P_{EM}: power from the electric motor

P_{EC}: power from the FC

The FC in FCHEVs works like an engine except the fact that it charges the ESS and at the same time provides current to the motor. In exceptional cases, when the state of charge (SOC) from the ESS is not enough, the FC can also be used to provide power to the wheels. The DOH is useful in order to determine the power components' size in the powertrain: the FC, batteries and Ultracapacitor. As it can be checked on (5), by increasing the ESS the DOH is higher. On contrary, by increasing the power generated from the FC, the DOH reduces.

4.2. FCHEV PMSs

The main goals to consider while developing a control strategy is to regulate the energy in such a way that power demand is always satisfied, the battery is sufficiently charged at all time and the overall system efficiency is maintained optimal [10]. In any FC vehicle powertrain configurations, the energy exchanges from the FC to the ESS operates in three modes:

- Charge – The FC supplies energy to the battery and the load.
- Discharge – The FC and battery supply energy to the load.
- Recovery – The energy is supplied by recovering power through regenerative braking and stored in the battery.

There are different techniques regarding control strategies. Those techniques are explained in more detail in the next section. Depending on the type of algorithm and control logic, the power management strategies can be categorized into two types:

- Rule based.
- Optimization based.

4.2.1. Rule based control strategy

That rule is computationally less expensive compare to optimization based strategies. They are good for real time problem solving. Basically, they are based on a set of rules on which various decisions like power split are calculated. The rule based category includes two subgroups for power management strategies which are exposed as follows:

4.2.1.1. Deterministic/Heuristic rule based

This method analyzes the amount of power that flows to each of the power sources in the powertrain taking into account the efficiency map of the fuel cell. So, the rules which govern this particular method are based in this previous information. While designing the PMS, there are certain conditions that must to take into account. That conditions are [11]:

- The power demanded by the vehicle has always to be satisfied.
- Take care that the ESS devices always are remained between a maximum and minimum limit operation. In order to make sure the health of those devices.
- The FC power and current is remained within its allowable limit for preventing starvation.

As follows, a flow chart (Figure 7) is represented in order to make it clearer how it works the rule based control strategy. It is shown the process of decision making regarding the conditions and the rules exposed above:

Pcomm: commanded power

Pfc-rated: rated power of the fuel cell system

Pfc: power of the fuel cell system

Pfc-min: minimum power of the fuel cell system

Ppps-traction: traction power extracted from the PPS

Ppps-charging: charging power in to the PPS

E: energy level of the PPS

Emin: Bottom line of the energy storage in the PPS

Emax: Top line of the energy storage in the PPS

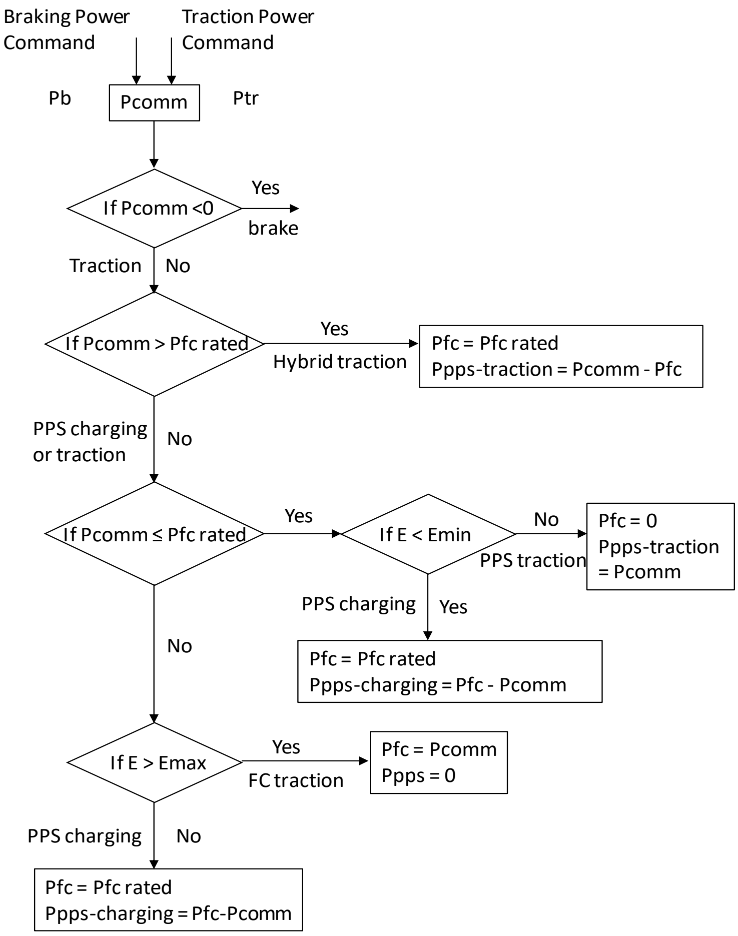

Figure 7. Rule based flow chart

In this flow chart can be seen that through a set of pre-defined the command power is satisfied.

4.2.1.2. Assist management strategy

Assist control is another subcategory of PMS included in rule based category. The principal parameters which depends this method are the stack voltage and the SOC of the battery. The purpose of this strategy is to reduce load in the FC by requesting more power out of the battery (as long as the SOC of the battery is above a certain limit [12]). This strategy can be split into the following rules:

- A better proportion of power is provided by the battery as long as the SOC of the battery is above a minimum limit. The rest of power comes from the FC. However, if the SOC drops below the minimum limit value, the FC provides a higher proportion of power.
- A higher proportion of the power is extracted from the FC in case that the stack voltage is higher than the maximum limit value. This condition remains valid until the first one becomes true again.

The limit values for the stack voltage and the SOC of the ESS depend on the fuel cell stack's size and the ESS. In a report done by Aouzellag and Ghedamsi was found an improvement of 5-16% in the fuel economy [13].

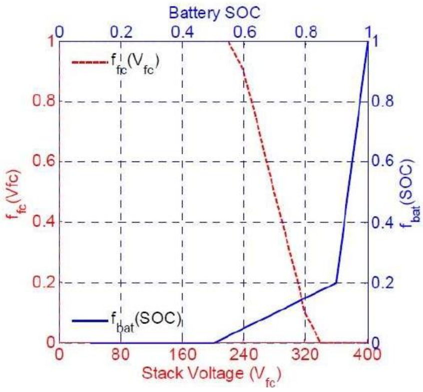

Figure 8. Power split in assist control strategy

4.2.1.3. Fuzzy logic

As seen in the report [13], the authors have designed a control strategy by using Fuzzy logic. The extracted power from the FC dictates the current extracted from its, which then, is easy to know the amount of hydrogen that is consumed. The main goal of this control strategy is to reduce the consume of hydrogen. The fuel cell power, which does not depend on the SOC of the ESS components, is used as a parameter in order to provide power requested by the vehicle. The other parameter used in this control strategy is the vehicle speed. The Table 4 summarize how it works the Fuzzy Logic algorithm:

*Table 4. Fuzzy Logic Energy Management [13]**¡Error! No se encuentra el origen de la referencia.***

Condition	**Power from Ultracapacitor**	**Power from the FC**
47 ≤ SOC ≤ 75 and Vv<60	Yes	No
47 ≤ SOC ≤ 75 and Vv>60	Yes	No

SOC > 75	Yes	No
SOC < 47 and 10 ≤ Vv ≤ 60	Yes	Yes
SOC < 47 and Vv > 60	No until charged, then Yes	Yes

4.2.1.4. Load following management strategy

In this kind of control strategy, the power limit depending on the SOC dictates the ON/OFF function of the FC. If the power requirement is higher than the limit maximum value, the controller turns ON the FC in order to fulfill the power that it lacks. This control strategy facilitates the maximum charge depletion of the battery pack [14]. Another thing to take into account is the dynamics and the time response of the FC due to it is not as fast as ICE. Figure 9 represents the power split between FC and ESS:

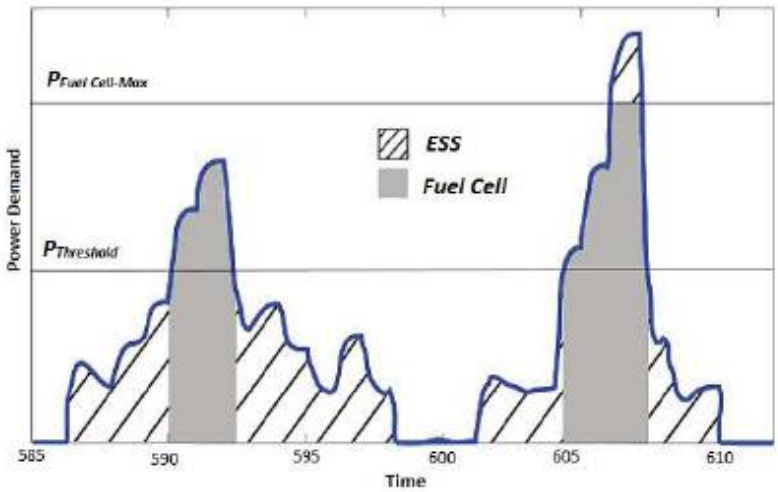

Figure 9. Power split between FC and ESS [14]

4.2.1.5. Thermostatic control strategy

As seen in [15], the goal of this control strategy is to maintain the SOC of the battery between SOC_{low} and SOC_{high}, which also supposed to extract the power from the FC between two values P_{FCmin} and P_{FCmax}. The following Figure 10 shows a representation of thermostatic control strategy in which it can be seen the limits of those parameters.

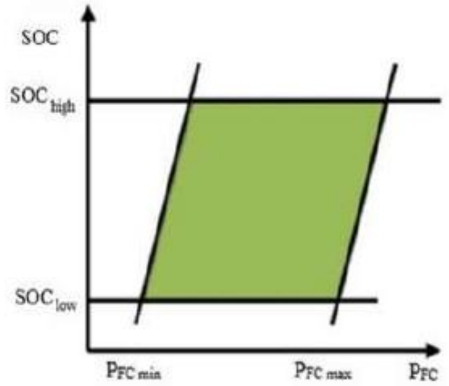

Figure 10. SOC vs P_{FC}

The thermostatic control strategy is easy to be implemented in real time driving conditions and let the battery an extended life of use by reducing the charge/discharge cycles. Some experimental results in [16] show that this strategy is more efficient than the load following management strategy at least in city driving. However, a negative point of this control strategy is when the SOC of the battery is below the SOC_{low} and the power demand is greater than P_{FCmax}, in that case the strategy is not able to cover the power requirements of the vehicle.

4.2.2. Optimized rule based management strategy

The difference between rule based and optimization based strategies is that the first one is real time implementable but don't necessarily provide the most efficient power split. On the other hand, the optimization rule based maximize the efficiency of the power train and at the same time minimize the losses [15]. In this method the optimal reference torques for power controllers are calculated by minimizing the hydrogen fuel consumption. When optimization is performed over fixed drive cycles, a global minimum can be found. Some optimization methods are computationally complex for processing and others also need the prediction of future paths in order to optimize the power management. In the next sections is explained four energy management strategies which are included in optimized rule based control strategy: driver pattern recognition, equivalent consumption minimization strategy and maximum power point tracking energy control strategy.

4.2.2.1. Driver pattern recognition

Depending on the driver demand, the rule based control strategy will be different completely. So, the advantage provided by driving pattern recognition is the ability to operate a vehicle in ''multi-mode'' control algorithm. The way of working of that algorithm is by identifying certain representative parameters of a drive cycle which describe driving pattern: speed, acceleration, deceleration, slope of the road and others. Recognition of driving pattern is done by measuring the data obtained in certain points. After the pattern's data is measured, features members are extracted from it. A feature vector is based on these feature members and is used for the driving pattern identification. A feature vector f would be the once defined in resource [17] and is expressed as in (6):

$$f = (k_1 x a_1, k_2 x a_2, k_3 x a_3, \dots, k_n x a_n)^T \tag{6}$$

a_i: feature member

k_i: weight factor (depend on the feature parameter)

n: dimension of the feature vector

On the following Table 5 is shown an example of each feature parameter (a) and its corresponding weight (k):

Table 5. Feature vector parameter [17]

Index number (i)	Feature Parameter (a)	Weight Factor (k)
1	Average speed (m/s)	10
2	Positive Average Acceleration (a > 0.1 m/s^2)	1
3	Low Speed Time (15-30 Km/h)/Total Time (%)	10

4	Mid High Speed Time (70-90 Km/h)/Total Time (%)	100
5	High Speed Time (> 90 Km/h)/ Total Time (%)	10
6	Extreme Deceleration Time (a> -2.5 m/s^2)/Total Time (%)	1000
7	High Deceleration Time (a<-2 & a>-2.5 m/s^2)/Total Time (%)	1
8	Maximum Cycle Acceleration (m/s^2)	100
9	Maximum Cycle Speed (Km/h)	6
10	Standard Deviation of Cycle Speed (Km/h)	1
11	Mid Deceleration Time (a<-1 & a>-1.5 m/s^2)/Total Time (%)	1000
12	Mid High Deceleration (a>-2 & a<-1.5 m/s^2)/Total Time (%)	1000
13	Mid Acceleration Time (a>-2 & a<2 m/s^2)/Total Time (%)	1
14	High Acceleration Time (a>2 & a<2.5 m/s^2)/Total Time (%)	1000
15	Extreme Acceleration Time (a>2.5 m/s^2)/Total Time (%)	1000

Once the feature parameters are calculated, it is possible to proceed by creating the feature vector (6). Normally standard driving cycles are used for the simulation (E.g. NEDS, UDDS…). After running the simulation, an output value tries to identify the driving cycle by assigning numbers depending on the cycle. An example can be seen below (Figure 11) regarding the effectiveness of the simulation for the driving pattern recognition:

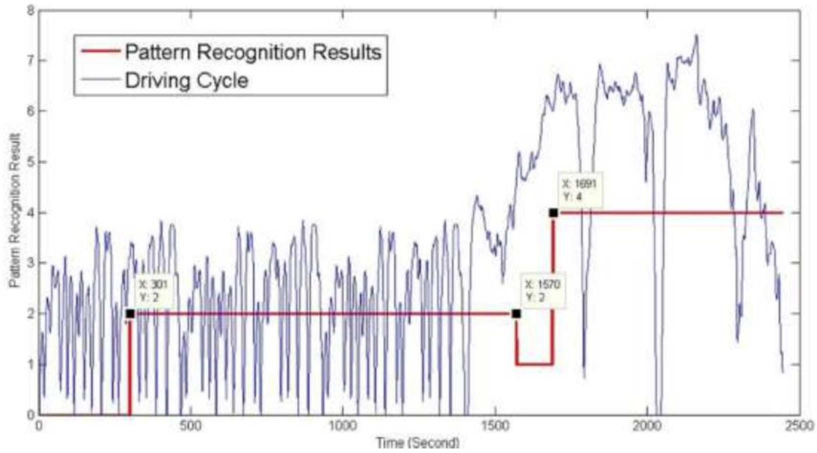

Figure 11. Efficiency of driving pattern recognition

After the driving cycle is identified, the fuel economy can be improved by modifying the controller parameters.

4.2.2.2. Equivalent consumption minimization strategy

This strategy is an instantaneous optimization which does not depend on the drive cycle or on the future route done by the vehicle. With an appropriate equivalence factor (EF) and conditions, it can generate a close optimal solution. In the case of FCHEV, the power comes from the FC and the battery. So, the following equation is used in this strategy for predicting the future hydrogen consumed [20]:

$$\dot{m}_{eqv} = \dot{m}_{H2} + \dot{m}_{equi.H2\ by\ ESS} = \dot{m}_{H2} + \frac{s}{LHV_{H2}} \tag{7}$$

$\dot{m}_{eqv}$: equivalent total hydrogen consumption

$\dot{m}_{H2}$: hydrogen consumption

$\dot{m}_{equi.H2\ by\ ESS}$: equivalent hydrogen consumption for rate from the battery or ESS

LHV_{H2}: Lower heating value of the hydrogen

s: equivalent factor

Once is calculated the equivalent hydrogen consumption from the battery, it is possible to obtain the power split ratio between the FC and the battery.

In equivalent consumption minimization strategy, the battery's SOC is considered as a state restriction and the goal of the strategy is to calculate an EF in which the battery's SOC remains between the limits in order to maintain the state restriction inactive. In case the SOC have values out of the limit range, it becomes an active state restriction and then, the solution of the equivalent consumption minimization is not optimal at that point. In order to avoid this, a penalty function can be added to the EF and provokes the adaptation of the equivalent consumption minimization by avoiding the state restriction become active. This penalty function is really useful for the energy management because prevents discharge of the battery in case of low SOC, or on the other hand, prevents charging in case of maximum SOC by using for example the normal braking instead of the regenerative ones. The penalty function is expressed in (8) as follows:

$$s(t) = s + f_p(t) \quad where, f_p(t) = \left| \begin{array}{ll} k_p(x_{max} - x) & x > x_{max} \\ 0 & x_{min} < x < x_{max} \\ k_p(x - x_{min}) & x < x_{min} \end{array} \right. \qquad (8)$$

k_p: penalty function

$k_p(x_{max} - x)$: penalty for SOC exceeding upper limit

$k_p(x - x_{min})$: penalty for SOC falling under below limit

Last but not least, this kind of strategy is heavy computationally, so is not the most used.

4.2.2.3. Maximum power point tracking energy control strategy

This control strategy is based by maximizing the efficiency of the FC and activate to the maximum power when the power demand is quite high [19]. The efficiency graphic indicates that the FC system has only one maximum power point, and is determined by operation conditions of the FC. With that operating conditions, the control strategy put the focus on calculating the maximum power that can be delivered to the wheels from the FC. The maximum power point and the maximum efficiency are defined as a fixed points, but in reality, these points may vary depending on the operating conditions of FC stack: pressure, temperature… [18] The maximum power point tracking energy management strategy tries to avoid these disadvantage. The main goal of this strategy is to give a current reference to the FC which corresponds with maximum power point. The following equation presented is used in the algorithm of this strategy and determines the change of FC power with respect to change of FC current. Being a derivative (9), by equaling to cero, will be possible to find the maximum which corresponds with the Maximum power point:

$$\frac{dP_{fc}}{dI_{fc}} = \frac{dV_{fc}}{dI_{fc}(I_{fc}, P_{H2}, P_{O2}, T_{fc})} \cdot I_{fc} = 0 \tag{9}$$

P_{fc}: Power from the FC

I_{fc}: FC current (perturbated in order to see in which direction the variation goes for finding the maximum power point).

V_{fc}: Voltage of FC

T_{fc}: Temperature of FC

P_{H2}: Pressure of hydrogen

P_{O2}: Pressure of oxygen

The maximum power is provided by this strategy in order to reduce charge/discharge cycles of the Battery. Last but not least, this strategy is best suited for low speed vehicles where the fuel cell is used as a range extender.

5. Modelling approach and simulation

The tools used for modelling and doing the simulations are crucial for the implementation and verification of these strategies in real applications. So, in this section, an effective vehicle simulator used in the initial phase for strategy development of vehicles is presented. An effective and trustworthy software tools play a critical role in the optimization of power management approaches. Some of the most popular software used in the field of vehicle research are: MATLAB/Simulink, ADVISOR and PSAT. MATLAB (meaning "matrix laboratory") developed by MathWorks Inc. is the software used for doing the different simulations and analyses in this project. The Simulink is a part of the package which has been used for running the vehicle model simulation with its components and for developing the power management strategy with the NN. Simulink contains different kind of toolboxes with different functions associated to that. The toolboxes use blocks that represent kind of a systems with a specific function. The blocks can be interconnected each other creating a block diagram for modelling and simulating systems. Particularly, the model implemented uses the Simscape Driveline and Simscape Electrical toolboxes.

The basic model has a PMS which determines the reference signals for the FC system, the DC/DC converter and the electric motor drives for distributing the power accurately from the two electrical sources, but taking care that the SOC is maintained between the 40 and 80%. The new model would consist with a battery and a FC as well but with the particularity that a NN has been implemented in order to looking for the optimal power management strategy. The final model with the NN has not been able to complete (maybe for the master's thesis).

The basic model consists of three main blocks below:

1) Electrical subsystem
2) Vehicle dynamics
3) Energy management subsystem (EMS)

Putting all these blocks together represent the FCHEV model (Figure 12):

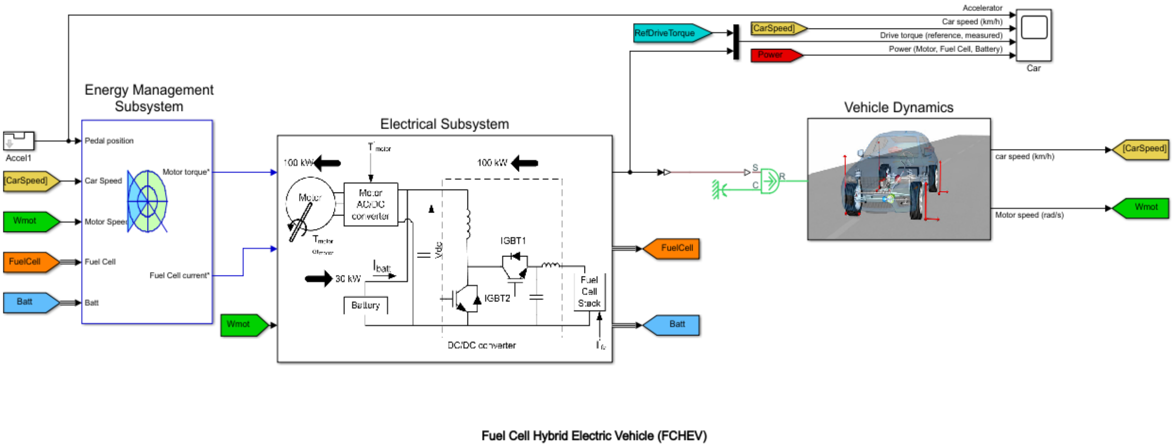

Figure 12. FCHEV global model

5.1. Electrical subsystem

The Electrical Subsystem from the FCHEV is composed of four parts:

- The FC Stack
- The DC/DC converter
- The battery
- The electrical motor.

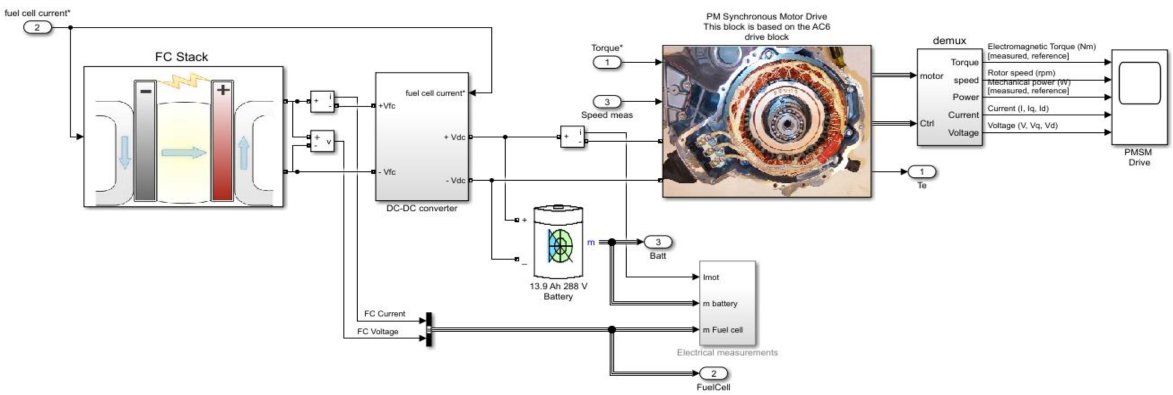

Figure 13. Electrical Subsystem MATLAB model

5.1.1. The FC Stack

The Fuel Cell Stack block, from electricdrivelib/Extra Sources library, implements a generic model parametrized in order to represent in that case a Proton Exchange Membrane Fuel Cell (PEMFC) stack [25]:

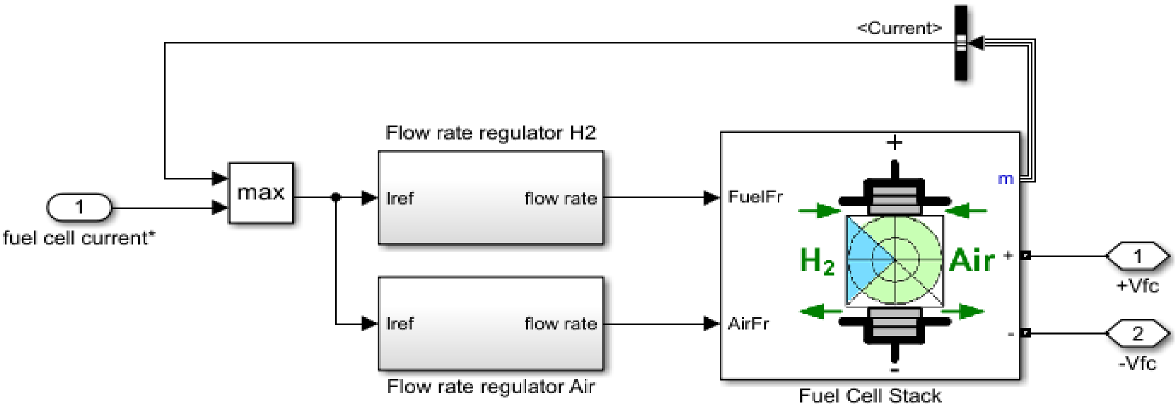

Figure 14. FC Stack MATLAB model

The inputs received by the FC stack system are: Fuel flow rate (FuelFr) and Air flow rate (AirFr). The specifications of the FC stack are listed below in Table 6:

Table 6. FC Stack specifications

Description	**Value**
Stack power	Nominal: 85,500 [W]
	Maximal: 100,022.4 [W]
FC Resistance	0.17572 [Ω]
Nernst voltage of one cell	1.1729 [V]
Voltage direct current	288 [Vdc]
Nominal utilization	Hydrogen (H_2): 95.24 %
	Oxygen (O_2): 50.03 %
Nominal Consumption	Fuel: 794.4 slpm
	Air: 1891 slpm

Nominal stack efficiency	57 %
Nominal supply pressure	Fuel (bar): 3 Air (bar): 3
Number of cells	400
Operating temperature	95℃

In order to work in the most efficient way, a H_2 and an air flow regulator has been implemented. The flow controller manages the consumption of hydrogen and air according to the highest value between the direct measurement of the FC (<current>) and the estimated FC current consumption (fuel cell current*) which is calculated in the power management system.

As seen in Figure 13, the FC Stack model is connected to a DC/DC converter in order to charge the Li-ion battery inside the electrical subsystem.

5.1.2. The DC/DC converter

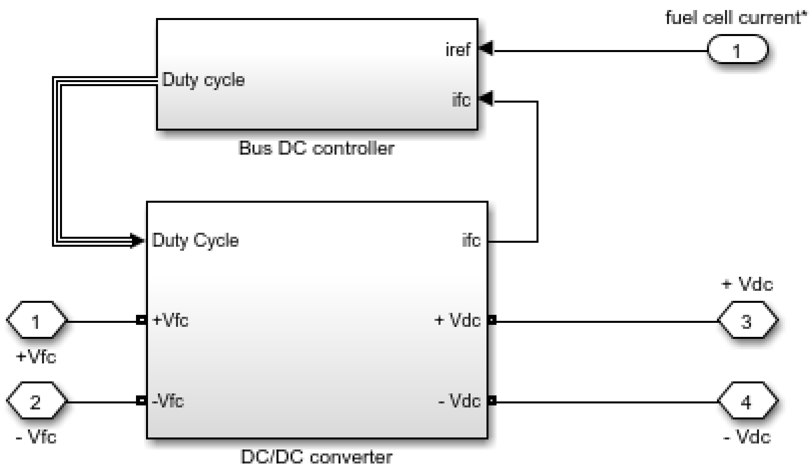

Figure 15. DC/DC converter MATLAB model

The DC/DC converter is a buck type and is regulated by current. It contains a Bus Duty Cycle Controller block which controls the Insulated Gate Bipolar Transistor (IGBT) device.

5.1.3. The battery

The main specifications of the 25 KW Lithium-Ion battery used are in the Table 7 below:

Table 7. Battery specifications

Description	Value
Nominal voltage	288 [V]
Rated capacity	13.9 [Ah]
Initial SOC	40.32 %

Another interesting graphic to take into account when modelling with batteries is the nominal current discharge curve (Figure 16):

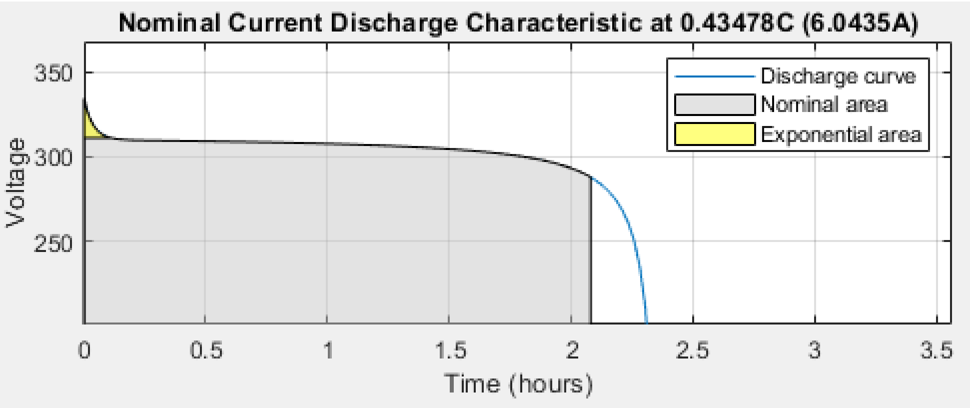

Figure 16. Nominal current discharge curve

5.1.4. The electrical motor

The electrical motor is a Permanent Magnet Synchronous Machine (PMSM). The motor has 8 poles and the magnets are buried (the rotor is the type of salient rotor). In order to reach a maximum motor speed of 12,500 rpm, a flux weakening vector control is used.

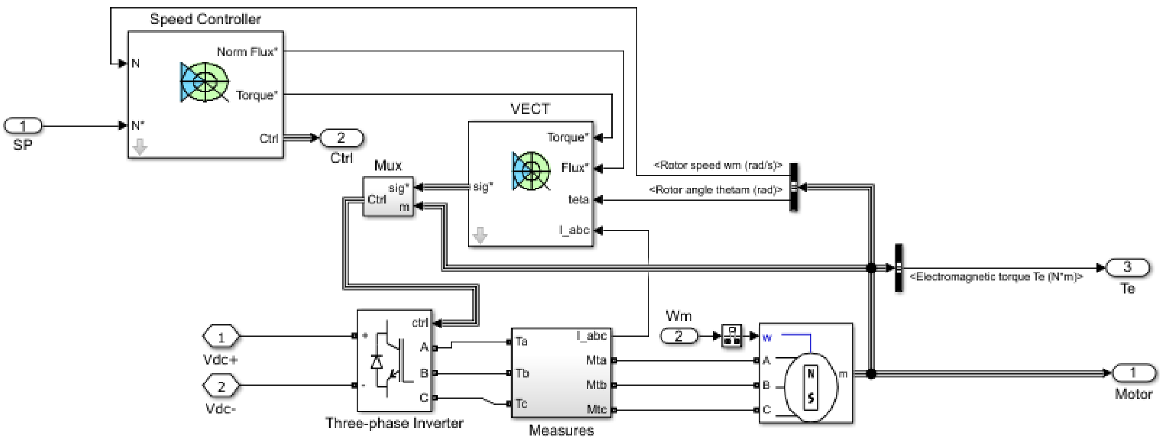

Figure 17. Electrical motor MATLAB model

5.2. Vehicle dynamics

The vehicle dynamics subsystem models all the mechanical parts of the vehicle. It represents the motion influence on the overall system. A MATLAB model of the vehicle dynamics can be seen below (Figure 18):

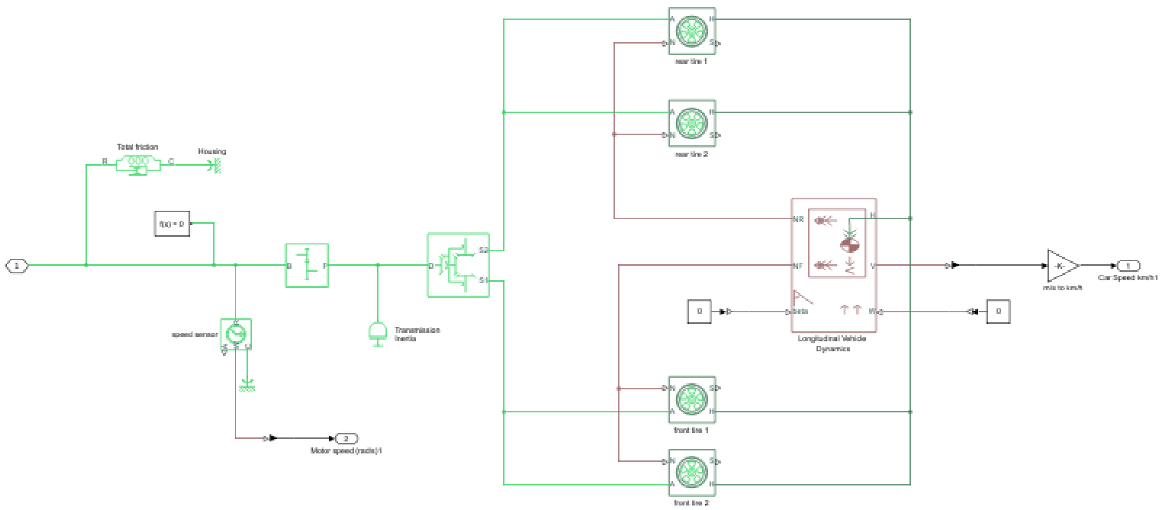

Figure 18. Vehicle dynamics MATLAB model

On the one hand, the single reduction gear reduces the motor's speed in order to increase the torque. The function of the differential is to split the input torque into two equal torques. The tires dynamics model the force applied to the ground. And finally, the viscous friction simulates all the losses of the mechanical system.

On the other hand, the longitudinal vehicle dynamics represents a two-axle vehicle body in longitudinal motion. Some of the settings which have been configured for the simulation are exposed in Table 8:

Table 8. Longitudinal Vehicle Dynamics specifications

Description	**Value**
Mass	1,625 [Kg]
Number of wheels per axle	2
Horizontal distance from CG to front axle	1.4 [m]
Horizontal distance from CG to rear axle	1.4 [m]
CG height above ground	0.5 [m]
Gravitational acceleration	9.81 [m/s^2]
Drag parameters	Frontal area: 2.71 [m^2]
	Drag coefficient: 0.26
	Air density: 1.18 [Kg/m^3]

5.3. Energy management subsystem

The energy management subsystem determines the reference signals for the FC stack system, the DC/DC converter and the electric motor drives in order to distribute accurately the power from the two electrical sources. The signals are calculated depending mainly on the position of the accelerator (between -100% and 100%) and the measured FCV speed. It is important to be said that the negative accelerator position represents a positive brake position. A representation of the energy management subsystem can be observed Figure 19:

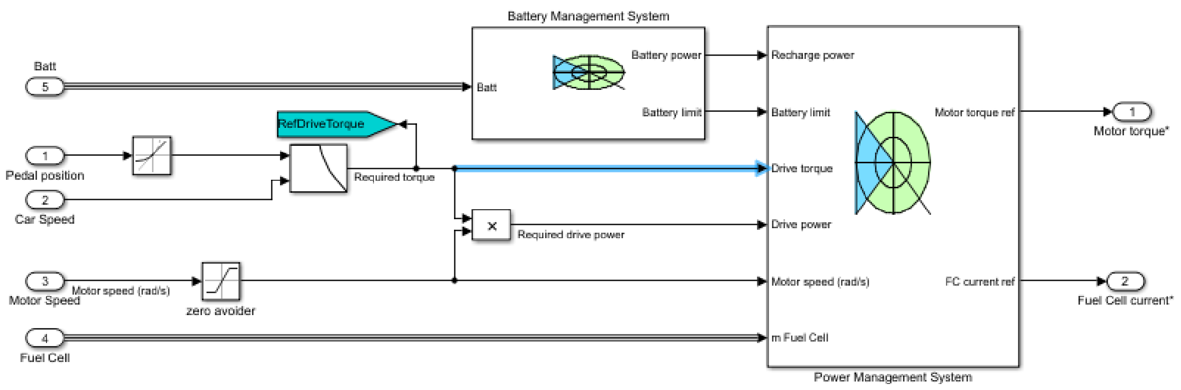

Figure 19. MES MATLAB model

Battery management system block controls that the SOC remains between 40 and 80%. Moreover, it prevents against voltage collapse by controlling the power required from the battery. Finally, the PMS block controls the reference power of the electrical motor by splitting the power demand as a function of the available power of the battery and the FC. This power is controlled by the DC/DC converter current. Some of the input signals to the PMS are the accelerator pedal position (Pedal position) and the vehicle speed (Car speed). On the other hand, the output signals are the reference motor torque (Motor torque*) and the reference current of the FC (Fuel Cell current*).

The Battery management system block determines the battery limit and the battery power according to battery state of charge (SOC).

5.4. Demonstration

In this section is shown how the FCHEV performs in different operating modes over one complete cycle: cruising, accelerating, recharging battery while accelerating and regenerative breaking. In Figure 21 can be seen that the car's speed starts from 0 Km/h to about 90 Km/h at 12 seconds, and then there is a diminution to 80 Km/h at 16 seconds. That is a consequence of maintaining the accelerator pedal constant to 70% for the first 4 seconds,

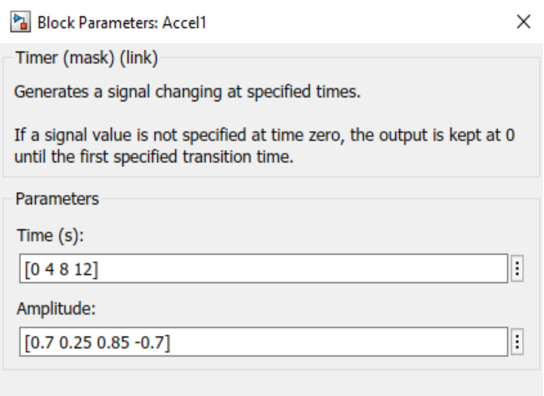

Figure 20. Accelerator parameters configuration

then the pedal is released to 25% for the next 4 seconds, after that the accelerator pedal is pushed again but this time to 85% for another 4 seconds and finally there is a braking (-70%) until the end of the simulation. Check Figure 20 for seeing the configuration of the acceleration parameters for the demonstration.

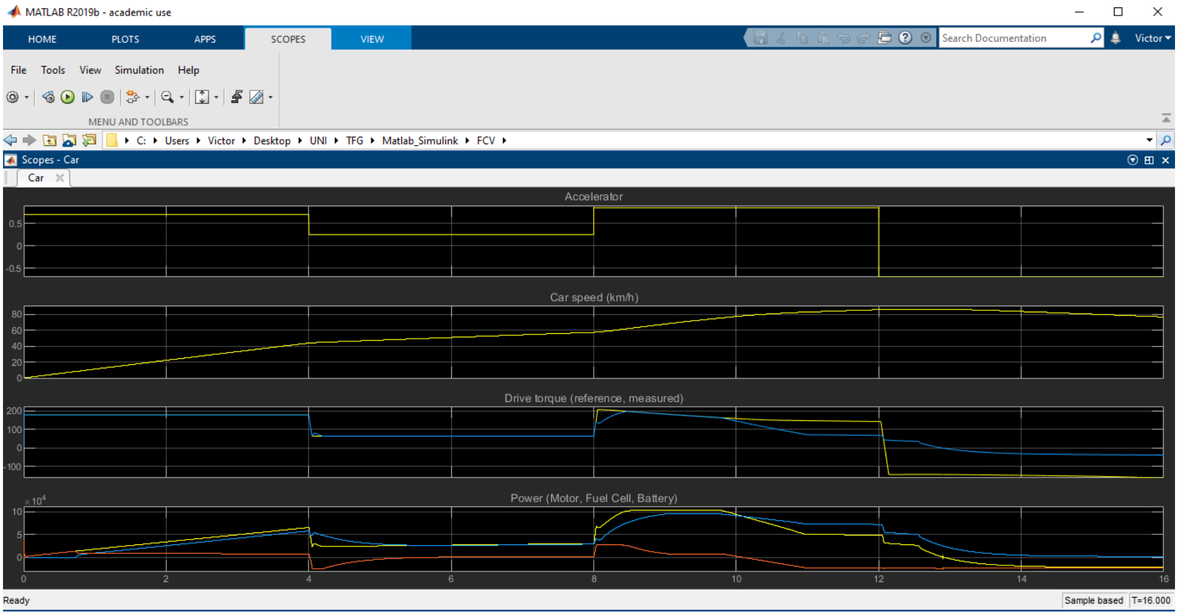

Figure 21. Car's scope

Showing up next, a more detailed explanation of what is happening in different intervals of time:

- At t = 0 s, as mentioned before, the driver pushes the accelerator pedal to 70%. On that moment, the battery provides the motor the power till the FC starts.
- At t = 0.7 s, the FC begins to provide power (blue line in the Figure 18), nevertheless is not able to reach the reference power due to its large time constant. That's why the battery continues to provide the electrical power to the motor (yellow line in Figure 18).
- At t = 4 s, because the accelerator pedal is released to 25%, the FC cannot reduce its power instantaneously, therefore the battery absorbs the FC power in order to maintain the required torque.
- At t = 6 s, the FC power is the same as the reference power. The battery is no more needed.
- At t = 8 s, the accelerator pedal is pushed to 85%. In that case, the battery supports the FC by providing an extra power of 25 kW.

- At t = 8.05 s, the total power (FC + battery) cannot reach the required power due to the FC response time.
- At t = 8.45 s, the measured reaches the reference. The FC power increases so the battery power is progressively reduced to 6 kW as seen in the graphic (Figure 18).
- At t = 10.9 s, the state of charge of the battery is lower than 40% (out of the bounds) which means then the battery needs to be recharged. The FC provides its power between the battery and the motor. Can be observed that the power from the battery is negative on this point, which means that the battery receives some power from the FC and recharges while the FCHEV is accelerating.
- At t = 12 s, the regenerative breaking is simulated (-70 % from the accelerator pedal). The electrical motor acts like a generator driven by the vehicle's wheels. The kinetic energy is transformed in electrical energy and then stored in the battery. On the other hand, the FC power decreases according to its response time.
- At t = 15 s, the FC power is at its minimum (2 kW).

6. Implementation of the NN

As mentioned before, the purpose of this bachelor's thesis is to develop a NN and implement it in the power management strategy for a FCHEV. So, first of all a short introduction about NN is going to be exposed, and then will be explained the process of how has been created and the way that could be implemented to the basic system modelled.

6.1. Introduction to the NN

A NN is a computational or mathematical model which tries to simulate a biological neural network. The NN is composed of interconnected group of neurons that processes the information through their connections. NN can be used for modelling complex relations between inputs and outputs. The structure of a neuron is shown below (Figure 22):

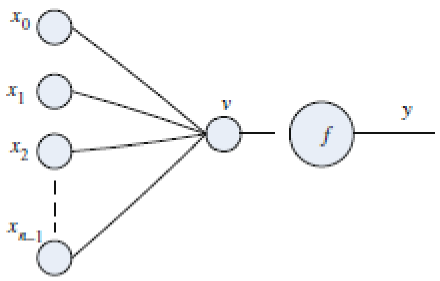

Figure 22. Structure of a neuron

A neuron is a function that is nonlinear, parametrized and bounded. The inputs from the neuron are variables (x_0, x_1,…,x_{n-1}), the "*v*" is a weighted sum of all the inputs with an additional bias, and the output " *y* " (*y=f(v)*) is the value of the neuron. The output is produced based on the input and the activation (basically is the *f*).

The goal of this structure is to ensure that the output and the target are so close enough that by adjusting the weights (the difference between them or the error) is minimized.

In Figure 23 is represented the internal architecture of a neuron in more detail:

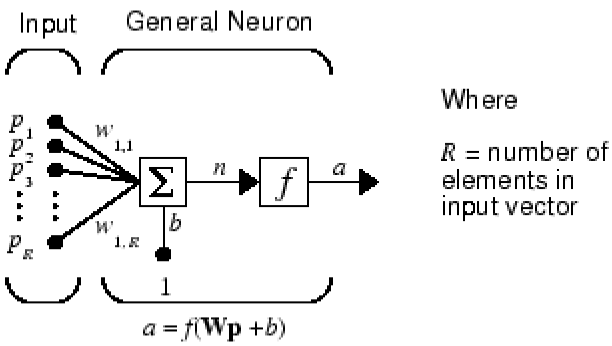

Figure 23. Detailed neuron architecture [26]

Each input is weighted with "*w*". The transfer function " *f* " would be the sum of the weighted inputs and the bias "*b*".

The " *f* " represents a parameterization function called transfer function. The choice of this transfer function is dependent on the user based on his/her application and every neuron uses any differentiable transfer function to be able to generate their output. The " *f* " can be expressed on two different forms:

$$y = f(v) = f\left(w_n + \sum_{i=0}^{n-1} w_i x_i\right) \tag{10}$$

w: weight of the parameters

n: number of inputs

The other type is when " *f* " is a radial basis function (RBF). The RBF is a local nonlinear and asymptotically disperse in all directions of the input space. For example, the output of a Gaussian RBF is:

$$y = exp\left[-\frac{\sum_{i=0}^{n-1}(x_i - w_i)^2}{2w_{n+1}^2}\right] \tag{11}$$

where w_{n+1} and w_i represent the standard deviation and the position of the center of the Gaussian, respectively.

6.2. Types of NN

Generally, there are three types of NN:

- Feedforward NN
- Recurrent (Feedback) NN
- Radial Basis Function (RBF) NN

6.2.1. Feedforward NN

Is a NN where the connections between neurons do not conform a directed cycle. The information flows from the inputs to the outputs in only one direction. Figure 24 represents the structure of this type of NN:

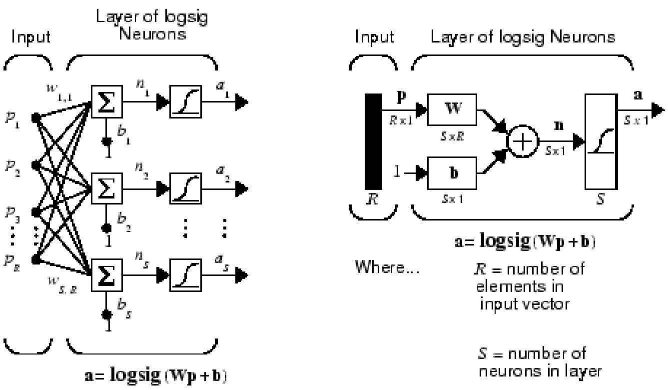

Figure 24. Feedforward NN structure [26]

The simplest type of feedforward NN is a single-layer perceptron network, where the inputs are directly connected to the outputs. Perceptron refers to networks which are formed only with one of these neurons. The perceptron can be trained with the delta rule learning algorithm.

On the other hand, it exists the multi-layer perceptron NN, where inputs are connected to outputs through hidden layers. The most common method to train this kind of perceptrons is called "back propagation" algorithm. Multi-layer perceptron NN using back propagation are useful to solve extremely complex problems like speech recognition, image recognition, machine translation and computer security.

6.2.2. Recurrent (Feedback) NN

Is a NN where the connections between neurons conform a directed cycle, ergo, a path that if the connections are followed leads back to the starting neuron. Figure 25 represents the structure of this type of NN:

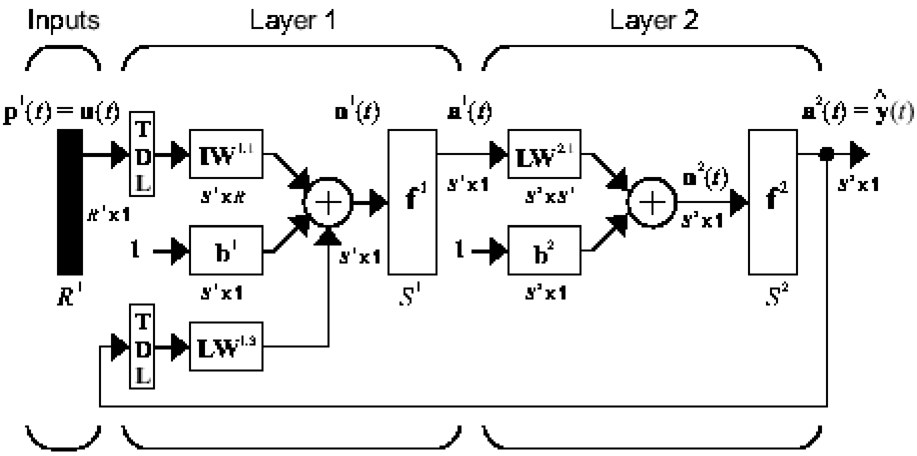

Figure 25. Recurrent NN structure [27]

As it can be seen in the figure above, new inputs are fed into the recurrent NN at each time step. The previous information of the hidden layer is transferred to the context layer, then the output of the context is fed back to the hidden layer.

The general linear system for recurrent neural networks is:

$$x(k) = Ax\,(k-1) + Bu\,(k-1)$$
$$y(k) = Cx\,(k-1) + Du\,(k-1) \qquad (12)$$

6.2.3. Radial Basis Function (RBF) NN

Is a NN that employs radial basis functions as activation functions. An RBF is a real-valued function whose value depends only on the distance from the origin or alternatively on the distance from some other point called a center. Figure 14 represents the structure of this type of NN:

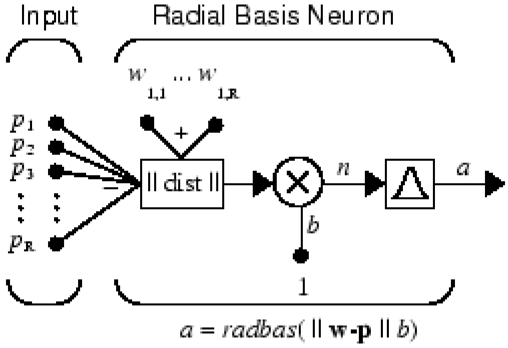

Figure 26. Radial basis NN [28]

The general equation for the RBF NN is:

$$y(x,w) = \sum_{i=1}^{N} w_i \emptyset\ (\|x - c_i\|) \tag{13}$$

x: input vector

$y(x,w)$: output of the network

w_i: weight

$\|x - c_i\|$: distance from the center

The Gaussian is the common RBF networked used. The output of the Gaussian RBF is:

$$y(x,w) = \sum_{i=1}^{N} \left[w_{N+1,i}\ exp\left(-\frac{\sum_{j=1}^{n} \left(x_j - w_{ij}\right)^2}{2w_i^2} \right) \right] \tag{14}$$

N: number of neurons in the hidden layer (N+1 is the output neuron)

x: input vector with “n” inputs

w: vector of (n+2)·N parameters

6.3. Learning methods

The learning of NN is the algorithm procedure where the parameters of the neurons are calculated in order to make errors of the NN as small as possible. There are two classes of learning methods:

- Supervised learning
- Unsupervised learning

6.3.1. Supervised learning

It is a machine learning technique for learning a function from training data. The pairs of input vectors and desired output vectors are considered as the training data.

In NN is often used the mean-squared as cost function, with the aim of minimizing the average squared error between the output of the network and the target value over all the example pairs. The equation below represents the mean-squared error:

$$MSE = \frac{1}{N}\sum_{i=1}^{n} e_i^2 \tag{15}$$

e_i: difference between the network output and the target value.

As mentioned before, the "back propagation" algorithm for training NN is obtained when gradient descent for multi-layer perceptron NN is used. What is called as a "teacher" provides examples of values of the inputs and of the corresponding values of the NN output. For example, given the (m+1)th training pattern, the weight can be updated as:

$$w_{ij}^{(m+1)} = w_{ij}^{(m)} + \Delta w_{ij}^{(m)} \tag{16}$$

$\Delta w_{ij}^{(m)}$: related with the supervision of the "teacher"

6.3.2. Unsupervised learning

It is a machine learning technique which determines how the data are organized. In this case, the network is provided with inputs but not with desired outputs. Unsupervised learning is closely related to density estimation in statistics. No teacher is present in this method since the learning have to find similar patterns between elements of the database and translate them into vicinities in the "map". One of the most common NN using unsupervised learning are self-organizing map (SOM) and adaptive resonance theory (ART).

6.4. NN in vehicle power management

The driving patterns are the immediate decisions of the driver to deal with the environment. This driving patterns have significant impact on emissions and fuel economy [21][22]. Standard driving cycles, such as the NEDC, are useful to determine the emissions of the vehicle and the fuel economy under a predefined driving pattern. It would not be possible for a driver to follow a fixed driving cycle in real life driving. Hence, the driving patterns need to be predicted in real-time driving of the automobile for better power management of it.

In recent years, pattern recognition has been used in helping power management of vehicles by predicting the drive cycle characteristics or driving profiles (drivers' behavior) [23][24].

The block diagram below (Figure 27) represents an overview of a NN that could be used to predict the roadway type and traffic congestion levels. Then this system could be embedded into an intelligent vehicle power management system controller (IPC).

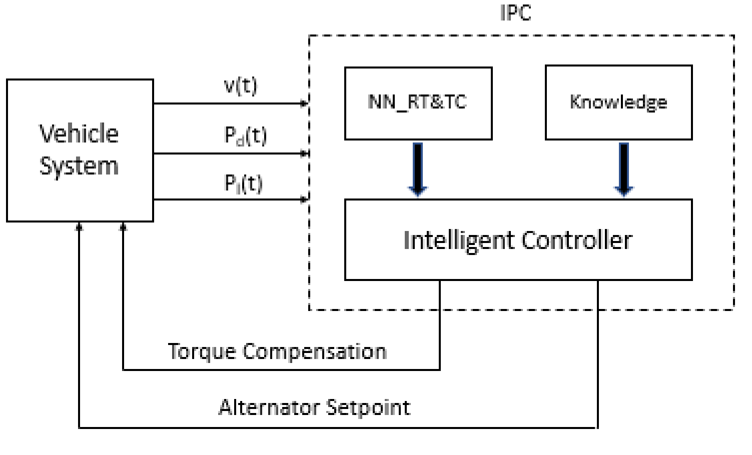

Figure 27. IPC block diagram

v(t): vehicle speed

P_d: required driveline power

P_l: required electric load power

The knowledge base existing in the IPC consists of the knowledge about the optimal alternator set point and torque compensation leant from different drive cycles. If the prediction results are used, the ideal values from the alternator set point and the torque compensation during the time interval [t, t+Δt] are the outputs obtained from the Intelligent Controller.

6.5. Development and implementation of the NN

The specific NN used for predicting the driving profile is from the type of feedback NN called time series nonlinear autoregressive network with exogenous inputs (NARX). The defining equation for NARX model is:

$$y(t) = f\left(y(t-1), y(t-2), \dots, y\left(t-n_y\right), u(t-2), \dots, u(t-n_u)\right) \tag{17}$$

where the next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal [27].

The NN's implementation with MATLAB is quite simple:

1) By typing in the MATLAB's command window "nnstart", a new window like Figure 28 will appear:

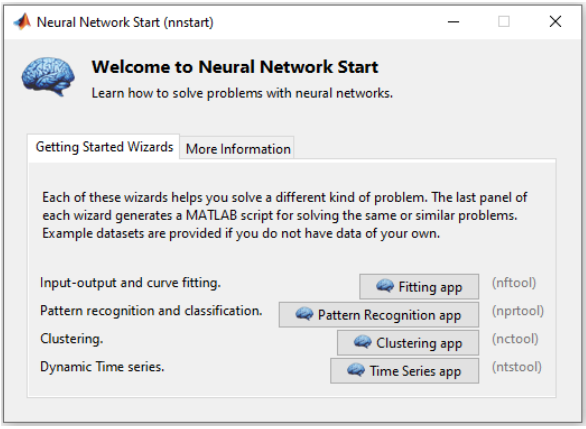

Figure 28. Neural Network Start

After that, the "Time Series app" option is going to be clicked.

2) Another window will be opened and NARX option is going to be selected (see Figure 29 below). Then, the "Next button" should be pressed to proceed for the next step:

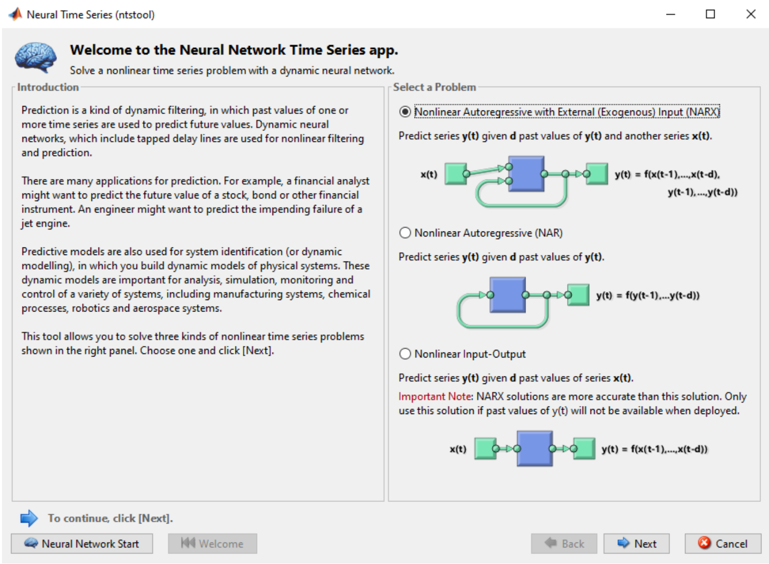

Figure 29.NARX selection

3) Next step is to select the data: the input values "x(t)" and the desired output "y(t)". In this case, the NEDC driving cycle have been selected as data for the NN. As an input value x(t) = [acceleration, duration] and as output value y(t) = [initial speed, final speed]. See Figure 30 below for better comprehension:

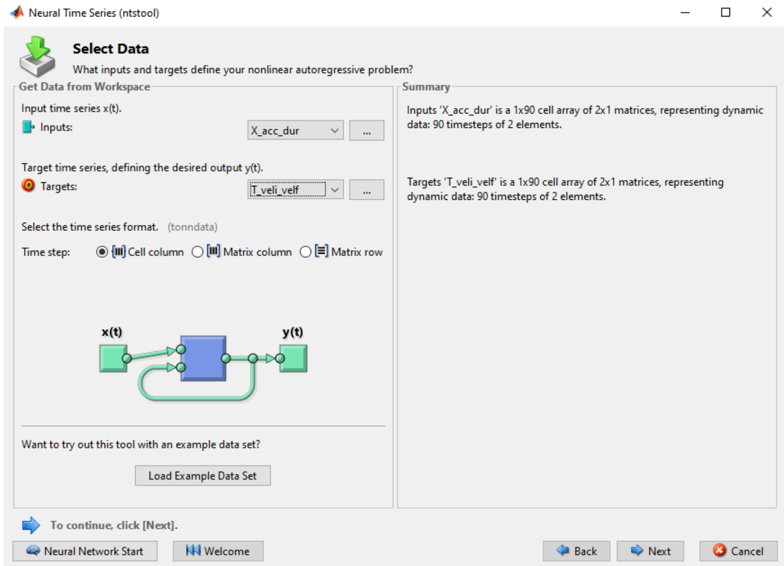

Figure 30. Select Data

4) Next step will be to define the number of hidden neurons and the input/feedback delays:

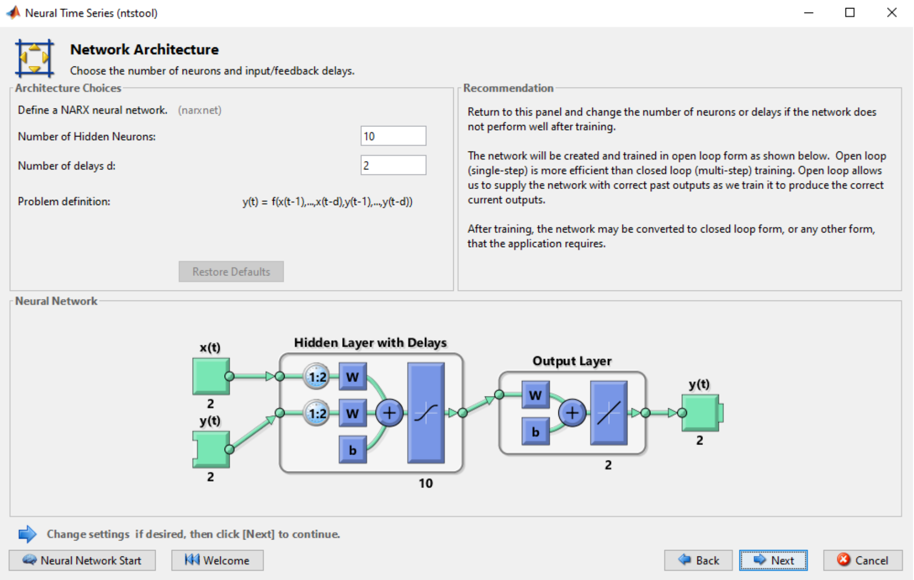

Figure 31. Network architecture

5) Finally, the NN is created and can start to be trained, but first, a training algorithm has to be selected. Levenberg-Marquardt training algorithm has been chosen on that case.

In the next section some of the results are discussed.

7. Results and discussion

On this section some important plots are commented:

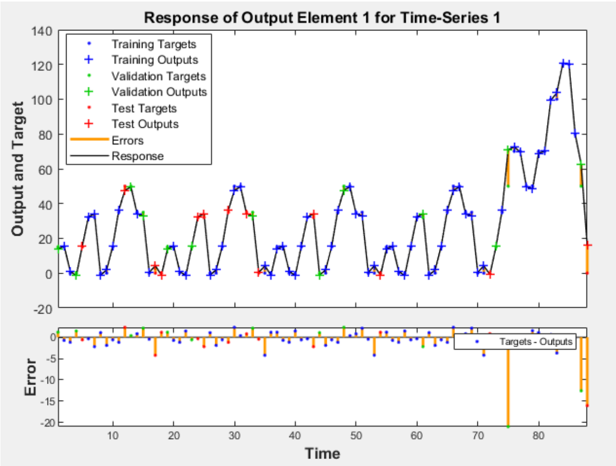

Figure 32. Response graph

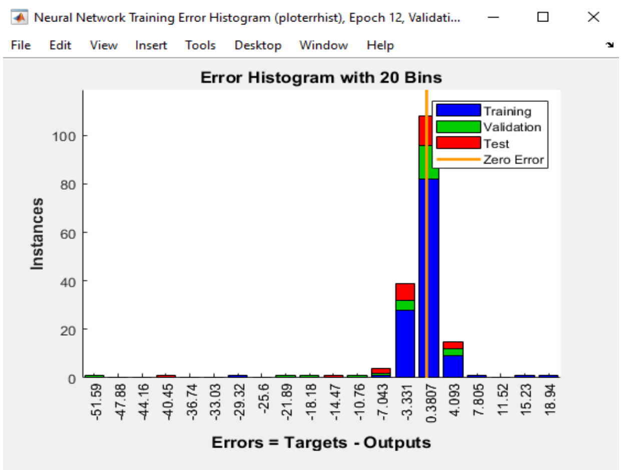

Figure 33. Error histogram

Figure 32 and Figure 33 represent two different ways of seeing the error.

On one hand, in Figure 32 the error is represented by the yellow lines. Other results as the training targets, training outputs, validation targets, validation outputs, test targets and test outputs are shown.

On the other hand, in Figure 33 can be observed the error histogram, which is calculated as targets minus outputs. The error should be close to zero. So, in that case is clear that the majority of the values are close to zero (see yellow vertical line in the graph), then this NN can be considered as a good option for be implemented into the FCHEV model.

Another results that the MATLAB NN app can do is the code generation (see in Appendix) and a Simulink diagram (see Figure 34 below):

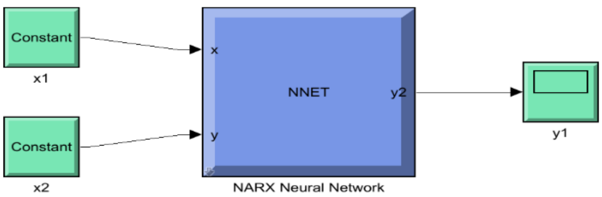

Figure 34. NN Simulink diagram

8. Conclusion

In this Bachelor's thesis a system that predicts the driving profile of a FCHEV has been developed in order to optimize the power demand required by the vehicle. The system is based on using deep learning method, more specifically, a time series NARX NN.

Firstly, an analyze on FCVs has been made. Nowadays, the FCVs' commercialization is a scarce market, but little by little is winning a place with the arrival of electric and hybrids vehicles. FCHEVs seem to have a promising future as they have the advantage of going longer range in one complete hydrogen tank.

Secondly, some knowledge has been acquired from some of the main power management components of FCHEVs, for instance the FC.

Once clarified how it works the power management of a FCHEV, researches have been made regarding power control strategies developed for predicting and optimizing the power required by the vehicle. This has helped for having an idea of how this special optimization algorithms work.

Thirdly, a FCHEV basic model has been implemented with the MATLAB/Simulink for be more familiarized with this powerful software and comprehend each of the most important blocks which form the model. On the other hand, as the idea was to implement the NN using MATLAB as well, it has been a must this part.

Last but not least, a time series NARX NN has been created and implemented by using the MATLAB NN app. Step by step has been described the development of the NN with the software. The results have shown an acceptable error for applying NN to the FCHEV basic model as a future scope.

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Appendix

Neural Networks MATLAB code:

```
function [y1,xf1,xf2] = myNeuralNetworkFunction(x1,x2,xi1,xi2)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 10-Jan-2020 01:24:00.
%
% [y1,xf1,xf2] = myNeuralNetworkFunction(x1,x2,xi1,xi2) takes these
arguments:
%   x1 = 2xTS matrix, input #1
%   x2 = 2xTS matrix, input #2
%   xi1 = 2x2 matrix, initial 2 delay states for input #1.
%   xi2 = 2x2 matrix, initial 2 delay states for input #2.
% and returns:
%   y1 = 2xTS matrix, output #1
%   xf1 = 2x2 matrix, final 2 delay states for input #1.
%   xf2 = 2x2 matrix, final 2 delay states for input #2.
% where TS is the number of timesteps.

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [-1.39;4];
x1_step1.gain = [0.823045267489712;0.0307692307692308];
x1_step1.ymin = -1;

% Input 2
x2_step1.xoffset = [0;0];
x2_step1.gain = [0.0166666666666667;0.0166666666666667];
x2_step1.ymin = -1;

% Layer 1
b1 = [2.1523104162151538432;-
0.59691879307517292652;0.39833076899648883762;-
0.44832250515697419369;0.14067776509380278127;-
0.61514243594655937386;0.083921413270994893452;-
0.82287571031099071561;0.41346438502531773773;-2.3696938883445133328];
IW1_1 = [0.67993056591573641789 -0.61482386550621792587 -
0.68259935090623391485 -0.50907670110851577228;0.22989448898612227512 -
0.83224609724168563396 0.075232939198772844 08 -
0.93697535271907272936;0.32537141649652939757 1.1404036749514596671
0.0038984753740487210205 -1.0096476647498144885;1.2172279573363324889
0.070487051914960546783 -1.7719457977038117757 -
0.23075055884779416271;0.037395934089823681945 0.19723566290185456928
0.69584108810109090992 0.27565336010910646003;-0.64094979141902785891 -
0.21619172292011734626 1.3575338208620433278 -
0.49436771647153698872;0.33021530672192983547 -0.47662236436933880235 -
1.9301762665943784647 -0.98082275180828193406;-2.2898599368615188965 -
1.4385060073955571 18 1.5162689150160313378 -1.1878290381142873056;-
0.1312641926280631588 1.7872474340643740298 0.82429675141051916842 -
0.29725028298384803538;-0.52340932057735667371 -0.62876530814010900272
0.049172303341453262038 0.61508287811050565974];
```

```
IW1_2 = [-1.4981970683327265892 -0.81205424166723139123
1.3972537557800726038 -0.35282117611769420185;2.9873105075332815339 -
2.4036407243459274596 0.015222650309081951769 -0.23921203691219664056;-
0.71644045226254771119 0.16014376121666068498 0.64953404059877117849
1.2195753056530913572;-1.0754545608019561165 0.88228046384771419142
0.88376346546053274889 -0.79711970242926455388;-0.35266985326827093861
1.2328390274626948031 0.74201728577637349193 -0.79508505031132525875;-
0.75989597202485825722 -0.21204954384119403881 3.0324469249312402397
0.89410601164977343558;-0.49976912955313645597 2.8529131331135850758 -
0.61157464595093469217 -0.51414895339477439951;0.66987858334957217643 -
0.36901252168593540182 0.89911689685358930912 0.45137316474480176692;-
0.068957072859922849406 -1.5854206280565872333 0.22189776372142172578
0.26903277395403307759;0.83856119752531177447 0.96911462300811401782
0.0098680213836566856717 0.25780591265764946085];

% Layer 2
b2 = [0.17896016904752937716;0.24386018977957071852];
LW2_1 = [-0.18669357342911729888 -0.082980645478709008644
0.31094967202783169169 -0.088361769204309659198 0.58265765620644860423
0.066826160778426318965 0.032500372452308627647 0.039697316608598126608 -
0.24946420302976285432 0.12849653432741250936;-0.80411654497781792639 -
0.90239080226808299212 -0.39367903043177210343 -0.50308846924135819378 -
0.049282060153761068891 0.74104475125317248452 0.74127246349765851807
0.083079349260493762223 0.27943091514789375474 -0.50363015905328578636];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = [0.0166666666666667;0.0166666666666667];
y1_step1.xoffset = [0;0];

% ===== SIMULATION ========

% Dimensions
TS = size(x1,2); % timesteps

% Input 1 Delay States
xd1 = mapminmax_apply(xi1,x1_step1);
xd1 = [xd1 zeros(2,1)];

% Input 2 Delay States
xd2 = mapminmax_apply(xi2,x2_step1);
xd2 = [xd2 zeros(2,1)];

% Allocate Outputs
y1 = zeros(2,TS);

% Time loop
for ts=1:TS

    % Rotating delay state position
    xdts = mod(ts+1,3)+1;

    % Input 1
    xd1(:,xdts) = mapminmax_apply(x1(:,ts),x1_step1);
```

```
    % Input 2
    xd2(:,xdts) = mapminmax_apply(x2(:,ts),x2_step1);

    % Layer 1
    tapdelay1 = reshape(xd1(:,mod(xdts-[1 2]-1,3)+1),4,1);
    tapdelay2 = reshape(xd2(:,mod(xdts-[1 2]-1,3)+1),4,1);
    a1 = tansig_apply(b1 + IW1_1*tapdelay1 + IW1_2*tapdelay2);

    % Layer 2
    a2 = b2 + LW2_1*a1;

    % Output 1
    y1(:,ts) = mapminmax_reverse(a2,y1_step1);
end

% Final delay states
finalxts = TS+(1: 2);
xits = finalxts(finalxts<=2);
xts = finalxts(finalxts>2)-2;
xf1 = [xi1(:,xits) x1(:,xts)];
xf2 = [xi2(:,xits) x2(:,xts)];
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```