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Energy Management of an Electrical Vehicle using Frequency-decoupling strategy and Neural Network Controller

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Dedication

RABIE TO

My dear and supportive beloved parents

my lovely sister

my brothers taha isak said

my fiancée

my whole family

my friends especially

ainsai jamais group

my colleague and dear friend Hassan

HASSAN TO

My dear and supportive beloved parents

my lovely sister

my brothers yacine tafa khodir

my fiancée

my whole family

my friends especially

F4E group

my colleague and dear friend Rabie

WE DEDICATE THIS WORK FOR YOU

Acknowledgement

First of all, we thank God for everything we have got, for every stage we have reached, then thanks to our families who support us all over the way.
Then We gratefuly Give our sincere appreciations to all of those who taught us even a letter since the begining, all teachers, all mentors...if it were not for you, we would not make so far, so thanks agin.
and a spacial thanks to Dr.Abdedaim Sabrina for guiding us through all university stages, we send you our gratitude.

abstract

ON this thesis we will be dealing with three major axis, the first we will look into it is the electric vehicles and how they have been evolved over time, also we discover the features, the components, the possible topologies of EV.
Then on the second axis we will limp on the energy management strategies of electric vehicle's power-train system, with almost the whole pack of strategies either Rule-based EMSs or Optimization-based EMSs, and even the Learning-based EMSs...
and the third one is the control of the drive-train of our system that combines a Lithium battery and supercapacitor as two power sources, using PI regulator to command the converters and control the system, by choosing the Frequency-decoupling strategy, that relays on decoupling of the low- and high-frequency components of the load demand signal, and applying low-frequency content to the high-energy source in the system (the battery), whereas the high-frequency is compensated using an auxiliary fast-responding source, which is in the studied case is the supercapacitor, Afterward we the integrate the artificial intelligence presented by Neural Network and visualizing and interpreting the results at and compare between them the end.

key words :

Electric Vehicle; Battery; Supercapacitor; Energy Manegment Strategy; Frequency-decoupling strategy; convertors; PI regulators; Power source;Neural Network.

résumé

SUR cette thése, nous allons traiter trois axes majeurs. Dans le premier nous allons examiner les véhicules électriques et comment elles sont évolués avec le temps, aussi nous découvrons les caractéristiques, les composants, les topologies possibles de EV.
Ensuite, sur le deuxième axe, nous allons parler sur les stratégies de gestion de l'énergie du véhicule électrique, présentant les plus connu stratégies soit : Rule-based EMSs ou Optimization-based EMSs, et même the Learning-based EMSs...
Et le troisième est le contrôle du drive-train de notre système qui combine une batterie au lithium et un super-condensateur comme deux sources d'énergie, en utilisant le régulateur PI pour commander les convertisseurs (les hacheurs) et contrôler le système, en choisissant la stratégie de découplage de fréquence(séparation de fréquence), qui relaie sur le découplage des composants à basse et haute fréquence du signal de charge, et en appliquant le contenu á basse fréquence à la source de haute énergie dans le système (la batterie), alors que la haute fréquence est compensée à l'aide d'une source auxiliaire à réponse rapide, qui est dans le cas étudié est le super-condensateur, Par la suite, nous intégrons l ' intelligence artificielle présenté par Neural Network et visualisons et interprétons les résultats et comparons entre eux á la fin

mots clés :

véhicule éléctrique; batterie; super-condensateur; stratégie de supération de fréquence; gestionnaire d'énergie; régulateur PI; source de puissance;Neural Network.

Energy Management of an Electrical Vehicle using Frequency-decoupling strategy and Neural Network Conroller

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General Introduction

THE world is facing enormous challenge of increasing consumption of fossil fuels, as consequence of that the problem of climate change. The solution of this challenge necessarily requires to design and use green technologies on a large scale. In that sense, the transport sector, which is an important part of the world oil consumption and one of the largest contributors of greenhouse gas, especially the light-duty vehicles such as cars. For example in The United States of America, the transport sector is the largest contributor of the greenhouse gas emissions with 28%, within 59% of this transportations are light-duty vehicles [2]. For these reasons, the transport sector is witnessing increasing integration of Hybrid Electric Vehicles(HEVs) and Electric Vehicles (EVs) in recent years as alternatives of the ordinary Internal Combustion (ICE) vehicles. EVs have the advantage of emitting few or no atmospheric pollutants, however it has disadvantage on the autonomy side, because of the batteries limitations. To improve the autonomy of the vehicle and protect the battery, other sources such as the hydrogen fuel cell (FC) and/or the supercapacitor (also called ultracapacitor) could be added, thus constituting hybrid sources. In the case of electric vehicles, the hybridization of the energy source allows to minimize the vehicles weight and to increase their driving ranges [3]. In this thesis, we have worked on the hybridization of battery/supercapacitor as sources of energy, and we chose the frequency-splitting technique for energy management using a low pass filter then using Neural Network as additional value to this thesis. This work consists of a General Introduction, three chapters and a General Conclusion. The first chapter started with general ideas about electric vehicles, their types and their different topologies. In addition, it contains a general review of all the energy management strategies (EMS) used within the EVs. The second chapter consists of the modelling of the different parts of the chosen energy system battery/supercapacitor. The third chapter is the simulation and its results of the system using Matlab/Simulink software. and comparing results.

Chapter 1

State of Art on EV & EMS

1.1 Introduction

ENVIRONMENTAL as well as economic issues provide a compelling impetus to develop clean, efficient, and sustainable vehicles for urban transportation. Automobiles constitute an integral part of our everyday life, yet the exhaust emissions of conventional internal combustion (IC) engine vehicles are to blame for the major source of urban pollution that causes the greenhouse effect leading to global warming,[4]

The dependence on oil as the sole source of energy for passenger vehicles has economic and politic implications, and the crisis will inevitably become acute as the oil reserve of the world diminishes. The number of automobiles on our planet doubled to about a billion or so in the last 10 years. The increasing number of automobiles being introduced on the road every year is only adding to the pollution problem. There is also an economic factor inherent in the poor energy conversion efficiency of combustion engines. Although the number for alternative electric vehicles is not significantly higher when efficiency is evaluated on the basis of conversion from crude oil to traction effort at the wheels, it makes a difference. Emission due to power generation at localized plants is much easier to regulate than that emanating from IC engine vehicles (ICEV) that are individually maintained and scattered. People dwelling in cities are not exposed to power plant related emissions, because these are mostly located outside urban areas. Electric vehicles (EV) enabled by high-

efficiency electric motors and controllers and powered by alternative energy sources provide the means for a clean, efficient, and environmentally friendly urban transportation system. Electric vehicles have no emission, having the potential to curb the pollution problem in an efficient way. Consequently, EVs are the only zero-emission vehicles possible. Electric vehicles paved their way into public use as early as the middle of the 19th century, even before the introduction of gasoline-powered vehicles[5].
However, The complexity of FCEVs, BEVs, PHEVs and HEVs as electro-mechanical-chemical systems implies the use of Energy Management Strategies (EMSs).
The ultimate objective of an EMS is to share power through the components of the powertrain efficiently by selecting the appropriate operation modes simultaneously with improving the fuel economy, reducing emissions (HEVs and PHEVs), ensuring drivability, and maintaining the state of charge and lifetime of the energy storage system by considering the limitations[6].
All of that without missing to maintain the requirements for individual mobility (such as range, acceleration and speed) [7].

1.2 EV Sysstem

An EV has the following two features:

- The energy source is portable and chemical or electromechanical in nature.
- Traction effort is supplied only by an electric motor.[5]

The Figure bellow (1.1)shows an EV system driven by a portable energy source. The electromechanical energy conversion linkage system between the vehicle energy source and the wheels is the drivetrain of the vehicle. The drivetrain has electrical as well as mechanical components.

1.2.1 EV History

The history of EVs is interesting. It includes the insurgence of EVs following the discovery of electricity and the means of electromechanical energy conversion

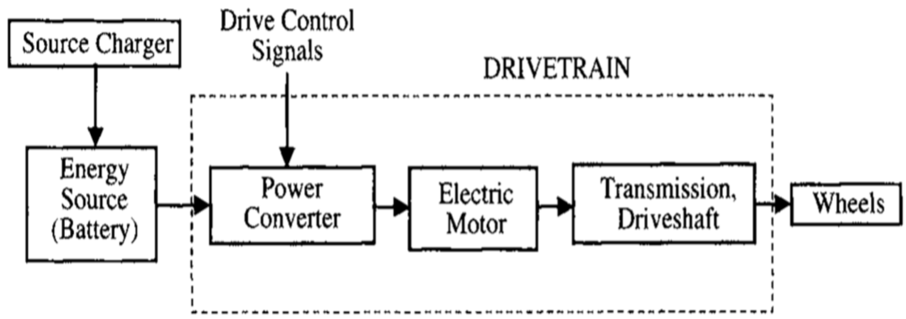

Figure 1.1: Top-level perspective of an EV system , [5] .

and later being overtaken by gasoline-powered vehicles. People digressed from the environmentally friendly mode of transportation due to lack of technology in the early years, but they are again focused on the correct track today.

- **THE EARLY YEARS**

  Prior to the 1830s, the means of transportation was only through steam power, because the laws of electromagnetic induction, and consequently, electric motors and generators, were yet to be discovered. Faraday demonstrated the principle of the electric motor as early as in 1820 through a wire rod carrying electric current and a magnet, but in 1831 he discovered the laws of electromagnetic induction that enabled the development and demonstration of the electric motors and generators essential for electric transportation. The history of EVs in those early years up to its peak period in the early 1900s is summarized below:

  * Pre-1830-team-powered transportation

  * 1831-Faraday's law, and shortly thereafter, invention of DC motor

  * 1834-Non rechargeable battery-powered electric car used on a short track

  * 1851-Non rechargeable 19 mph electric car

  * 1859-Development of lead storage battery

  * 1874-Battery-powered carriage

  *Early 1870s-Electricity produced by dynamo-generators

  * 1885-Gasoline-powered tricycle car

The factors that led to the disappearance of EV after its short period of success were as follows:

1) Invention of starter motor in 1911 made gas vehicles easier to start.

2) Improvements in mass production of Henry T (gas-powered car) vehicles sold for 260 $ in 1925, compared to 850 $ in 1909. EVs were more expensive.

3) Rural areas had limited access to electricity to charge batteries, whereas gasoline could be sold in those areas.

- **1960s**

Electric vehicles started to resurge in the 1960s, primarily due to environmental hazards being caused by the emissions of ICEVs. The major ICEV manufacturers, General Motors (GM) and Ford, became involved in EV research and development. General Motors started a $ 15 million program called Electrovair and Electrovan. The components and specifications of two Electrovair vehicles (Electrovair I (1964) and Electrovair II (1966) by GM) are given below:
Systems and characteristics:

Motor:three-phase induction motor, 115 hp, 13,000 rev/m

Battery:silver-zinc (Ag-Zn), 512 V, 680 lb

Motor drive :DC-to-AC inverter using a silicon-controlled rectifier (SCR)

Top speed:80 mi/h

Range:40 to 80 miles

Acceleration:0-60 mi/h in 15.6 s

Vehicle weight:3400 lb

- **1970s:**

The scenario turned in favor of EVs in the early 1970s, as gasoline prices increased dramatically due to an energy crisis. The Arab oil embargo of 1973 increased demands for alternate energy sources, which led to immense interest in EVs. It became highly desirable to be less dependent on foreign oil as a nation. The case study of a GM EV of the 1970s is as follows:

Motor:separately excited DC, 34 hp, 2400 rev/m

Battery pack:Ni-Zn, 120 V, 735 lb

Auxiliary battery :Ni-Zn, 14 V

Motor drive :armature DC chopper using SCRs; field DC chopper using bipolar junction transistors (BJTs)

Top speed:60 mi/h

Range:60 to 80 miles

Acceleration:0-55 mi/h in 27 s.

- **1980s and 90s** In the 1980s and the 1990s, there were tremendous developments of high-power, high-frequency semiconductor switches, along with the microprocessor revolution, which led to improved power converter design to drive the electric motors efficiently.
The case studies of two GM EVs of the 1990s are given below:

Motor:one, three-phase induction motor; 137 hp; 12,000 rev/m

Battery pack:lead-acid (26), 12 V batteries connected in series (312 V), 869 lb

Motor drive DC-to-AC inverter using insulated gate bipolar transistors (IGBTs)

Top speed:75 mi/h

Range:90 miles on highway

Acceleration:0-60 mi/h in 8.5 s.

- **RECENT EVs AND HEVs:**
All of the major automotive manufacturers have production EVs, many of which are available for sale or lease to the general public. The status of these

vehicle programs changes rapidly, with manufacturers suspending production frequently due to the small existing market demand of such vehicles. Examples of production EVs which are or until recently have been available are GM EVl, Ford Think City, Toyota RAV4, Nissan Hypermini, and Peugeot 106 Electric. There are also many prototype and experimental EVs being developed by the major automotive manufacturers. Most of these vehicles use AC induction motors or PM synchronous motors. Also, interestingly, almost all of these vehicles use battery technology other than the lead-acid battery pack. The list of EVs in production and under development is extensive, The manufacturers of EVs in the 1990s realized that their significant research and development efforts on ZEV technologies were hindered by unsuitable battery technologies. A number of auto industries started developing hybrid electric vehicles (HEVs) to overcome the battery and range problem of pure electric vehicles. The Japanese auto industries lead this trend with Toyota, Honda, and Nissan already marketing their Prius, Insight, and Tino model hybrids. The hybrid vehicles use an electric motor and an internal combustion engine and, thus, do not solve the pollution problem, although it does mitigate it. It is perceived by many that the hybrids, with their multiple propulsion units and control complexities, are not economically viable in the long run, although currently a number of commercial, prototype, and experimental hybrid vehicle models are available from almost all of the major automotive industries around the world. Toyota, Honda, and Nissan are marketing the hybrid vehicles well below the production cost, with significant subsidy and incentive from the government. However, the cost of HEVs and EVs are expected to be high until production volume increases significantly. Fuel cell electric vehicles (FCEV) can be a viable alternative to battery electric vehicles, serving as zero-emission vehicles without the range problem. Toyota is leading the way with FCEV, announcing the availability of its FCEV in 2003. The Toyota FCEV is based on the Toyota RAV4 model.[5]

1.2.2 Compenents Of an EV

The primary components of an EV system are the motor, controller, power source, and transmission. The detailed structure of an EV system and the interaction among its various components are shown in Figure X. Figure X also shows the choices available for each of the subsystem level components. Electrochemical batteries have been the traditional source of energy in EVs. Lead-acid batteries have been the primary choice, because of their well- developed technology and lower cost, although promising new battery technologies are being tested in many prototype vehicles. The batteries need a charger to restore the stored energy level once its available energy is near depletion due to usage. Alternative energy sources are also being developed for zero-emission vehicles. The limited range problem of battery-driven EVs prompted the search for alternative energy sources, such as fuel cells and flywheels. Prototypes have been developed with fuel cells, while production vehicles will emerge in the near future. The majority of electric vehicles developed so far are based on DC machines, induction machines, or permanent magnet machines. The disadvantages of DC machines pushed EV developers to look into various types of AC machines. The maintenance-free, low-cost induction machines became an attractive alternative to many developers. However, high-speed operation of induction machines is only possible with a penalty in size and weight. Excellent performance together with high-power density features of permanent magnet machines make them an attractive solution for EV applications, although the cost of permanent magnets can become prohibitive. High-power density and a potentially low production cost of switched reluctance machines make them ideally suited for EV applications. However, the acoustic noise problem has so far been a deterrent for the use of switched reluctance machines in EVs. The electric motor design includes not only electromagnetic aspects of the machine but also thermal and mechanical considerations. The motor design tasks of today are supported by finite element studies and various computer-aided design tools, making the design process highly efficient. The electric motor is driven by a power-electronics-based power-processing unit that converts the fixed DC voltage available from the source into a variable voltage, variable frequency source controlled to maintain the desired operating point of the vehicle. The power electronics circuit comprised of power semiconductor devices saw tremendous development over the past 3 decades. The enabling technology of power electronics is a key driving force in developing efficient and high-performance power-train units for EVs. High-power devices in compact packaging are available today, enabling the development of lightweight and efficient power-processing units known as power electronic motor drives. Advances in power solid state devices and very large-scale integration (VLSI) technology are responsible for the development of efficient and compact power electronics circuits. The developments in high-speed digital signal processors or microprocessors enable complex control algorithm implementation with a high degree of accuracy. The controller includes algorithms for the motor drive in the inner loop as well as system-level control in the outer loop[8]

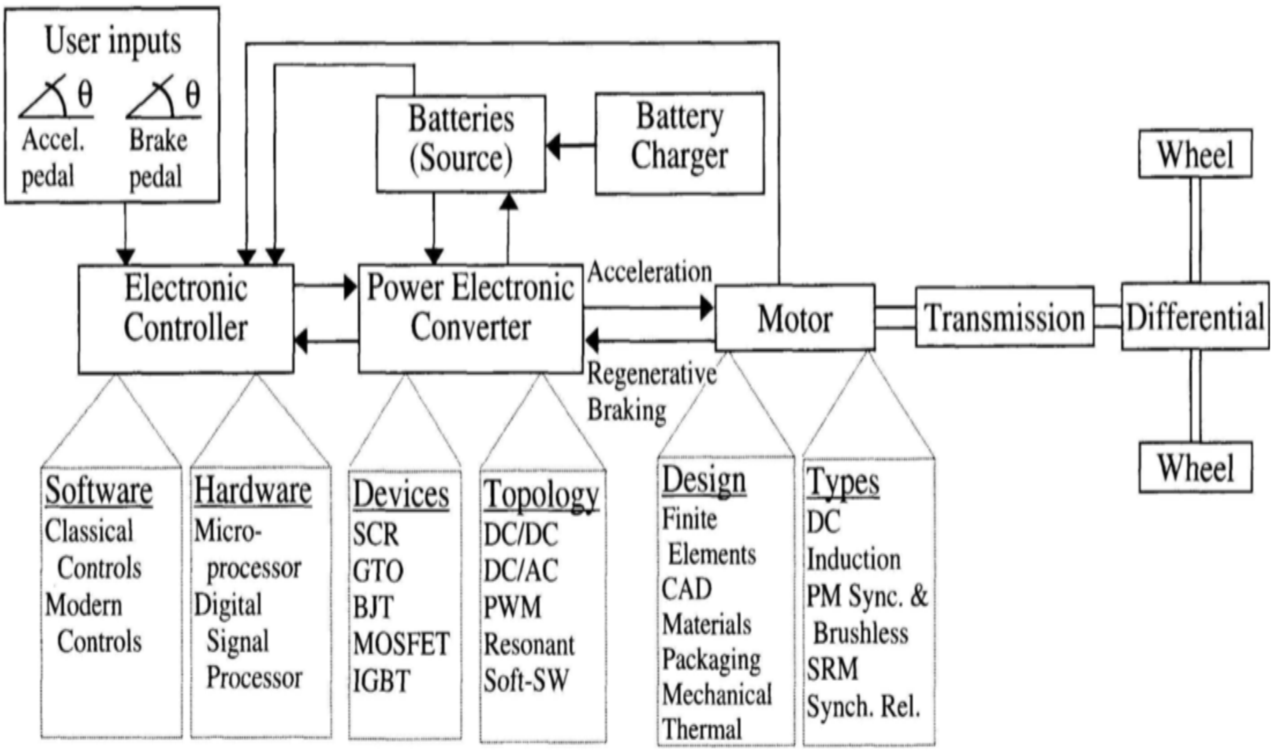

Figure 1.2: Major electrical components and choices for an EV system [8] .

1.2.3 Topologies of EV HEV

There are various configurations of EVs and according to their energy sources, they are two global kinds: pure Electric vehicles and Hybrid vehicles.[6]

- **A) Pure Electric vehicle:**

  Previously, the EV was mainly converted from the existing ICEV by replacing the internal combustion engine and fuel tank with an electric motor drive and battery pack while retaining all the other components, drawbacks such as its heavy weight, lower flexibility, and performance degradation have caused the use of this type of EV to fadeout. A modern electric drivetrain is concepted usually of three major subsystems: electric motor propulsion, energy source, and auxiliary. The electric propulsion subsystem is comprised of a vehicle controller, power electronic converter, electric motor, mechanical transmission, and driving wheels. The energy source subsystem involves the energy source, the energy management unit, and the energy refueling unit. The auxiliary subsystem consists of the power steering unit, the climate control unit, and the auxiliary supply unit. [6]

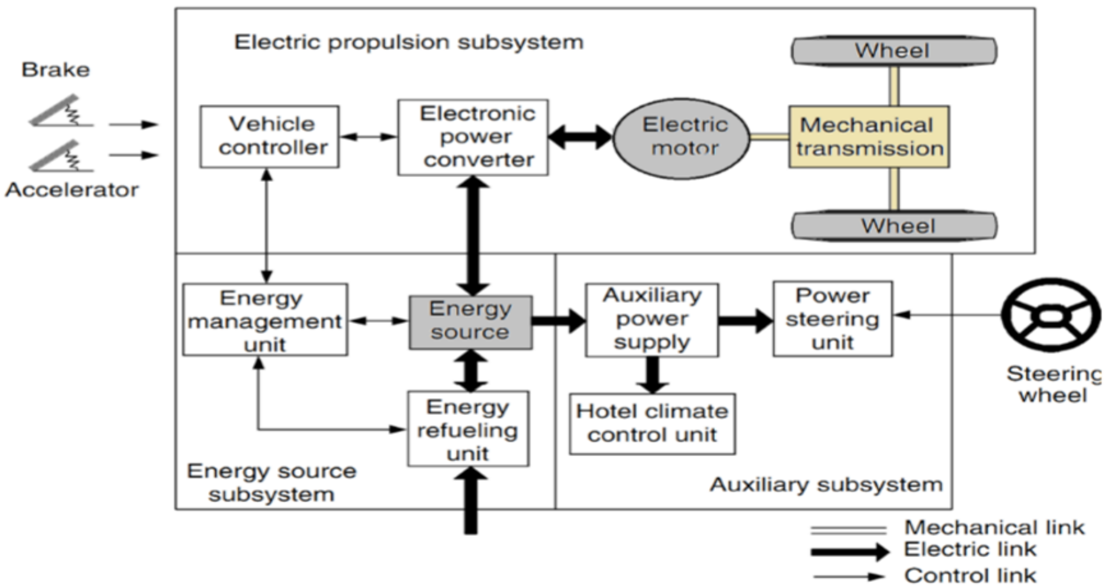

Figure 1.3: Pure electric vehicle [8] .

We have two main parts in full (Pure) electric vehicles:

Battery-based FEVs: In battery-based configurations, the battery is the main source with a high-energy content. Thus, the battery can be combined with other high- power density devices such as a supercapacitor (SC) (also known as an ultra-capacitor (UC), or electric double-layer capacitor (EDLC)), high power battery, or lithium-capacitor (LiC) to form a hybrid energy storage system (HESS). In general, batteries have a high energy density and low power density in contrast to an SC. Hence, An HESS can store sufficient energy and satisfy sudden power demands for the vehicle to achieve a required acceleration performance. Compared to a standalone battery-based FEV configuration, An HESS-based configuration exhibits numerous advantages such as a higher energy/power density, longer battery life span, faster dynamic response in acceleration mode, and the capability of absorbing more energy in regenerative braking mode. HESS-based systems can vary when considering the converter type and their positions through a powertrain. A HESS can be classified into two main types:

a semi-active configuration or a fully active configuration.[6]

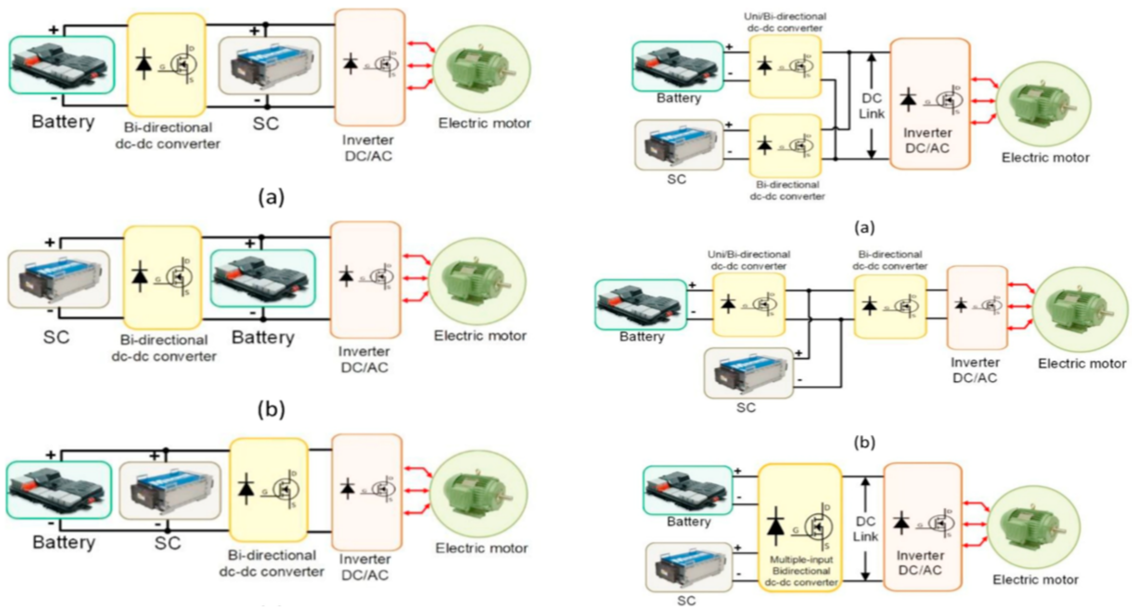

Figure 1.4: semi-active configuration (on the left) or a fully active configuration (on the right) [6] .

Fuel cell-based FEVs:

In fuel-cell (FC)-based FEVs, the FC is the main energy source used to generate electricity from hydrogen and air. The specific energy of an FC and its specific power are close to and much less than those of gasoline, respectively. Because FC systems have slow dynamics, fast power transients can lead to a gas starvation, resulting in permanent damage to the FC. Therefore, batteries, SCs, or battery-SCs can be integrated into a system to improve the dynamic performance and extend the FC lifespan. In this regard, the possible configurations and combinations FC-Bat, FC- SC, or FC-Bat-SC are illustrated in Fig 1.5

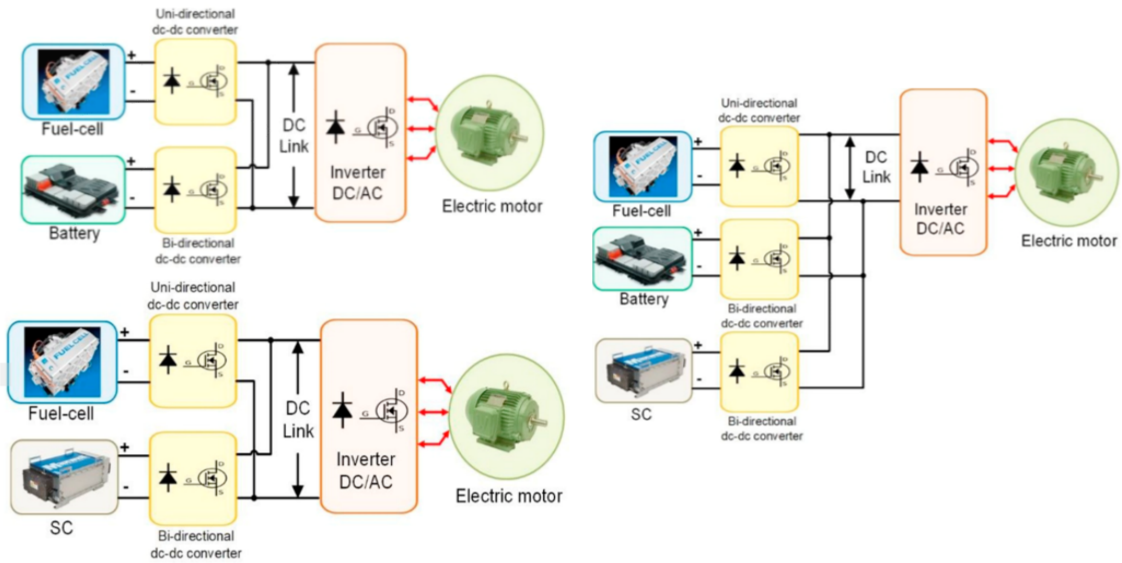

Figure 1.5: configurations and combinations FC-Bat, FC- SC, or FC-Bat-SC [6] .

Advantages of pure EV:

* Zero mission * Silent * Easy use and driving.

Disadvantages of pure EV:

* Travel range obstacle * Oriented only for urban uses * High cost

- **Hybrid vehicle:**

A Hybrid Electric Vehicle (HEV) is a vehicle that uses two or more sources of power. The two sources are electricity from batteries and mechanical power from an internal combustion engine. This combination offers very low emissions of vehicles with the power and range of gasoline vehicles. They also offer up to 30 more miles per gallon perform as well or better than any comparable gasoline powered vehicle and never have to be plugged in for recharging .A hybrid road vehicle is one in which the propulsion energy during specified operational missions is available from two or more kinds or types of energy stores, sources, or converters, of which at least one store or converter must be on board. Many configurations are possible for HEVs as series and parallel HEVs.[8]

Series HEV

A series hybrid is one in which only one energy converter can provide propulsion power. The heat engine or ICE acts as a prime mover in this configuration to drive an electric generator that delivers power to the battery or energy storage link and the propulsion motor. The component arrangement of a series HEV is shown in fig 1.6

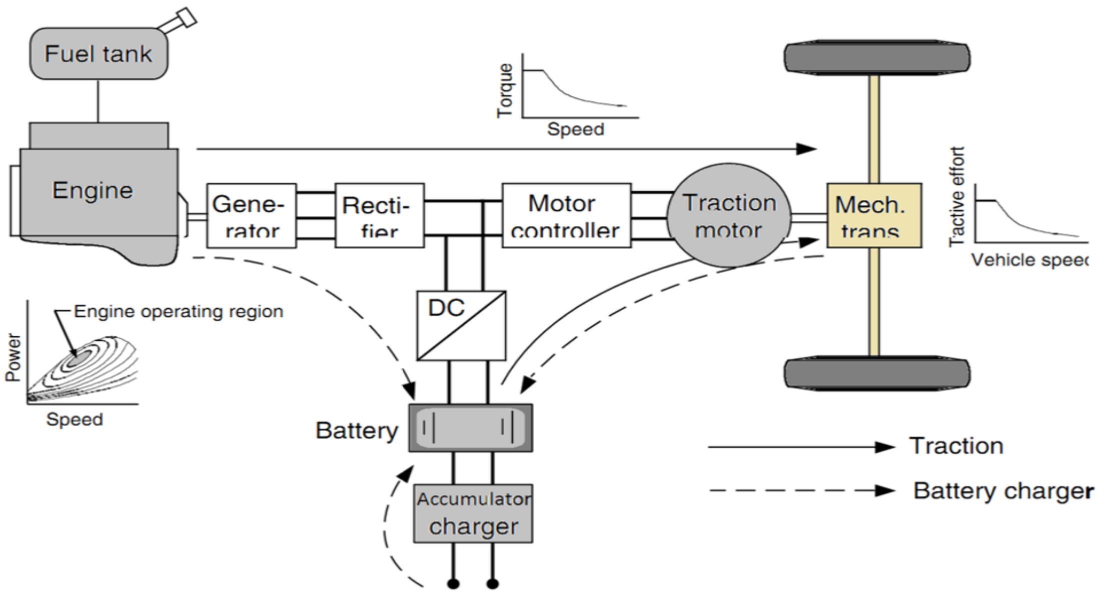

Figure 1.6: Series HEV [8] .

Advantages of series HEV:

* Flexibility of location of engine-generator set

* Simplicity of drivetrain

* Suitability for short trips.

Disadvantages of series HEV:

* It needs three propulsion components: ICE, generator, and motor * The motor must be designed for the maximum sustained power that the vehicle may require, such as when climbing a high grade. However, the vehicle operates below the maximum power most of the time; * All three drivetrain components need to be sized for maximum power for long- distance, sustained, high-speed driving. This is required, because the batteries will exhaust fairly quickly, leaving ICE to supply all the power through the generator.

*** Parallel HEV**

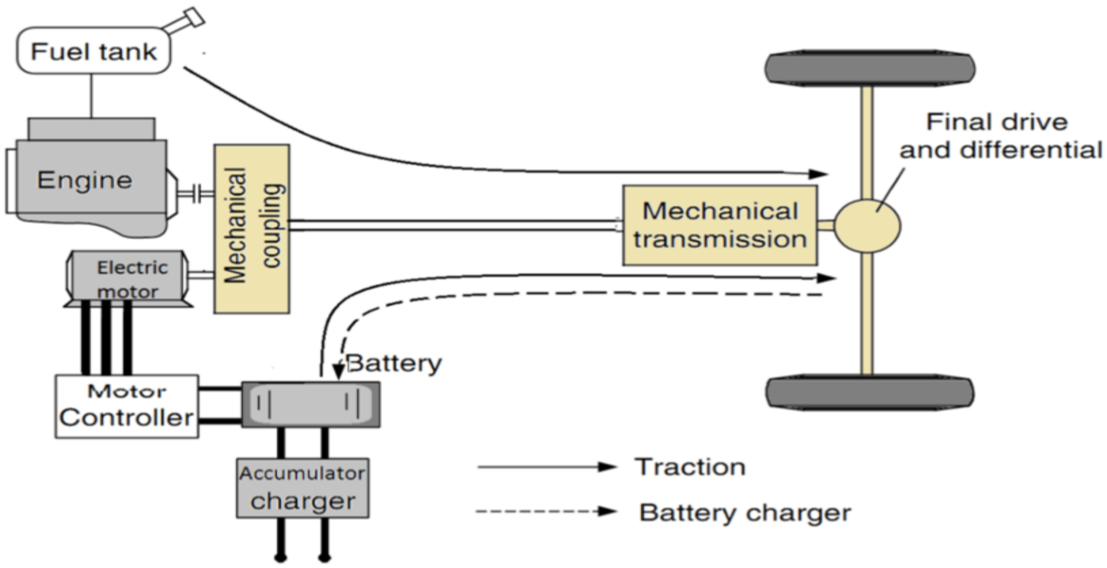

Figure 1.7: Parallel HEV [8] .

A parallel hybrid is one in which more than one energy source can provide propulsion power. The heat engine and the electric motor are configured in parallel, with a mechanical coupling that blends the torque coming from the two sources. The component arrangements of a parallel hybrid are shown in Fig 1.7.

Advantages of hybrid HEV

* It needs only two propulsion components: ICE and motor/generator. In parallel HEV, the motor can be used as the generator and vice versa;
* A smaller engine and a smaller motor can be used to get the same performance, until batteries are depleted. For short-trip missions, both can be rated at half the maximum power to provide the total power, assuming that the batteries are never depleted. For long-distance trips, the engine may be rated for the maximum power, while the motor-generator may still be rated to half the maximum power or even smaller.

Disadvantages of hybrid HEV:

* The control complexity increases significantly, because power flow has to be regulated and blended from two parallel sources;
* The power blending from the ICE and the motor necessitates a complex mechanical device.

Series-parallel combination:

Although HEVs initially evolved as series or parallel, manufacturers later realized the advantages of a combination of the series and parallel configurations for practical road vehicles. In these combination hybrids, the heat engine can also be used to charge the battery. The recently available Toyota Prius is an example of such a hybrid, where a small series element is added to the primarily parallel HEV . The small series element (yellow element in Fig1.8. ensures that the battery remains charged in prolonged wait periods, such as at trafic lights or in a trafic jam. These hybrid combinations can be categorically classified under parallel hybrids, because they retain the parallel structure of a component arrangement. It is important to stress the fact that the detailed configuration of an HEV depends on the application and the trade-off between cost and performance.

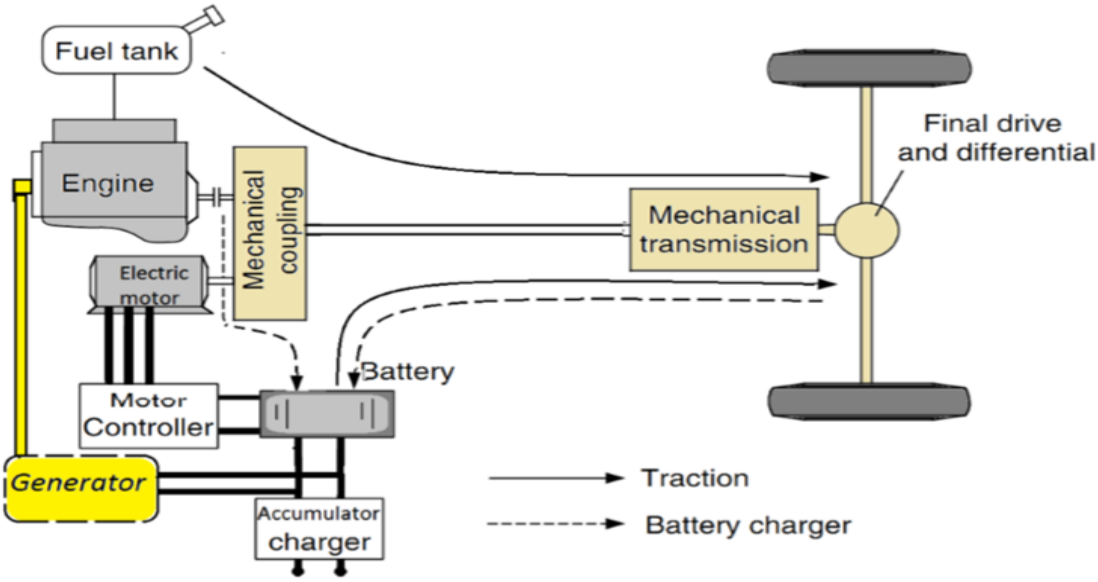

Figure 1.8: Series-parallel combination [8] .

AdvantagesSeries-parallel combination HEV:

* high autonomy and travel range;

* The most sold

* Rival to ICE vehicle.

* less polluting.

disadvantagesSeries-parallel combination HEV:

* High complexity of the drive traine;

* High complexity of its management components

*High cost and mass.

1.2.4 EV Motor Drives Evaluation

In EVs, the electric motor is the propulsion unit, while in hybrid electric vehicles (HEVs), the electric motor and the ICE together in a series or parallel combinations provide the propulsion power. In an EV or an HEV, the electric traction motor converts electrical energy from the energy storage unit to mechanical energy that drives the wheels of the vehicle. The major advantages of an electric motor over an IC engine are that the motor provides full torque at low speeds and the instantaneous power rating can be two or three times the rated power of the motor. These characteristics give the vehicle excellent acceleration with a nominally rated motor. As so far, four types of motor drive shave been applied to EVs. They are Direct Current Motor (DCM)drives, Induction Motor (IM) drives, Permanent Magnet Synchronous Motor (PMSM) drives, and Switched Reluctance Motor (SRM) drives.[5]

- **Direct current motor**

  Among the classic motors used in EV, the DCM with independent excitation, is the most economical solution through its armature chopper-type converter with two switches (the inductor is also powered by a small power chopper). This is the technology used by many automakers to commercialize EVs first generation. But the DCM has a number of well-known drawbacks. Positive attributes of DC machines are as follows:

  * Ease of control due to linearity;

  * Capability for independent torque and flux control;

  * Established manufacturing technology.

  Disadvantages of DC machines include the following:

  * Brush wear that leads to high maintenance;

  * Low maximum speed;

  * Low power-to-weight ratio.

  The separately excited DCM used in an EV or HEV has two separate DC/DC converters supplying the armature and field windings from the same energy source, The DC/DC converters process the fixed supply voltage of the energy source to deliver a variable DC to the armature and field circuits. The power rating of the converter supplying the armature windings is much larger than that of the converter supplying the field winding. Control inputs to the converter circuits are the desired torque and speed of the motor. Control outputs of the converters are the voltages applied to the armature and field circuits of the DC motor. The performance analysis and modelling of used DCM in the studied EV will be shown in the next chapter.

- **Induction motor drives**

  Induction motors are of simple construction, reliability, ruggedness, low maintenance, low cost, and ability to operate in hostile environments. The absence of brush friction permits the motors to raise the limit for maximum speed, and the higher rating of speed enable these motors to develop high output. Speed variations of induction motors are achieved by changing the frequency of voltage. Field orientation control (FOC) of an IM can decouple its torque control from field control. This allows the motor to behave in the same manner as a separately excited DCM. This motor, however, does not suffer from the same speed limitation sasin the DCM. Extended speed range operation beyond base speed is accomplished by flux weakening, once the motor has reached its rated power capability. A properly designed IM, e.g., spindle motor, with field oriented control can achieve field weakened range of 3-5 times the base speed. However, the controllers of IMs are at higher cost than the ones of DCM. Furthermore, the presence of a breakdown torque limits its extended constant-power operation. At the critical speed, the breakdown torque is reached. Generally, for a conventional IM, the critical speed is around two times the synchronous one. Any attempt to operate the motor at the maximum current beyond this speed will stall the motor. Although FOC may extend constant power operation, it results in an increased breakdown torque thereby resulting in an over-sizing of the motor. In addition, efficiency at a high-speed range may suffer in addition to the fact that IMs efficiency is inherently lower than that of a Permanent Magnet Synchronous Motors (PMSM) and Switched Reluctance Motors (SRMs) due to the absence of rotor winding and rotor copper losses.

- **Switched Reluctance Motor Drives**

  SRM drives are gaining much interest and are recognized to have a potential for EV applications. These motor drives have definite advantages such as simple and rugged construction, fault-tolerant operation, simple control, and outstanding torque-speed characteristics. SRM drives can inherently operate with an extremely long constant-power range. The torque-speed characteristics of SRM drives match very well with the EV load characteristics. The SRM drive has high speed operation capability with a wide constant power region. The motor has high starting torque and high torque-inertia ratio. The rotor structure is extremely simple without any windings, magnets, commutators or brushes. The fault-tolerance of the motor is also extremely good. Because of its simple construction and low rotor inertia, SRM has very rapid acceleration and extremely high-speed operation. Because of its wide speed range operation, SRM is particularly suitable for gearless operation in EV propulsion. In addition, the absence of magnetic sources (i.e., windings or permanent magnets) on the rotor makes SRM relatively easy to cool and insensitive to high temperatures. The latter is of prime interest in automotive applications, which demand operation under harsh ambient conditions. An extended range of 2-3 times the base speed is usually possible using an appropriate control. The disadvantages of SRM drives are that they have to suffer from torque ripple and acoustic noise. However, these are not potential problems that prohibit its use for EVs application.

- **Permanent Magnet Synchronous Motors**

  The PMSM can be thought of as a cross between an AC IM and a brushless DCM. They have rotor structures similar to DCM motors which contain permanent magnets. Advantages of PMSM are well known. The greatest advantage is low volume of the PMSMs in contrast with other types of motors, it makes them suitable for wheel motor applications. On the other hand, the traction drive with PMSM has to meet special requirements typical for overhead line fed vehicles. The drives and specially their control should be robust to wide overhead line voltage tolerance (typically from -30 % to +20 %), voltage surges and input filter oscillations. These aspects may cause problems during flux weakening operation. PMSM motor drives have the drawbacks in that the magnet is expensive and that the mechanical strength of the magnet makes it dificult to build a large torque into the motor. PM BLDC motors have no brush to limit speed, but questions persist over the fixing intensity of the magnet because it restricts the maximum speed if the motors are of an inner-rotor type. Furthermore, this motor suffers from a rather limited field weakening capability. This is due to the presence of the PM field which can only be weakened through production of a stator field component which opposes the rotor magnetic field. Nevertheless, extended constant power operation is possible through the advancing of the commutation angle.[5]

- **Comparison between four types of EV motor drives**

  The most appropriate choice for EVs among four types of motor drives is determined according to the following factors: weight factors in efficiency, weight, and cost. From the above summarized features of four types of motor drives for EVs, Table 3.1 lists weight factors in efficiency, weight, and cost of four types of motor drives..

Indes	DCM	IM	PMSM	SRM
Effeciency	medium	high	high	high
Weigh	medium	medium	high	low
Cost	low	medium	high	high

Table 1.1: Comparison between four types of EV motor drives

The above table indicates that DCM drives will continue to be used in EVs because DC motor drives are available at the lowest cost. From the point of view of efficiency, PMSM motor drives are the best choice. SRM drives have the lowest weight among four types of motor drives for EVs. If the choice of motor drives for EVs is determined by three factors that are weight, efficiency and cost, it is clear that SRM drives are the best choice for EVs. Except for the efficiency, weight and cost, SRM drives also have the ascendancy in the aspects of cooling, maximum speed, fault tolerance, and reliability.[5]

1.2.5 EV Advantages

The relative advantages and disadvantages of an EV over an ICEV can be better appreciated from a comparison of the two on the bases of efficiency, pollution, cost, and dependence on oil. The comparison must be executed with care, ensuring fairness to both systems.[5]

- **EFFICIENCY COMPARISON**

  To evaluate the efficiencies of EV and ICEV on level ground, the complete process in both systems starting from

$$P_{IN} = P_{IN\ PROCESS} + P_{IN\ RAW}$$

crude oil to power available at the wheels must be considered. The EV process starts not at the vehicles, but at the source of raw power whose conversion efficiency must be considered to calculate the overall efficiency of electric vehicles. The power input PIN to the EV comes from two sources-the stored power source and the applied power source. Stored power is available during the process from an energy storage device. The power delivered by a battery through electrochemical reaction on demand or the power extracted from a piece of coal by burning it are examples of stored power. Applied power is obtained indirectly from raw materials. Electricity generated from crude oil and delivered to an electric car for battery charging is an example of applied power. Applied power is labeled as PIN AW while stored power is designated as PIN PROCESS. Therefore, we have the following:

The complete EV process can be broken down into its constituent stages involving a chain of events responsible for power generation, transmission, and usage, as shown in Figure 1.9. Raw power from the applied source is fed to the system only at the first stage, although stored power can be added in each stage. Each stage has its efficiency based on total input to that stage and output delivered to the following stage. For example, the efficiency of the first stage based on the input and output shown in Figure 1.9 is :

$$\eta_1 = \frac{P_1}{P_{INRAW} + P_{INPROCESS1}} \tag{1.1}$$

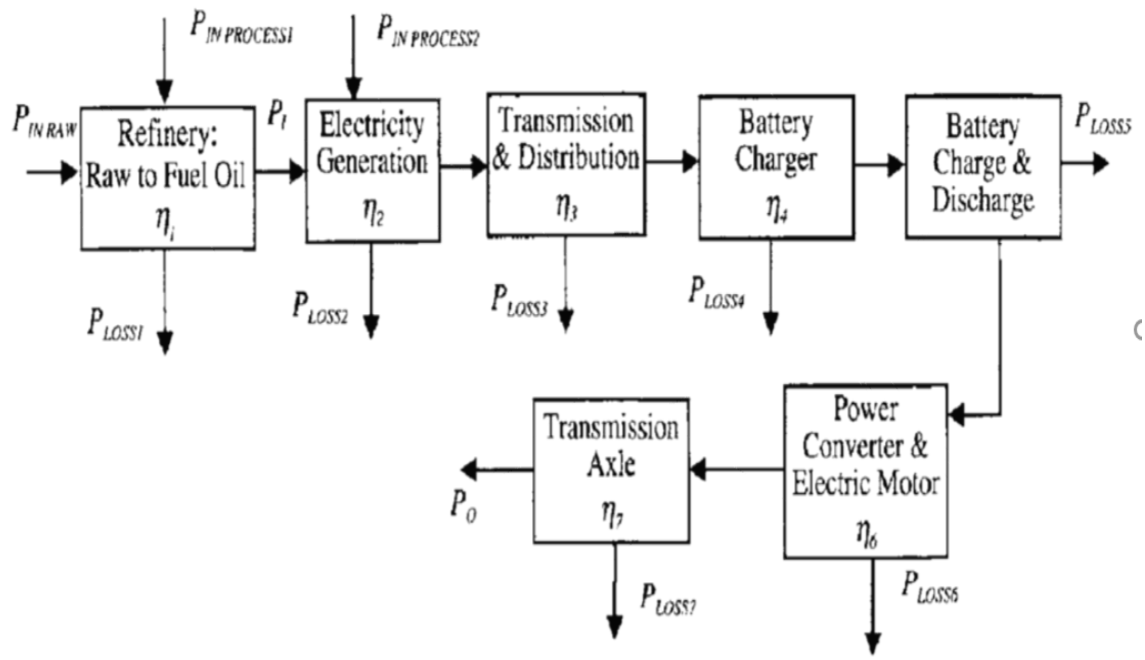

Figure 1.9: The complete EV process broken into stages. [5]

The efficiency of each stage must be calculated from input-output power considerations, although the efficiency may vary widely, depending on the technology being used. Finally, overall efficiency can be calculated by multiplying the efficiencies of the individual stages. The overall efficiency of the EV system shown in Figure 1.9 is

$$\eta_{EV} = \frac{P_0}{P_{IN}} = \frac{P_0}{P_0 + \sum_{i=1}^{7} P_{LOSSi}} = \eta_1\eta_2\eta_3\eta_4\eta_5\eta_6\eta_7 \tag{1.2}$$

The overall ICEV process is shown in Figure1.10, while the process details are illustrated in Figure 1.11. Starting from the conversion of crude oil to fuel oil in the refinery, the ICEV process includes the transmission of fuel oil from refinery to gas stations, power conversion in the internal combustion engine of the vehicle, and power transfer from the engine to the wheels through the transmission before it is available at the wheels. The efficiency of the ICEV process is the product of the efficiencies of the individual stages indicated in Figure 1.11 and is given by

$$\eta_{KCEV} = \eta_1\eta_2\eta_3\eta_4 \tag{1.3}$$

A sample comparison of EV and ICEV process efficiencies based on the diagrams of Figure 1.9 and 1.11 is given in Table 1.2. Representative numbers have been used for the energy conversion stages in each process to convey a general idea of the efficiencies of the two systems. From Table 1.2, it can be claimed that the overall efficiency of an EV is comparable to the overall efficiency of an ICEV.

TABLE 1.2 EV and ICEV Efficiencies from Crude Oil to Traction Effort

ICEV	Efficiency (%) Max.	Efficiency (%) Min.	EV	Efficiency (%) Max.	Efficiency (%) Min.
Crude oil			Crude oil		
Refinery (petroleum)	90	85	Refinery (fuel oil)	97	95
Distribution to fuel tank	99	95	Electricity generation	40	33
Engine	22	20	Transmission to wall outlet	92	90
Transmission/axle	98	95	Battery charger	90	85
Wheels			Battery (lead/acid)	75	75
			Motor/controller	85	80
			Transmission/axle	98	95
			Wheels		
Overall efficiency (crude oil to wheels)	19	15	Overall efficiency (crude oil to wheels)	20	14

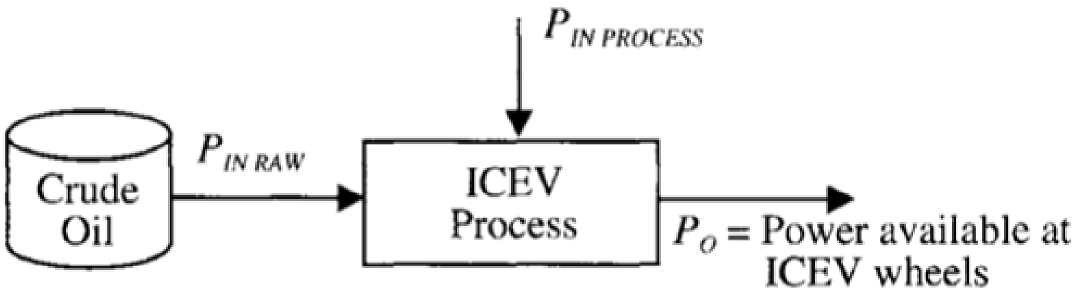

Figure 1.10: ICEV process from crude oil to power at the wheels [5]

POLLUTION COMPARISON

Transportation accounts for one third of all energy usage, making it the leading cause of environmental pollution through carbon emissions. The DOE projected that if 10% of automobiles nationwide were zero-emission vehicles, regulated air

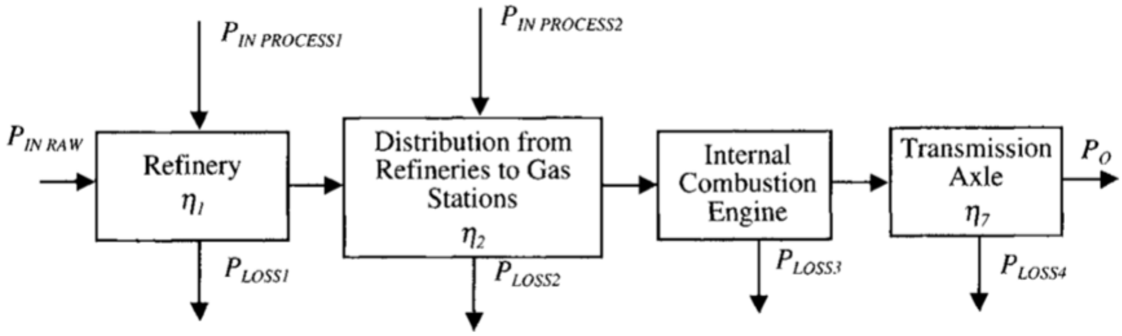

Figure 1.11: The complete ICEV process broken into stages [5]

pollutants would be cut by 1,000,000 tons per year, and 60,000,000 tons of greenhouse carbon dioxide gas would be eliminated. With 100% electrification, i.e., every ICEV replaced by an EV, the following was claimed:

* Carbon dioxide in air, which is linked to global warming, would be cut in half.
* Nitrogen oxides (a greenhouse gas causing global warming) would be cut slightly, depending on government-regulated utility emission standards.
* Sulfur dioxide, which is linked to acid rain, would increase slightly.
* Waste oil dumping would decrease, because EVs do not require crankcase oil.
* EVs reduce noise pollution, because they are quieter than ICEVs.
* Thermal pollution by large power plants would increase with increased EV usage. EVs will considerably reduce the major causes of smog, substantially eliminate ozone depletion, and reduce greenhouse gases. With stricter SO2 power plant emission standards, EVs would have little impact on SO2 levels. Pollution reduction is the driving force behind EV usage.

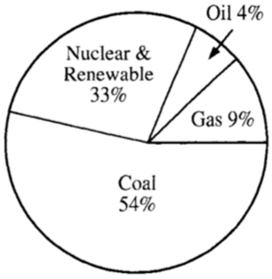

Figure 1.12: Electricity generation Pie chart [5]

CAPITAL AND OPERATING COST COMPARISON

The initial EV capital costs are higher than ICEV capital costs primarily due to the lack of mass production opportunities. However, EV capital costs are expected to decrease as volume increases. Capital costs of EVs easily exceed capital costs of ICEVs due to the cost of the battery. The power electronics stages are also expensive, although not at the same level as batteries. Total life cycle cost of an EV is projected to be less than that of a comparable ICEV. EVs are more reliable and will require less maintenance, giving a favorable bias over ICEV as far as operating cost is concerned.

1.3 Energy Management Strategies For EVs

1.3.1 Classification of EMSs

EMSs can be divided into three principle types: Rule-Based (RB), Optimization-Based (OB), and Learning-Based (LB). The RB-EMSs is working based on a set of predefined rules without prior knowledge of the trip. The OB-EMSs are aiming to find the optimal control sequence that minimizes a cost function. They have received more attention than RB-EMSs. However, the LB-EMSs use previous driving data for online learning, and they have shown promising potential.[8]As it shown in fig1.13.

We can find a versatile EMS which can include a mixture of different techniques (RB, OB, and LB) forming an integrated EMS (iEMS).[8]

In order to Improve the performance of the vehicles we can integrate a cloud database in an intelligent transportation system (ITS) and traffic information in a global positioning system (GPS) into EMS.[9]

In general, GPS or ITS information is used to update the control rules or parameters of an EMS. Different predictive techniques have been proposed by researchers to recognize and predict future driving conditions, including GPS- or ITS-based techniques, Statistic and Clustering Analysis techniques, and Markov Chain-based techniques.[8]

- **Rule-based EMSs**

  RB-EMSs' Rules are generally based on heuristics, intuition[10]or human expertise without a priori knowledge of the driving cycle. [1] They rely on a set of rules to decide the value of the control to apply at each time, and they do not involve explicit minimization or optimization.[10]

  The main advantages are their simplicity, robustness to vehicle parameter uncertainties and effectiveness in computation. Therefore RB-EMSs are appropriate for real-time implementation.[11]] However, an RB-EMS has several disadvantages. The first is its lack of optimality. In addition, requirement of a significant calibration effort to guarantee the performance within a satisfactory range for any driving cycle. The setting rules are not scalable to different powertrain architectures or different component sizes. Other optimization and recognition techniques can be integrated into an RB-EMS to enhance their performance. Such strategies include a multi-mode strategy combined with an ECMS, a thermostat combined with driving recognition, and a multi-mode EMS based on driving pattern identification using learning vector quantization and a neural network. Although a rule-based EMS may not obtain the optimal solution, it has still received attention owing to its simplicity in terms of a real-time implementation. RB-EMSs can be further sub-classified into deterministic and fuzzy-logic EMSs.[8]

  A) Deterministic strategies:

  In a deterministic RB-EMS, the rules can be extracted from experience, in which the main energy sources (i.e. ICE and fuel cell) are controlled to perform mostly under optimal working conditions or in a high efficiency region to enhance the fuel economy and minimize the energy transmission loss [1]. Typically, the algorithms are implemented through look-up tables[11].

  *** Optimal working condition based strategies:**

  \- Thermostat (on/off) strategy:

  In the thermostat strategy(known as an on/off strategy), ICE operates at its

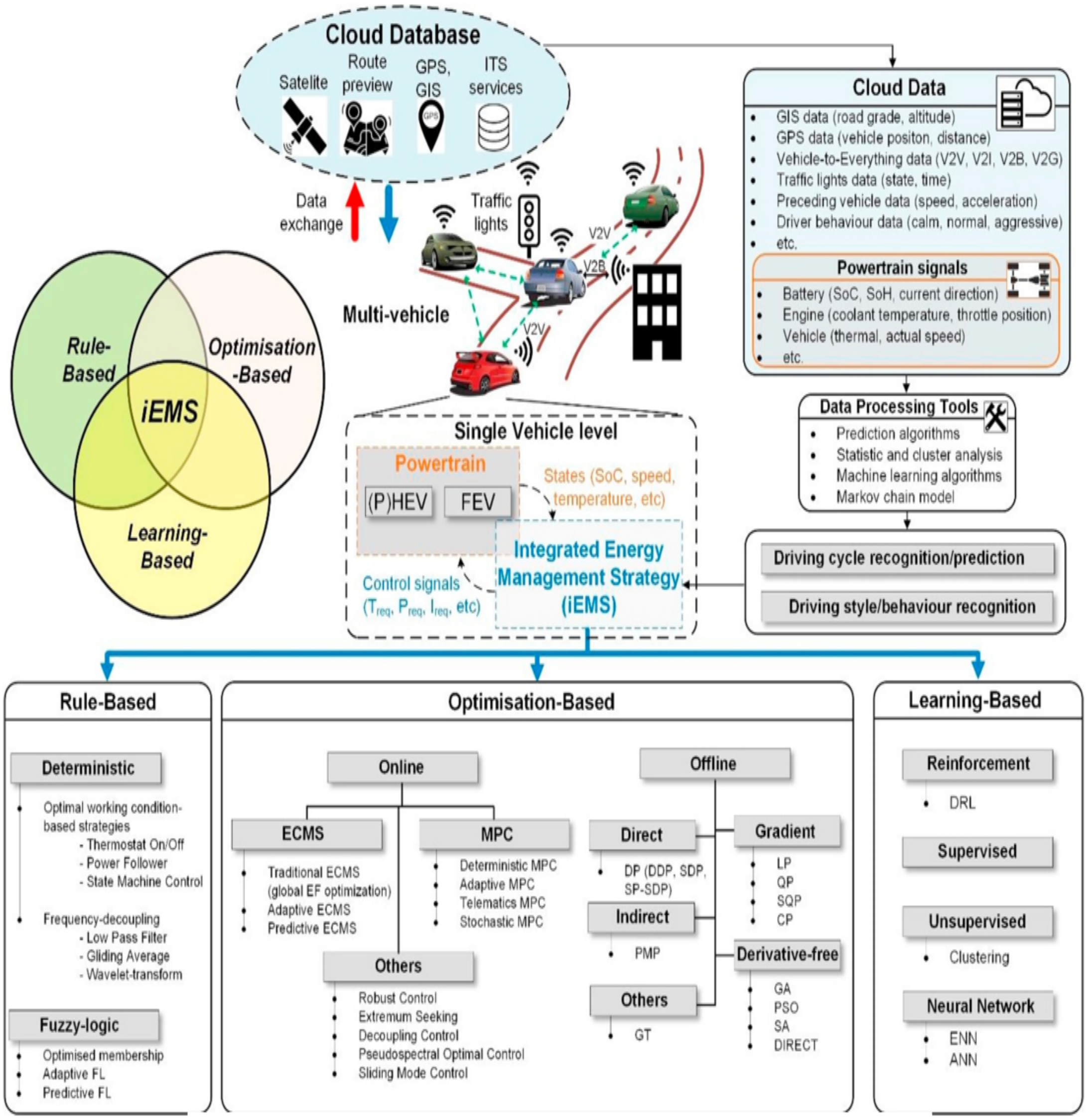

Figure 1.13: : Classification of EMSs and the iEMS concept. [8]

highest efficiency point once it turns on, while battery SOC is always maintained between its preset upper and lower bounds by turning on or turning off ICE. Although the thermostat strategy provides best efficiency for the engine-generator set, overall system efficiency of HEV is low. Furthermore, the battery pack requires high performance to satisfy power demands under various operating conditions. Therefore, the thermostat strategy is mostly used in series HEVs. [12]Similarly, the thermostat strategy can be applied in an FC-battery-SC system. In this case, the FC operates at the most efficient power level and turns on/off when the battery SoC reaches the low/high limit, respectively [8].

- Power follower (baseline) strategy:

The power follower strategy (known as a baseline control) uses ICE as main power source, ICE works along its optimal working curve as much as possible while EM is used to provide additional power and sustain battery SOC. Compared to the thermostat strategy, the power follower strategy improves overall system efficiency and the durability of the battery pack and other electrical components. The power follower strategy is applicable to parallel HEVs and series-parallel HEVs. [12]

Combining the advantages of both strategies above, a hybrid thermostat and power follower can further improve the fuel economy of a series HEV and a parallel HEV.[8]

- State machine strategy (multi-mode strategy):

The state-machine based strategy (SMS), also known as a multi-mode strategy, is composed of a set of states, a set of transitions, and actions. In this strategy, first, all possible vehicle operation modes are identified and defined as controller states. Next, the transitions between these states are determined by considering a change in driver demand, a change in vehicle operating condition, or a system or a subsystem fault, in conjunction with the performance and drivability objectives. In the final stage, transitions are analyzed for exclusivity in order to guarantee single-valued decisions within the state machine. Dynamic control or optimization algorithms may be used to generate output commands to each powertrain subsystem according to desired power demand and vehicle states. This strategy is applicable to any hybrid powertrain configuration, furthermore it can be applied to an FCEVs as it's done by Xu et al[13]]. Although it has a simple and robust structure for practical implementation, its use cannot guarantee optimization of the performance objectives, such as fuel economy or emissions[11].

- Frequency-decoupling strategies:

This strategy relies on a decoupling of the low- and high-frequency components of the load demand signal and applying low-frequency content to the high-energy source in the system, whereas the high-frequency is compensated using an auxiliary fast-responding source. Frequency-decoupling can be realized through a simple low-pass filter (LPF), a gliding average strategy (known as a Phlegmatising strategy), or a time-frequency representation tool such as a wavelet-transform (WT) [8]. Low-pass filtering incorporated with load-leveling, which is mainly applied in series HEVs [12]. This strategy can also be applied to FCEV and FC-battery systems to soften the battery and FC peak current demand, respectively [8] . Compared with the thermostat strategy, it can improve fuel economy, decrease emissions and increase battery life simultaneously [12].

B)Fuzzy logic strategies:

An FL strategy converts human experience and reasoning into a set of IF-THEN rules. This conversion process consists of five stages: input quantization, fuzziness, fuzzy reasoning, inverse fuzziness, and output quantization. The performance of an FL strategy is determined by the membership function and fuzzy rules at the fuzzy reasoning stage. Because the fuzzy rules can be easily tuned, the advantage of this method is its robustness owing to its independence from the mathematical model of the controlled system and its adaptation. This enables the FL strategy to handle the multi-domain, time-varying, and nonlinear problems found in the EMS of the vehicle system. As an example, It can be used to coordinate the operation of parallel HEV subsystems or to efficiently control the engine operation or to determine the power split between the engine and motor using a forward-facing model built in PSAT. However, FL strategies cannot guarantee an optimal performance .[8]

- Optimised-fuzzy-rules control:

An optimised FL controller is used to tune the controller through an optimisation algorithm to achieve the control objectives, such as a minimisation of the fuel consumption, a minimisation of the emissions, and SoC maintenance, and enhance the driving performance. To improve the fuzzy RB strategy applied, the membership function and fuzzy rules can be optimised by utilising evolutionary optimization algorithms such as the proportional factor algorithm, PSO, GA, and Bee algorithm for an HEV, or the DIRECT algorithm for a fuel-cell HEV [8].

-Adaptive fuzzy logic control:

Adaptive algorithms are integrated in an FL-RB strategy to improve its self-adaption. There are many combinations such as: the decentralized adaptive control system (DACS) which was applied for a four-wheel-drive HEV power-train for adaptation with unknown tire dynamics, changing road surfaces, and vehicle loading. The adaptive neural fuzzy interference system to maximize the vehicle torque and minimize the fuel consumption. The compensation fuzzy neural network (CFNN) with two neural-network-based adaptive estimators was used for the torque and speed of both the EM and engine, can obtain a better acceleration and deceleration performance of an HEV. The CFNN is a hybrid control system that merges the features of both a fuzzy neural network controller and an adaptive compensated controller. the learning optimal power sources (LOPPS) and a fuzzy power controller for an HEV powertrain based on multiple sources. The LOPPS algorithm learns from simulation data on the possible requested power with SoC constraints, and then generates the optimal power sharing between the power sources for an online EMS application [8].

- Predictive fuzzy logic control:

Predictive FL control works based on the predicted future state of the vehicle, performing real-time control tasks and generating control power sharing signals. Predictive FL-RB can be designed to determine how a vehicle reacts to the future states of a traffic flow and steep grade gathered from a GPS [8].

- **Optimisation-based EMSs** The objective of optimization-based (OB) EMS is to find the optimal control sequence (i.e. reference power demand) that minimizes a cost function while meeting the dynamic state constraints such as the global state constraints (e.g. battery SoC) and local state constraints (e.g. power limit, speed limit, and torque limit). The cost functions can be in different representations such as the fuel consumption, the hybridization costs, the payload weight of the vehicle, the exhaustive gases emissions (i.e. NOx, HC, and CO), the power efficiency of the electric generation path in a series HEV, the hydrogen consumption in an FC-FEV, and the root mean square (RMS) of the battery current in an FEV. The OB strategies can generally be grouped into two types, offline and online strategies, according to their dependency on a priori knowledge and information of the driving conditions [8].

A)Offline strategies:

An offline OB strategy is a non-causal and global optimisation strategy because it requires a priori knowledge from typical driving cycles. The importance of finding non-causal optimal solutions of offline strategies is in providing a benchmark solution (global optimum) that other causal strategies can be compared against, and providing modified online strategies. Therefore, offline strategies are still gaining attention from researchers. Because power flow paths are different between powertrain topologies, the problem formulation is also different. For example, an optimisation problem in a series HEV can be a minimisation of the energy consumed along the generation path. In a parallel HEV, the optimisation problem can be a minimisation of the fuel consumption and the selected emission species over the driving cycle. The constraints are normally the power demand for the vehicle, the boundary of the battery SoC, or the drivability. After defining the problem and constraints, an algorithm needs to be employed to find a solution, such as in a gear-shifting sequence, or a power-split between the ICE and the EM. Regarding the problem-solving approaches used for the EMS problem, offline OB strategies can generally be sub-divided into four types: direct, indirect, gradient, and derivative-free types. Direct algorithms approximate an optimal control problem as a static optimisation through a discretisation, whereas indirect algorithms are based on the optimal control theory and a calculus of the variations. By contrast, gradient algorithms use the derivative information of the objective function, which is under mathematic conditions such as the continuity, differentiability, or satisfying the Lipschitz condition, to solve the optimisation problem. To avoid a dependency on the derivatives, derivative-free algorithms use a stochastic search iteratively over the entire design space to find the global optimum. A classification of offline OB EMS strategies according to the problem-solving approach is shown in Fig1.14

-direct algorithms:

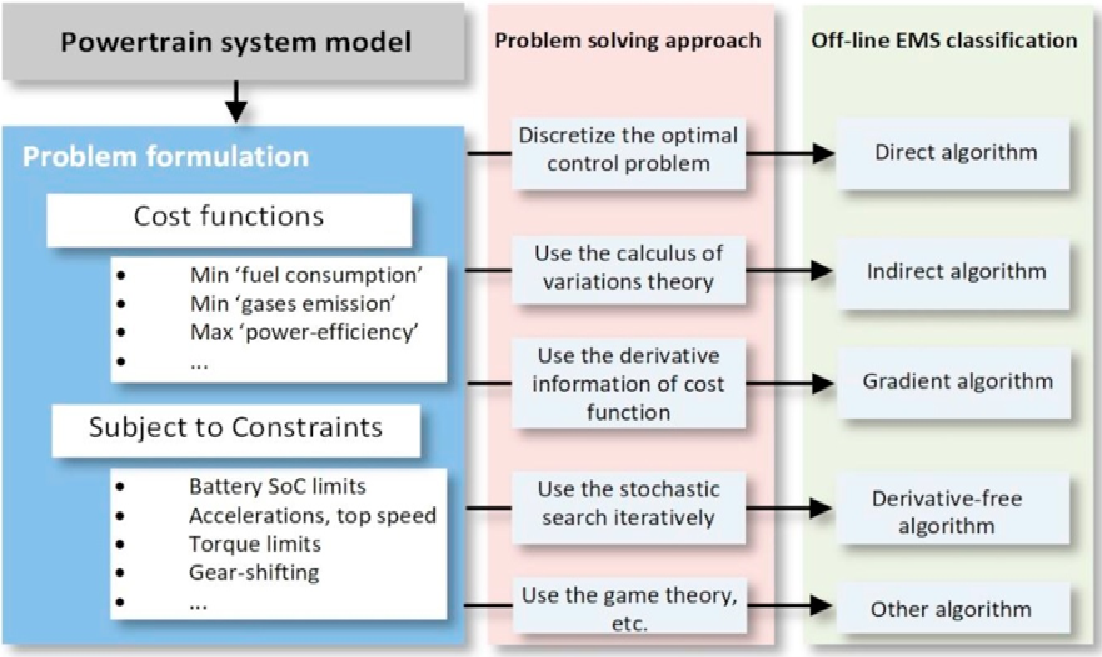

Figure 1.14: : Classification of offline OB-EMSs based on problem solving approach [8]

The most widely used algorithm for solving the EMS optimisation problem directly in an offline application is dynamic programming (DP), which was pioneered by Bellman during the 1950s to find numerical solutions. Because DP requires a priori knowledge of the driving cycle, it is also known as deterministic DP (DDP). The basic ideas behind DDP is that the nonlinear dynamic optimisation problem is subdivided into sub-problems in a discrete time. A cost-to-go function is then formulated at each sample time. The same optimal control policy can be achieved by using a backward recursive method or a forward dynamic programming technique to solve the sub-problems. The utilisation of DDP can be found in various types of HEVs, PHEVs and for a fuel cell-battery FEVs to minimise the cost function formulated from a serial multiplication function of a SoC deviation, the hydrogen consumption, and the excess oxygen ratio. The drawbacks of DDP make it infeasible for real-time implementation. Although DDP can be only used offline, it has been still useful as an optimal benchmark for other controllers or as a method to extract the control parameters for the RB EMSs. To overcome DDP issues, the stochastic DP (SDP) was developed, in which the model of the driver demand is treated as a Markov chain with transition probabilities. The EMS is then optimised over a family of random driving cycles in an average sense. However, SDP still has certain drawbacks. To handle them a new technique was developed a shortest path SDP (SP-SDP), which is known to be a variation on an infinite horizon SDP. The SP-SDP technique achieves a better SoC control and has fewer parameters to tune owing to a minimisation of the total undiscounted costs.[8]

-Indirect algorithms:

The most well-known algorithm for solving the optimal control problem indirectly is Pontryagin's minimum principle (PMP), which is an extension of the calculus of variations, particularly the Euler-Lagrange equation. For an optimum solution, the PMP provides only the necessary conditions while the sufficient conditions are satisfied using the Hamilton-Jacobi-Bellman equation. The key idea of the PMP is that the constrained global optimisation problem is reduced to the local Hamiltonian minimisation problem. The Hamiltonian is characterised by a costate, which is interpreted as a weighting factor for the electrical usage. The optimal value of the initial costate can be found through an iterative process if full knowledge of driving cycle is pre-determined. With different driving cycles, the initial costate may have different values. The PMP has a heavy computation load, because the size of the look-up table will increase exponentially with the number of dimensions. This means the storage capacity and computational power of the controllers also need to be increased, leading the PMP to be inapplicable for direct use in real-time applications. PMP was tested for a parallel HEV, a hybrid electric refuse truck, FEV, for an FC-SC vehicle combined with Markov chain.Although the PMP offers optimal solutions close to the DP results, the initial costate has a considerable effect on the SoC variation. Therefore, a number of solutions have been proposed to estimate the initial costate [8]

-Gradient algorithms: Vehicle powertrains have become more sophisticated with nonlinear models of the ICE, EM, battery, and complex constraints. To reduce the calculation time and increase the robustness of the optimisation solution, the powertrain systems or objective functions need to be efficiently simplified as analytical equations for use in the gradient algorithms. Such algorithms use the derivative information of an objective function, which is under mathematic conditions, such as the continuity or differentiability, or satisfy the Lipschitz condition to solve the optimisation problem. Gradient algorithm-based EMSs are mainly classified into linear programming (LP), quadratic programming (QP), sequential quadratic programming (SQP), and convex programming (CP). The LP frames the algorithms for a solution to the optimisation problems with linear objectives and constraints, the QP frames the algorithms for a solution to the optimisation problems using quadratic objective and linear constraints, and CP frames the algorithms for a solution to the optimisation problems using convex objective and concave inequality constraints.

-Derivative-free algorithms:

The use of derivative-free algorithms (DFAs) in an EMS control application is among the potential techniques to solve problems in which derivative information is unavailable, unreliable, or impractical to obtain. Compared with gradient algorithms, DFAs are able to converge at a global solution. The DFAs for EMS control found in the literature mainly consists mainly of metaheuristic algorithms such as simulated annealing (SA), the genetic algorithm (GA), multi-objective genetic algorithm (MOGA), particle swarm optimisation (PSO), and divided rectangular (DIRECT) algorithm [8]

. **- Other algorithms:**

Game theory (GT) was applied to develop an EMS for a Jaguar Land Rover Freelander 2 HEV. Driver intention regarding the desired vehicle performance (called the leader) and the fuel economy (called the follower) were considered as two non-cooperative players who have conflicting objectives in a competitive game. In non-cooperative GT, most of the drivers do not think or explicitly try to optimise their driving behaviour for a better fuel economy and emissions while driving. GT was applied also to an FC HEV in which the powertrain

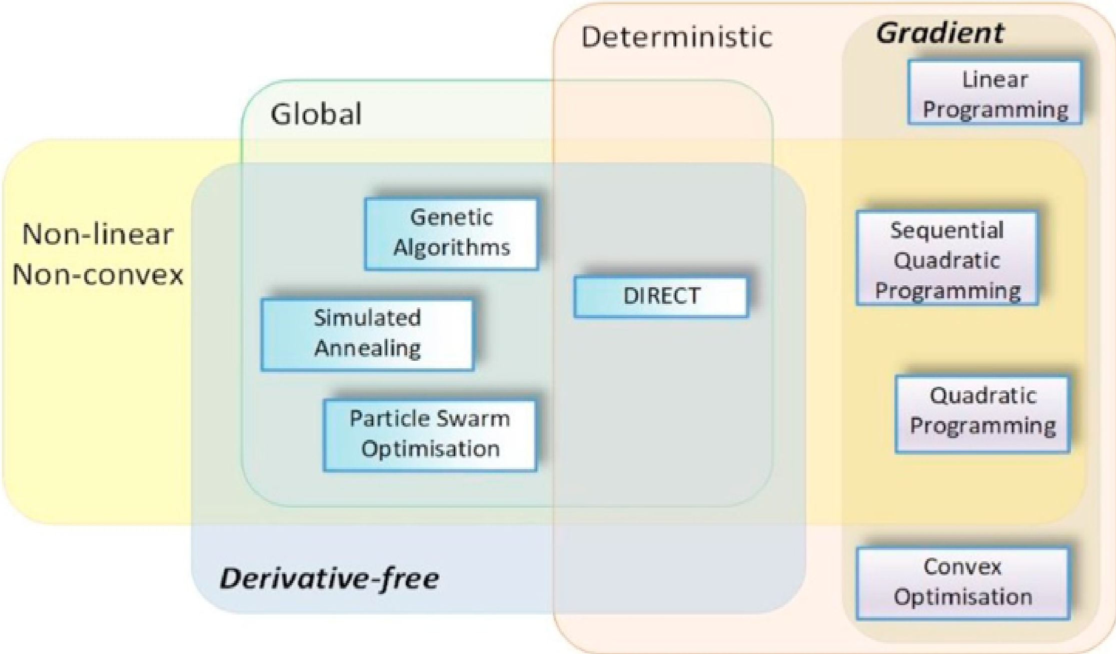

Figure 1.15: : Classification of offline OB-EMSs based on problem solving approach [8]

efficiency and vehicle performance are conflicting interests. Although GT uses simpler equations than DP and a similar receding horizon as MPC, the computation burden of GT can be comparable to that of DP, making its application difficult for online implementation. In addition, the dependency of GT to certain component models makes the extension of its applicability limited to the use in a broad range of powertrain systems [8]

B)Online strategies:

An online strategy is a causal and local optimisation strategy because it neither requires a priori knowledge of the driving cycle nor ensures the optimal solution in a real-time implementation. Conceptually, the global optimisation problem of an offline EMS is formulated in an instantaneous optimisation problem for implementation with a limited computational time and memory resources in real-time, An equivalent consumption minimisation strategy (ECMS) and model predictive control (MPC) are the most well-known real-time EMSs and have been extensively used in different applications.

- Equivalent consumption minimisation strategies:

The ECMS, as a realisation of offline PMP was originated for parallel HEVs that operate under a charge-sustaining condition. The global optimisation problem of PMP is reformulated into a local optimisation problem by minimising the equivalent fuel consumption. The ECMS calculates the equivalent fuel factor, which accounts for the actual fuel consumption required to recharge the batteries and to recuperate the regenerating braking energy. The equivalence factor (EF) of the ECMS has the same role as the costate of the PMP. Researchers have focused on a proper estimation of the EF, which is generally dependent on three unpredictable factors: the battery SoC limits, the direction of the electric current, and the driving cycle information. Many researchs' results show that the ECMS can provide the best performance in the hydrogen consumption reduction and minimum stress on the fuel-cell system.

- Model predictive control based strategies:

Model predictive control was introduced to tackle the issue of the DP algorithm [8]. MPC solves the power management optimization problem online at each time interval in a future time frame, based on the predicted states and inputs, while respecting the limitations and time-varying constraints of powertrain components such as the engine, motor, generator, and battery. In each time interval, new optimizations are completed using updated predictions and new measurement data. In such controllers, instead of using information about the future drive cycle, a mathematical model is used to estimate the torque demand and the resulting velocity over a future prediction horizon. The main advantage of MPC algorithms is their ability to handle constraints directly in the design procedure [11].

-Other algorithms:

*Robust control:

The objective of robust control (RC) is to determine an output feedback controller that minimises the fuel consumption. The effectiveness of RC can be used for the EMS of an FC-SC hybrid system of an FEV. It was reported that an RC-based EMS can operate the FC preferably at maximum efficiency to improve the hydrogen economy [8].

*Extremum seeking:

As an online adaptive optimisation algorithm, the extremum seeking (ES) method can be effectively employed to find an extremum (maximum or minimum) value of a static nonlinear system in real-time. The ES algorithm formulates a sliding surface where the objective function is forced to follow a time increasing function, and a discontinuous switching function is selected for the optimisation parameter [8].

* Decoupling contro:

Decoupling control (DC) is a modelbased strategy used to handle conflicting performance objectives, such as the fuel economy, SoC regulation, and drivability. By exploiting the structure of the powertrain dynamic model, decoupling means that the battery control and drivability control are decoupled using the power request constraint and vice versa [8]

. *Pseudospectral optimal control:

Another recent variation of an optimisation-based mathematical method extended to an EMS is pseudospectral optimal control (PSOC) which is a direct method for solving optimal control problems. PSOC transcribes an optimal control problem into a nonlinear programming (NLP) problem by parameterising the state and control variables using global polynomials at a set of collocation nodes. Therefore, it is necessary to model the powertrain components using analytic expressions rather than look-up tables [8].

*Sliding mode control

: Sliding mode control (SMC) has gained popularity in automotive application thanks to its robustness against time-varying parameters and the highly nonlinear nature of a vehicle system. Concerning a series HEV application proposed two chattering-free SMCs to restrict the engine operation to its region of optimal efficiency. One of the designed SMCs applies engine speed control whereas the other SMC controls the engine/generator torque, and together they maintain the engine to within the optimal efficiency region of the torque-speed curve. In a hybrid system of an FC, battery, and SC an SMC for three operational modes (i.e. normal, discharging, and charging) was used to keep the FC operating in only nearly steady state conditions. The SMC ensures a high safety and fast dynamics of the FC current. However, a fast sliding mode current loop for the SC converter is used to satisfy the power demand by the load and to share the current load demand between the FC and the SC [8].

c)Learning-based EMSs:

Learning-based EMS (LB-EMS) employs advanced data mining schemes for massive historical and real-time information to derive the optimal control law. In the LB-EMS, the precise model information is no longer required to make the control decision. However, it is difficult and time-consuming to establish a correct database the structure and size of which have a direct effect on the controller performance. Data-driven methods and machine learning are adaptive and are able to manage large datasets efficiently under different external driving conditions and drivers. LB algorithms can be incorporated into model-based approaches to tune the control parameters optimized for different driving cycle types (e.g. urban or highway), derive the thresholds for rule-based EMSs, or recognize the driver's driving style (e.g. calm or aggressive). By grouping the algorithms based on their learning type, an LB-based EMS can be sub-categorized into reinforcement learning, supervised/unsupervised learning, neural network learning, and classification learning approaches [8]

-Reinforcement learning : A reinforcement learning (RL) system consists of two components: a learning agent and an environment where the learning agent interacts continuously with the environment. At each time step, the learning agent receives an observation of the state of the environment. The learning agent then chooses an action, which is subsequently input to the environment. The environment then moves to a new state owing to the action, and the reward associated with the transition is calculated and fed back to the learning agent. Along with each state transition, the agent receives an immediate reward, which is used to form a control policy that maps the current state to the best control action upon that state. At each time step, the agent makes the decision based on its control policy. Ultimately, the optimal policy can guide the learning agent to take the best series of actions to maximise the cumulated reward over time, which can be learned after sufficient training. A graphical illustration of the learning system is given in Fig1.16. 6. The RLEMS can autonomously learn the optimal policy based on the data inputs, without any prediction or predefined rules. Several RL-based EMSs have recently been reported. An RL-EMS was proposed for a series HEV. A recursive updating algorithm representing the real-time power-request transition probability was proposed, leveraging the power-request transition probability in the near past and previous history. The Kullback-Leibler (KL) divergence rate was applied to measure the difference in the power-request transition probability. The RL algorithm was triggered to update the EMS online when the power-request transition probability differs significantly according to the KL divergence rate. A temporal-difference-learning strategy was adopted for the RL problem in a plug-in HEV. the RL method with a continuous state and action spaces, called an Actor-Critic method, was used to derive the optimal control strategy for a PHEV. A nested RL framework was presented for a parallel HEV, in which the inner-loop RL minimizes the operating cost and the outer-loop modulates the battery SoH degradation globally. Deep reinforcement learning (DRL)-based EMS combines a deep neural network, called a deep Q-network, with a conventional RL. a DRL-based EMS was designed for a PHEV using a fixed target Q network that can obtain the action directly from the driving state. However, the critical issue of the RL and DRL is how to output the continuous actions; otherwise, the ICE output torque will suffer from violent oscillations owing to the discretized output action. [8]

-Supervised learning:

In supervised learning, a model is prepared through a training process in which it is necessary to make predictions and corrections based on the prediction errors. The training process continues until the model achieves the desired level of accuracy of the training data. In supervised learning, the training data requires corresponding labels for the sake of a problem classification. Supervised learning has been considered for an EMS based on an error-correction learning approach. This assumption implies that the training data are labelled, and the desired output of the training input set is known to feed the training al-

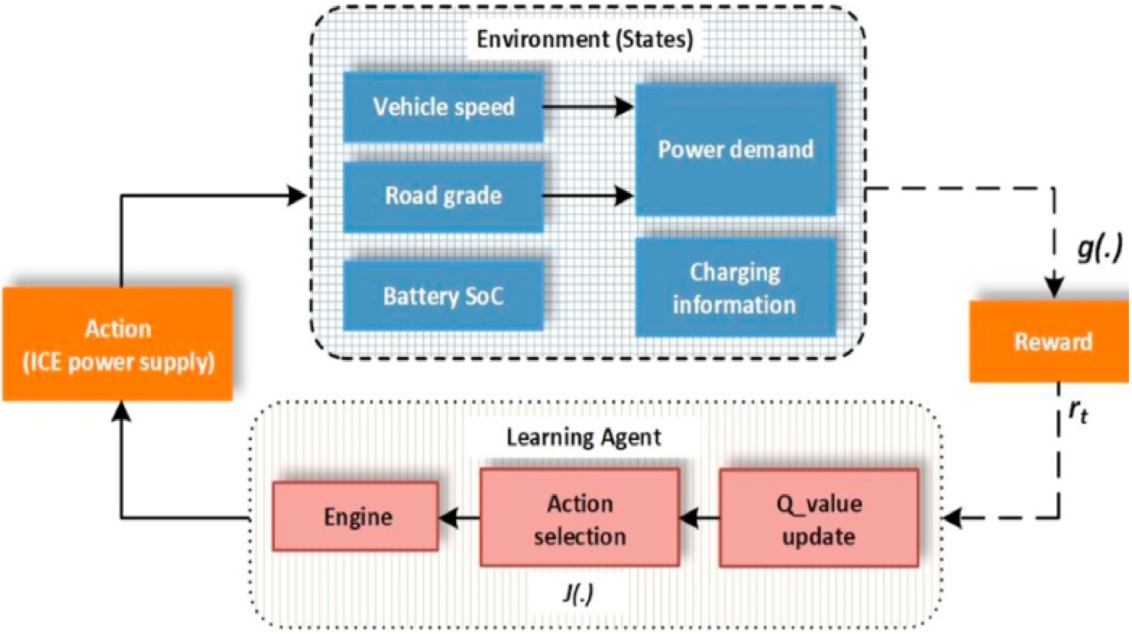

Figure 1.16: :Graphical illustration of a reinforcement learning system [8]

gorithm for a computation of the parameters and an emulation of the desired behaviour. In this regard, the root mean square error was used to assess the performance of the selection algorithm, which is precompiled from all possible conditions in the knowledge database storing the sensor data of the EM and gas engine, such as the fuel system status, engine coolant temperature, and throttle position. [8]

-Unsupervised learning:

In unsupervised learning, a model is prepared by deducing structures presented in the input data. The deduction procedure can (i) extract general rules, (ii) apply a mathematical process to systematically reduce the redundancy, or (iii) organise the data based on the similarity. The input data may come with an associated cost function for minimisation. The c-means clustering was used to group the elements of the database that contain the optimal hybridisation degree over standard driving cycles along with the corresponding state-vector of the vehicle, such as the vehicle speed, the battery SoC, the catalyst temperature, and the ICE temperature. A knowledge-based control strategy based on a fuzzy c-means clustering algorithm will be trained throughout all the driving cycles. Based on the same concept, to extract the RB control strategies for a parallel HEV, a clustering algorithm was used that is preliminarily run to generate the set of clusters.

D)Neural network learning :

Neural network learning (NNL) is modeled based on neurons in the human brain. Like a real neuron, which has multiple connections (i.e. synapses), nodes are objects in a neural network that have multiple inputs and outputs. By connecting many of these neurons into layers forming a network, different types of behaviors can be modelled. a machine learning framework that includes an artificial neural network was introduced for the roadway types and traffic congestion level prediction and another learning optimal energy control (i.e. the DP algorithm). Another type of NNL-based EMS for a vehicle is an Elman neural network (ENN), which can gradually learn by imitating the human brain. In essence, it improves the learned knowledge and the neuron weight. the instantaneous optimal control rules based on an ECMS was used to train the ENN and to maintain the SoC value within a high efficiency range and reduce the computational time by 60%. Other types of NNL such as neural dynamic programming, and a back propagation neural network can be used for an EMS in an HEV [8].

Chapter 2

Modelization of EV Electric System

THE electric vehicle that we will be working on it is illustrated on the diagram bellow. Which contains two main power sources A Lithium ion battery and super capacitor:

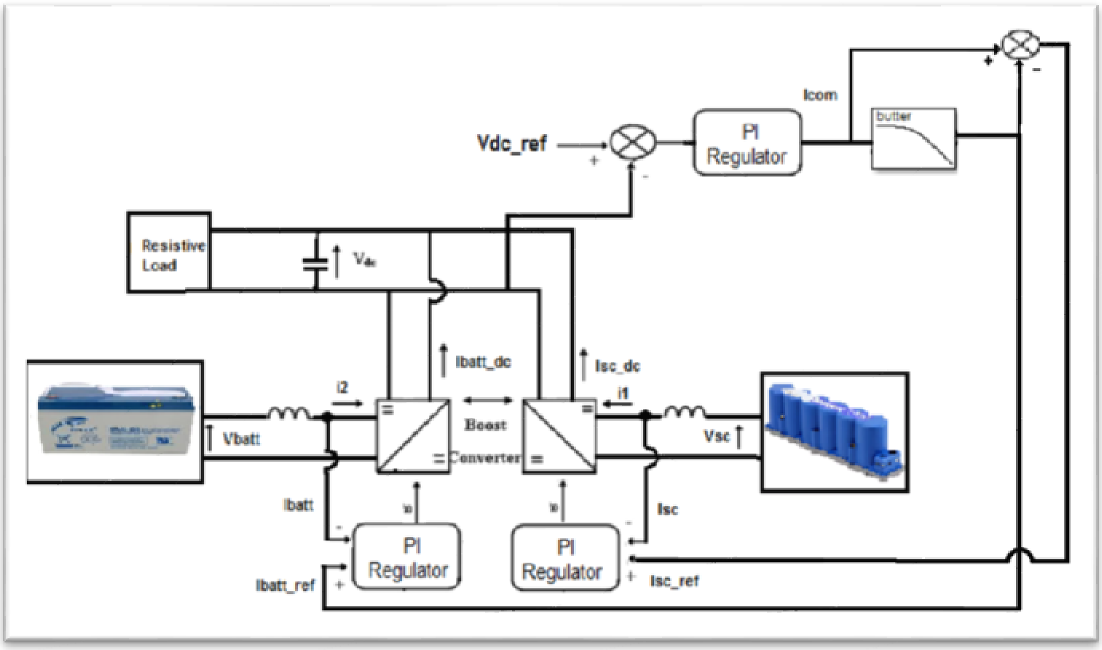

Figure 2.1: EV and EMS studied

The strategy we have chosen to manage the power demanded by the load from the two power sources we have,the Frequency-decoupling strategy, it relays on decoupling of the low- and high-frequency components of the load demand signal, and

applying low-frequency content to the high-energy source in the system (the battery), whereas the high-frequency is compensated using an auxiliary fast-responding source, which is in the case studied is the super capacitor.
So what happened exactly is that the load which presenting the motor on electric vehicle demand current (variable) and voltage (constant), so to keep the voltage coming from the DC bus stable we used a PI regulator who is responsible for generating a reference current then get decoupled to high and low frequency current by a low pass filter, afterword it applies low-frequency content to the high-energy source (the battery), and the high-frequency get compensated by the auxiliary fast-responding source (super capacitor), now likewise the firs phase, each one of the battery and Sc reference currents get compared with the real currents on each source then the regulator generate a signal that controls the duty cycle on the corresponding converter of each source to generate the suitable current that keeps the voltage of DC bus stable.
Now we are going to modulate the principle components of our system that contain initially, the lithium ion battery and back boost converter also a super capacitor and finely the PI regulators.

2.1 The Lithium Battery

Lithium is one of the lightest metals and have very interesting characteristics from electrochemical perspective. Indeed, it allows a very high thermodynamic voltage, which results in a very high specific energy and specific power.

- Lithium-Ion (Li-Ion) Battery:

Since its first announcement in the beginning of the 90's, Li-ion battery technology has seen an unprecedented rise to reach to what is now considered to be the most promising rechargeable battery of the future thanks to its poly-advantages, Although still at the development stage, the Li-ion battery has already being the suitable choice for EV and HEV applications.
Many battery manufacturers, such as SAFT, GS Hitachi, Panasonic, SONY, and VARTA, are actively engaged in the development of the Li-ion battery. Recently, SAFT reported the development of Li-ion high-power batteries for HEV applications

with a specific energy of 85 Wh/kg and a specific power of 1350 W/kg. They also announced high-energy batteries for EV applications with about 150 Wh/kg and 420 W/kg (at 80% SOC, 150 A current, and 30 sec) respectively. [8].

2.1.1 Lithium-ion Cell Principle of Function

During cell discharge, lithium ions (Li+) are released from the negative electrode that travels through an organic electrolyte toward the positive electrode. In the positive electrode, the lithium ions are quickly incorporated into the lithium compound material. The process is completely reversible[5]. The chemical reactions at the electrodes are as follows:
At the negative electrode:

$$\mathrm{Li_xC_6} \quad \mathrm{C6} + \mathrm{xLi^+} + \mathrm{xe^-} \qquad \text{where } 0 < \mathrm{x} < 1 \tag{2.1}$$

At the positive electrode:

$$\mathrm{xLi^+} + \mathrm{xe^-} + \mathrm{Li_{(1-z)}CoO_2} \quad \mathrm{LiCoO_2} \tag{2.2}$$

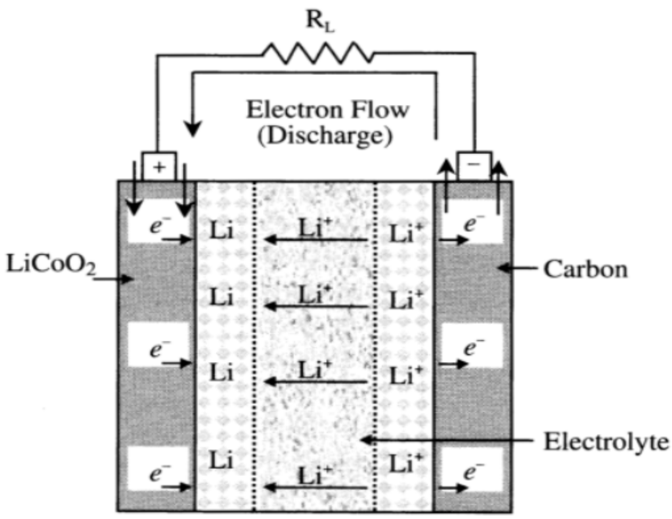

Figure 2.2: Lithium-ion cell [5]

During cell charge operation, lithium ions move in the opposite direction from the positive electrode to the negative electrode. The nominal cell voltage for a Li-ion battery is 3.6 V.

2.1.2 Battery Performance Characteristics

explained the concept of energy source/storage systems, including batteries and their parameters. This section describes the mathematical representation of battery performance characteristics and its related parameters, including capacity and state of charge (SoC)[11]

- **Battery Capacity:**
  batteryâs capacity Generally is the amount of electric charge that a battery can store in. The battery capacity size directly relates to the amount of electrolyte and electrode material inside the battery, the most electrolyte and electrode material are provided the more capacity gained. The battery capacity is also a function of other battery parameters such as the magnitude of the current, the allowable terminal voltage of the battery, the temperature, and other factors. The measurement unit of a batteryâs capacity is Ah (1Ah= 3600C or coulomb). In vehicle applications, it is preferable to measure energy stored in the battery as watt-hour (Wh). The energy capacity of a battery measured in Wh can be converted to Ah using Ohmâs rule that states battery power Pb= vb* ib, where vb and ib are the voltage and current of the battery[11] Thus:

  $$Eb = \text{ power* } \text{ time } = vb^{*} \text{ ib } ^{*} \text{ time} \tag{2.3}$$

  Therefore:

  $$\mathrm{Wh} = \mathrm{Ah}^{*}\mathrm{vb} \tag{2.4}$$

  The capacity can be expressed in energy unit if the voltage of the battery is known. It is noted that the theoretical capacity of a battery in is derived with assumption of constant current while, in practice, a variable electrical current is the case. Thus, the usable capacity, CU;b, of a battery is the electric current i(t) integrated over time:

$$CU,b = \int_{t0}^{tcut} i(t) \quad (2.5)$$

where, t0 is the time when a battery is at a full charge and tcut is the time when a battery terminal voltage is at the voltage cut, vcut. battery capacities are limited to the voltage cut in order to prevent sustaining permanent damage. Hence, the practical capacity is always less than the theoretical one because of practical limitations.

- **State of Charge/Discharge :**
  State of the charge (SoC) is a measure of residual capacity of a battery and is the equivalent of a fuel gauge for the battery pack in EVs/HEVs. In other words, it is the amount of capacity that remains after the discharge from the fully charged condition. The units of SoC are percentage points (0% =empty; 100% = full). Direct determination of SoC is not usually possible. However, it can be theoretically calculated using battery voltage and current.
  In the voltage method, the battery voltage is converted to SoC by a given discharge curve (voltage vs. SoC). However, the voltage is significantly affected by the battery current and temperatures. Therefore, the discharge curves are subject to variation under different operating conditions, thereby making this method unreliable. On the other hand, SoC can be theoretically calculated using the battery current and integrating it in time. The current is the rate of charge given by[11]:

$$I(t) = C_{T,b}\frac{dq}{dt} \quad (2.6)$$

where q is the per-unit charge (charged divided by the capacity) flowing thorough the circuit. For a time interval, dt, the theoretical battery state of charge, SoCT,b is:

$$dSoC_{T_\alpha b} = -dq = -\frac{1}{C_{T,b}}i(t)dt \quad (2.7)$$

Integrating from the initial time, t0, to the final time, t, and with consideration of dSoCT,b typically measured as the percentage of battery capacity, the instantaneous battery SoC is:

$$dSoC_{Tbh}(t) = SoCT_{\mu}b\,(\mathrm{t}_0) - \left(\frac{1}{CT,b}\int_{t0}^{t} i(\tau)d(\tau)\right) \tag{2.8}$$

Discharging the battery results in an decrease of the SoCT,b. If the state of the charge is 100% at initial time, then the SoCT,b is:

$$SoCT,b = 1 - \frac{\int_{t}^{t0} i(\tau)d(\tau)}{CT,b} \tag{2.9}$$

If i(t) represents the charging current and the state of the charge is zero at initial time, the formula for SoCT,b is:

$$SoCT,b = \frac{\int_{t}^{t0} i(\tau)d(\tau)}{CT,b} \tag{2.10}$$

It is noted that calculation of SoC using the afore-mentioned equations requires integration of the current signal, which can suffer from long-term drift and lack of a reference point. A more accurate estimation of SoC can be obtained by more advanced estimation algorithms such as Kalman filters.[11]

Provided us with this equation :

$$\frac{dSoC_{T,b}}{dt} = -\frac{V_b \pm \sqrt{V_b^2 - 4R_{bi}P_b}}{2R_{bi}C_{T,b}} \tag{2.11}$$

- **Depth of Discharge:**

  depth of discharge, DoD, is a measure of the amount of discharged energy capacity from the battery, typically expressed as a percentage of maximum capacity. The state of discharge can be given as:

$$DoD_{T,b} = \frac{1}{C_{T,b}}\int_{t_0}^{t} i(\tau)d\tau - DoD_{T,b}\,(t_0) \tag{2.12}$$

  Deep discharging beyond the cut-off voltage must be avoided, especially under heavy loads, to prevent serious damage to the batteries.

- **Specific power:**

  In high power demand applications, such as EV and HEV applications, Specific power is important in the reduction of a battery weight, The specific power of a chemical battery depends usually on the batteryâs internal resistance, the maximum power that the battery can supply to the load is[8]:

$$P_s = \frac{V_{int}^2}{4\,(R_c + R_{int})}(W/kg) \tag{2.13}$$

- **Energy efficiency:**

  The energy or power losses either on discharging and charging a battery expressed by voltage losses. Thus, the efficiency of the battery during discharging and charging can be defined at any operating point as the ratio of the cell operating voltage to the thermodynamic voltage, that is [8]

$$\begin{cases} \mathrm{nd} = \frac{\mathrm{V}}{\mathrm{Vint}} \\ \mathrm{nc} = \frac{\mathrm{Vint}}{\mathrm{V}} \end{cases} \tag{2.14}$$

  where nd and nc are the energy efficiency during discharging and charging, respectively

- **Battery electric equivalent circuit:**

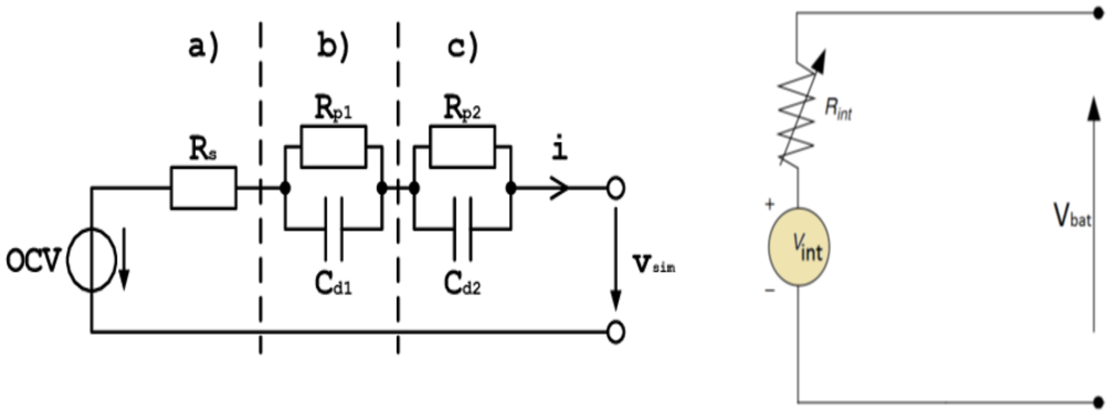

Figure 2.3: Battery electric equivalent circuit [5]

2.2 Supercapacitors

For the EV applications, the energy sources such as batteries and fuel cells allow to have a large amount of energy with a reasonable weight; but, with acceleration when crossing hills and effective regenerative braking, it must be possible to supply or store high power for a relatively short time in power source either a mechanical device (flywheel); or an electrochemical device (supercapacitor) as itâs illustrated in Fig 2.4 The use and the management of flywheel storage within an EV is described in[14]. However, the Supercapacitors (SCs), also called Ultracapacitors (UCs), are the power source that have received widest attention [8].

The first patent related to supercapacitors was granted to Becker (General Electric engineer) in 1957 while experimenting with devices using porous carbon electrode. In 1969, the company Sohio granted another patent for a non-aqueous electrolyte supercapacitor allowing higher voltages. The marketing of supercapacitors only took place in the 1970s, by the two companies NEC and Matsushita[15]

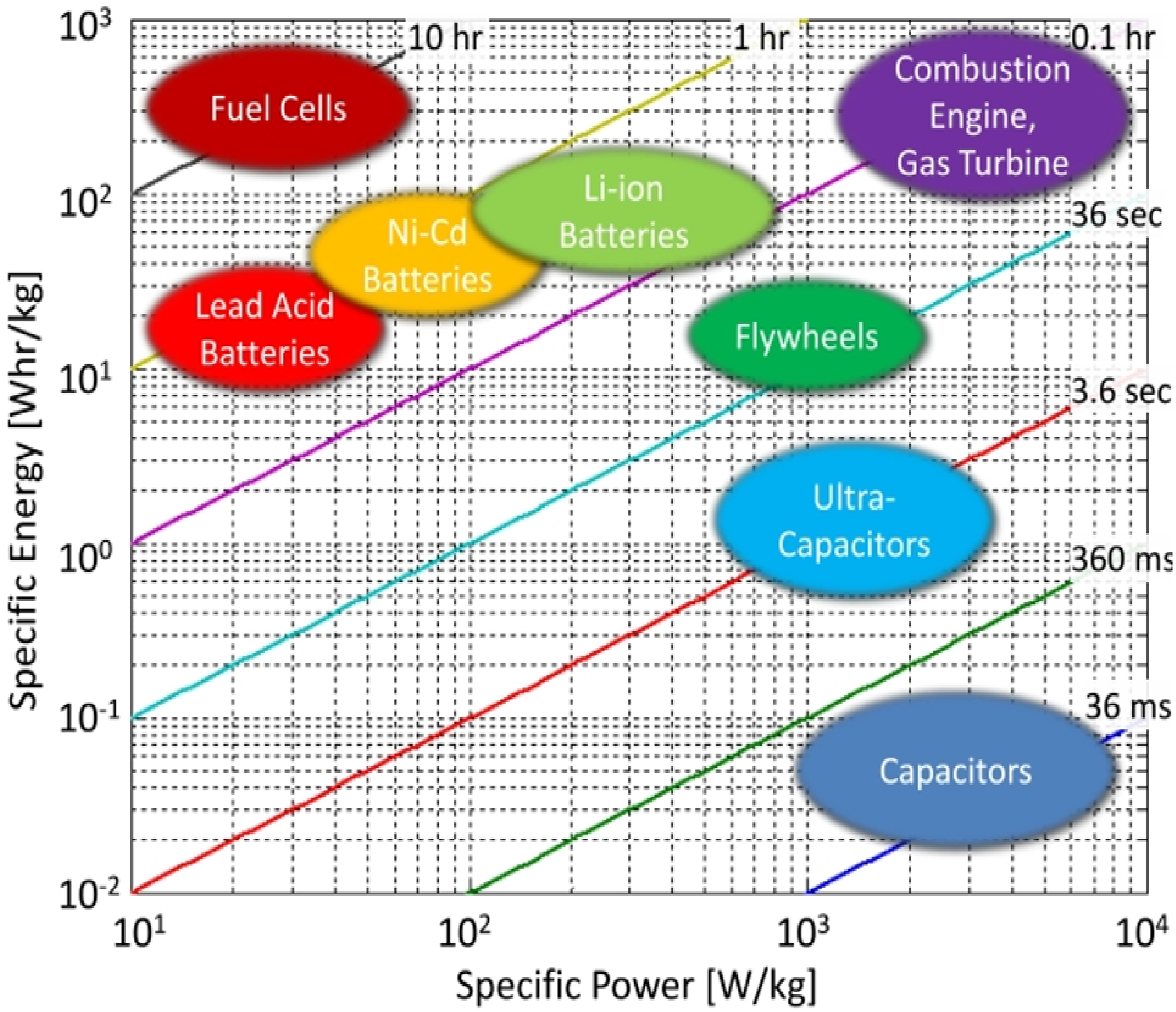

Figure 2.4: Ragone plot of energy density vs. power density for various energy-storing [16]

2.2.1 Basic Principles Of Supercapacitors

Unlike the battery cells, the operational mechanism of Electrochemical SC consists of two electrodes separated by an ion permeable membrane (separator), and an electrolyte connecting electrically the both electrodes [17]. An electric double layer at both electrodes is formed by applying a voltage to the capacitorâs collectors, which has a positive or negative layer of ions deposited in a mirror image on the opposite electrode [18]. The principle of a double-layer capacitor is presented in Fig2.5

When two carbon rods are immersed in a thin sulphuric acid solution, separated from each other and charged with voltage increasing from zero to 1.5 V, almost nothing happens up to 1 V; then at a little over 1.2 V, a small bubbles will appear on the surface of both the electrodes. Those bubbles at a voltage above 1 V indicate electrical decomposition of water. Below the decomposition voltage, while the current does not flow, an "electric double layer" then occurs at the boundary of electrode and electrolyte, then electrons are charged across the double layer[8].

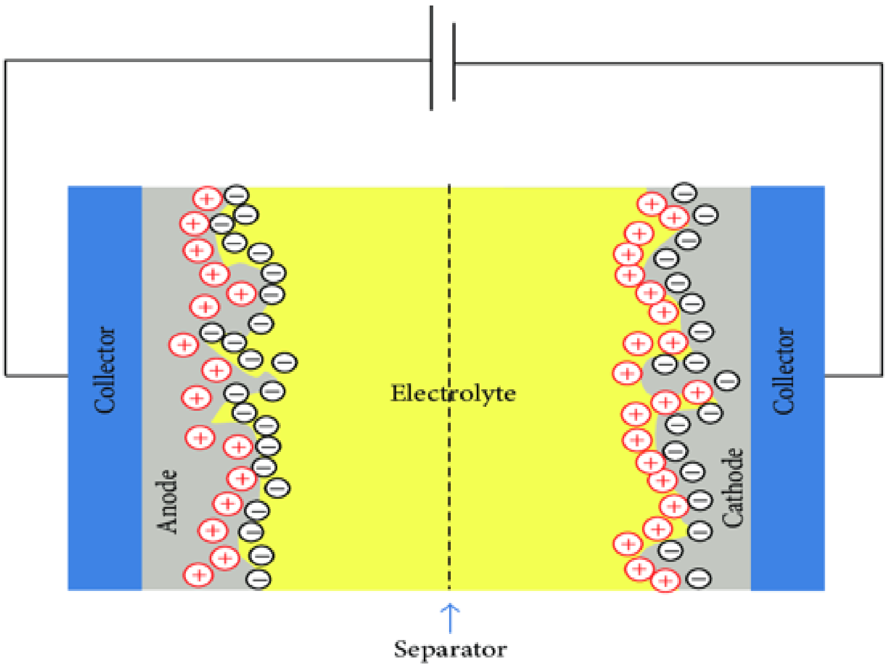

Figure 2.5: Principle construction of a supercapacitor [16]

2.2.2 Technologies

We can distinguish different supercapacitor types: Electrochemical double layer capacitors (EDLCs), Pseudocapacitors and Hybrid capacitors[18]. There are several electrode technologies, they can be:
- made of activated carbon materials
- in inorganic materials: based on transition metal oxide (MnO2, V2O5, ...) or noble metal oxide (ex: RuO2, ...)
- in organic materials: polymers with electronic conduction The most common supercapacitors are with activated carbon electrodes. Their performances are variables depending on the type of electrolyte:
- aqueous electrolyte: it has low resistance because ionic conductivity of the order of 800mS.cm-1, but also low voltage (around 1V).
- organic electrolyte: higher voltage (around 3V), but high resistance because ionic conductivity of the order of 10mS.cm-1 and use, for the electrolyte, of acetonitrile (methyl cyanide), a flammable compound and harmful for health [15].

2.2.3 The SC Electric Equivalent Circuit

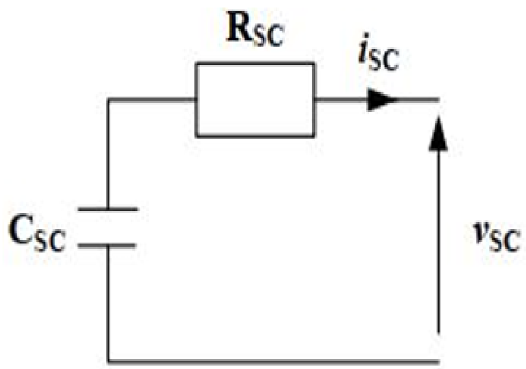

Figure 2.6: The SC electric equivalent circuit

There are many different models of supercapacitor have been described in the literature. In this work we used the standard model. The standard model is a simple model, the definition of which is given in the European standard IEC 62391 [20]., relating to the use of supercapacitors. It is an equivalent electric circuit model consisting of a capacitance Csc and a resistor Rsc in series Fig2.6This model is often used in the context of functional modeling for the study of energy systems [12][22][21] [19]. The relation between the UC voltage Vsc and its current isc is given bellow: [12]

$$V_{SC} = V_C - R_{SC} \cdot i_{SC} \tag{2.15}$$

The state of charge SoCsc can be estimated using this equetion [12] :

$$\text{So}\, C_{sc}(t) = 100 \frac{V_{sc}^2}{V_{scMax}^2} \tag{2.16}$$

Where Vsc.max is its maximal voltage.

2.3 Modeling Of The Buck-Boost Convertors

In a hybrid energy system composed of continuous sources, the choppers control the power and the output voltage. Choppers are DC / DC converters used to obtain a fixed or variable voltage from any DC voltage. The input DC voltage can be the output voltage of a fuel cell, a supercapacitor, a battery, or a photovoltaic system. There are three types of non-isolated choppers: the Boost chopper, the Buck chopper, and the Buck-Boost chopper[23]
In this work, we are particularly interested in the Buck-Boost choppers, which are often used to control the energy supplied or absorbed by the sources, in our case the battery and the supercapacitor, according to the chosen energy management strategy. The converter must therefore be reversible in current

2.3.1 The Average Model of the Buck-Boost

In many cases, it is in our interest to transform the original system into a continuous system which macroscopically represents better the dynamic and static behaviors of the circuit. For this purpose, the average behavior is quite suitable. We can find a wide range of applications of the average model, whether in control, simulation or even in mode analysis. The average model allows to meet three essential requirements:
- Simplicity of implementation and use.

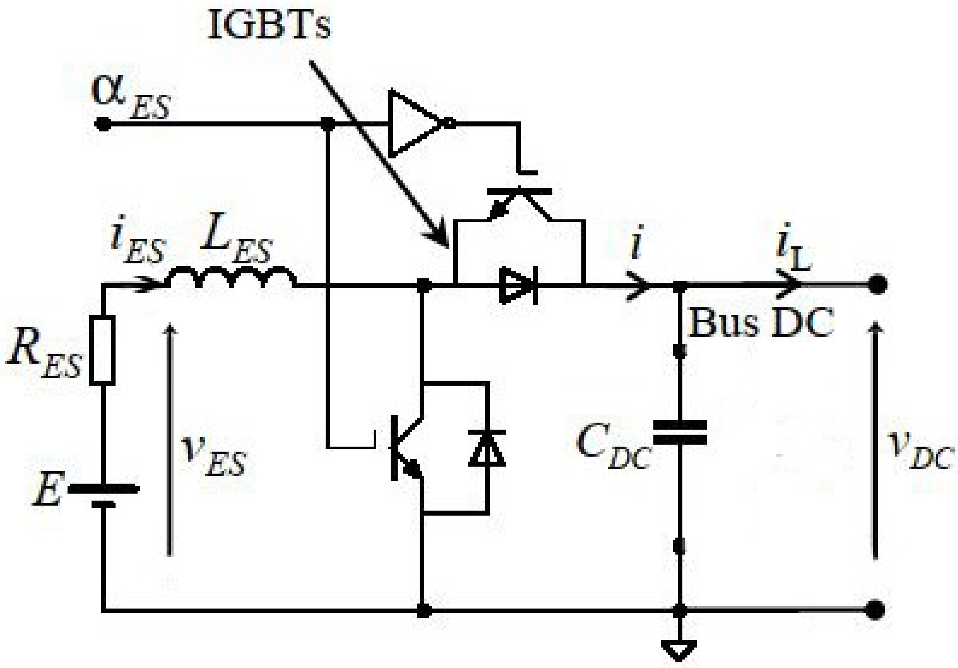

Figure 2.7: The Buck-boost power converter model [24]

- Sufficient precision in its field of validity.

- The possibility of use in a closed loop: possibility of switching to a transfer function

***Operating sequences and state equations:**

The average model of the Buck-Boost converters will test the control algorithms in continuous models of the global system. A distinction is made between the two switching phases of IGBTs, represented by a wire when they are closed and the lack of connection when they are open. Thus, the switching period (Tpwm) is splitted into two.

-The first conduction sequence t $\in$ [0; α_{ES} *Tpwm] :

The dynamic equation of v_{ES} and i_{DC} in the second sequence are written:

$$V_{ES} = L_{ES}\frac{di_{ES}}{dt} + R_{ES} \cdot i_{ES} \tag{2.17}$$

$$C_{DC}\frac{\mathrm{d}v_{DC}}{\mathrm{d}t} = -i_L \tag{2.18}$$

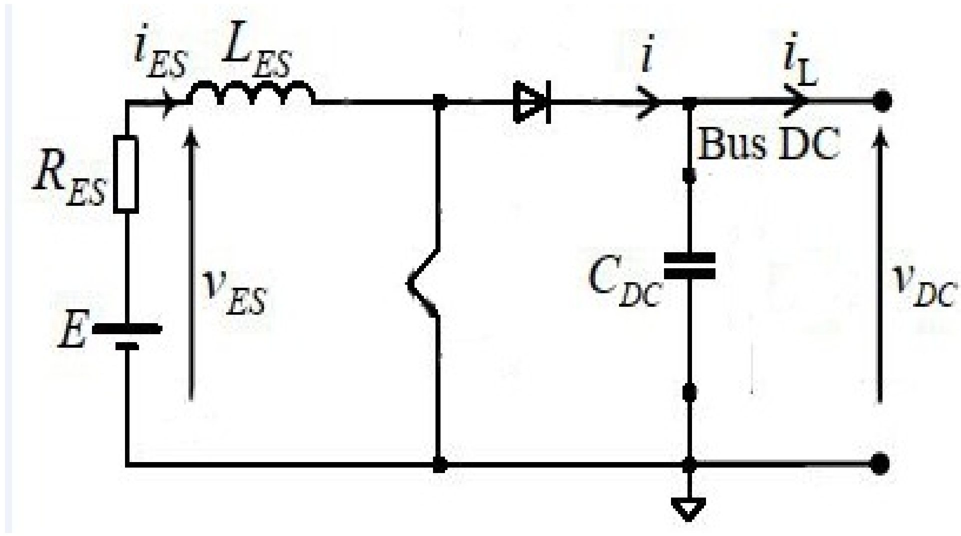

Figure 2.8: The schematic diagram of the first conduction sequence

-The second conduction sequence t $\in$ [α_{ES} *Tpwm; Tpwm] :

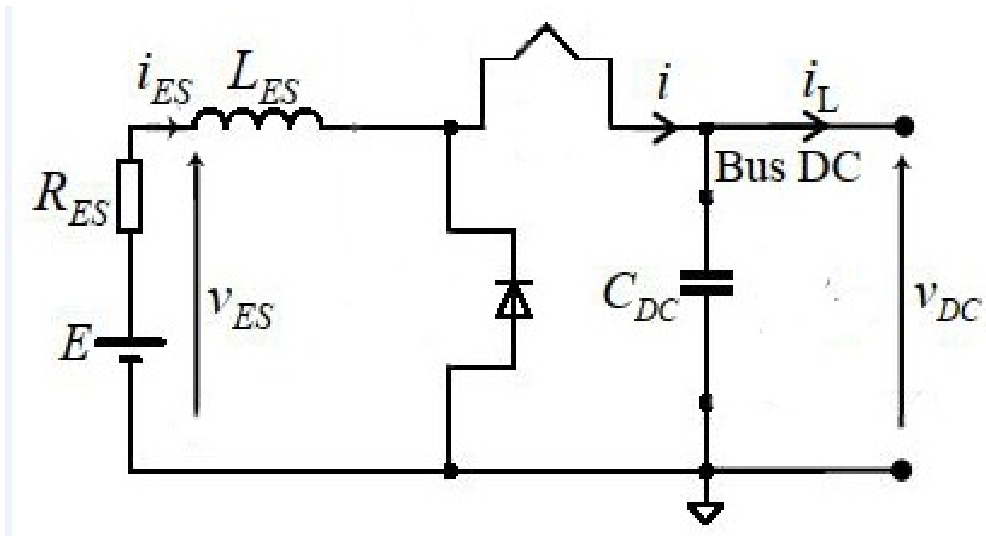

Figure 2.9: The schematic diagram of the second conduction sequence

The dynamic equation of v_{ES} and i_{DC} in the second sequence:

$$V_{ES} = L_{ES}\frac{di_{ES}}{dt} + R_{ES} \cdot i_{ES} + V_{dc} \tag{2.19}$$

$$C_{DC}\frac{\mathrm{d}v_{DC}}{\mathrm{d}t} = \sum i_{ES} - i_L \tag{2.20}$$

-The temporal average of these two equations thus gives an average model of this converter[24]

$$L_{ES}\frac{\mathrm{d}i_{ES}}{\mathrm{d}t} = v_{ES} - v_{DC} \cdot (1-\alpha_{ES}) - R_{ES} \cdot i_{ES} \tag{2.21}$$

$$C_{DC}\frac{\mathrm{d}v_{DC}}{\mathrm{d}t} = \sum i_{ES} \cdot (1-\alpha_{ES}) - i_{L} \tag{2.22}$$

Where: R_{ES} is the internal resistance of the source, L_{ES} is the inductance of the converter. v_{ES} and i_{ES} are the voltage and current respectively of the electric power source, C_{DC} is the capacity of the DC bus, α_{ES} is the corresponding duty cycle of converter, i_{L} is the load current.

$$L \cdot \frac{\mathrm{d}i_{\mathrm{bat}}}{\mathrm{d}t} = v_{\mathrm{bat}} - v_{DC} \cdot (1-\alpha_{\mathrm{bat}}) - R_{\mathrm{bat}} \cdot i_{\mathrm{bat}} \tag{2.23}$$

$$L \cdot \frac{\mathrm{d}i}{\mathrm{d}t} = v_{SC} - v_{DC} \cdot (1-\alpha_{SC}) - R_{SC} \cdot i_{SC} \tag{2.24}$$

$$C_{DC} \cdot \frac{\mathrm{d}v_{DC}}{\mathrm{d}t} = i_{\mathrm{bat}} \cdot (1-\alpha_{\mathrm{bat}}) + i_{SC} \cdot (1-\alpha_{SC}) - i_{L} \tag{2.25}$$

2.4 The Closed-Loop Transfer Functions Of The System

The transfer function of the two converters can be written as follows:

$$H_{ES}(s) = \frac{i_{ES}}{1-\alpha_{ES}} = \frac{-V_{BUS}}{L_{ES} \times s + R_{ES}} = \frac{-K}{T \cdot s + 1} \tag{2.26}$$

Where T= L_{ES} / R_{ES} , K= V_{BUS} / R_{ES} . Following this modeling, a conventional proportional integral (PI) control structure (with anti-saturation loop) is used to follow the references of the currents of the battery and the supercapacitor , respectively.

$$H_{PI}(s) = K_p\left(1 + \frac{1}{T_i}\right) \tag{2.27}$$

So, The closed-loop transfer function of the system of the two converters is:

$$H_{BFES}(S) = \frac{H_{pI}(s) \cdot H_{ES}(s)}{1 + H_{PI}(s) \cdot H_{ES}(s)} \tag{2.28}$$

After simplification we get :

$$H_{BFES}(s) = \frac{T_i \cdot s + 1}{-\frac{T_i \cdot T}{K_p \cdot K} \cdot s^2 + \left(-\frac{T_i}{K_p \cdot K} + T_i\right) \cdot s + 1} \tag{2.29}$$

The parameters of the regulator K p and Ti are determined according to the form of the desired closed-loop response, for which two adjustment factors are available the response time corresponding to the cut-off frequency To and the damping ratio m, a second order equation is written as:

$$H(s) = \frac{K}{T_0^2 \cdot s^2 + 2mT_0 \cdot s + 1} \tag{2.30}$$

In order to ensure the stability of the system, the internal loop must be faster than the external loop for this purpose. A response time of the internal loop which is equal to five times that of the external loop is chosen and an optimal damping is chosen which is equal to 0.707 to calculate the gains of the three regulators.

$$\begin{aligned} K_P &= \tfrac{1}{K} \cdot \left(\tfrac{2mT}{T_0} - 1\right) \\ T_i &= 2mT_0 - \tfrac{T_0^2}{T} \end{aligned} \tag{2.31}$$

-In the case of an unknown load, each load power variation modifies the DC bus voltage. Hence its measurement is essential in order to estimate power demand. Consequently, the DC voltage loop has to control the bus voltage VBUS (t) and allows to generate the load current (iLoadEST(t) $\approx$ iLoad(t)) which represents the power demand image since VBUS (t) is constant. The PI controller is designed following a similar strategy to the current loop. So, the closed-loop transfer function of the system can be deduced as a second-order transfer function [24] , where:

$$\begin{aligned} &H_{BFBUS}(s) = \frac{\frac{1}{C_{BUS} \cdot S} \frac{K_{PBUS} \cdot S + \omega_{IBUS}}{S}}{1 + \frac{1}{C_{BUS} \cdot S} \frac{K_{PBUS} \cdot S + \omega_{IBUS}}{S}} = \frac{1 + \tau_{BUS} \cdot S}{1 + 2m_{BUS} \frac{S}{\omega_{nBUS}} + \left(\frac{S}{\omega_{nBUS}}\right)^2} \\ &\omega_{nBUS} = \sqrt{\frac{\omega_{IBUS}}{C_{BUS}}},\ m_{BUS} = \frac{K_{PBUS}}{2\sqrt{\omega_{IBUS} \cdot C_{BUS}}} \text{ and } \tau_{BUS} = \frac{K_{PBUS}}{\omega_{IBUS}} \end{aligned} \tag{2.32}$$

So, the PI controller parameters of the DC bus loop are:

$$\omega_{IBUS} = C_{BUS} \left(\omega_{nBUS}\right)^2 \text{ and } K_{PBUS} = 2m_{BUS}C_{BUS}\omega_{nBUS} \tag{2.33}$$

2.5 The Used Energy Management Strategies

The energy management in this system which is consisted of the battery and the supercapacitor associated to the charge, is on aim to minimize the variation of the current from the battery towards the load during the chosen driving cycle.

2.5.1 the frequency-decoupling strategy

This strategy relies on a decoupling of the low- and high-frequency components of the load current demand signal and applying low-frequency content to the high-energy source in the system (the battery), whereas the high-frequency is compensated using an auxiliary fast-responding source (the supercapacitor). Frequency-decoupling can be realized through a simple low-pass filter (LPF) as it is shown on fig 2.10

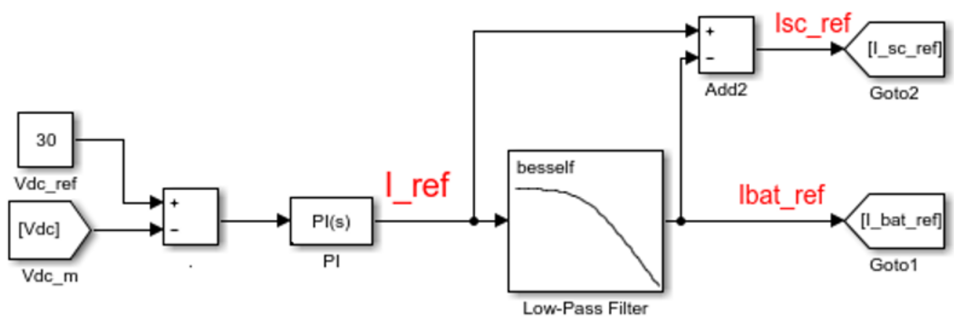

Figure 2.10: The Low-Pass filter, and frequency decoupling

2.5.2 Neural Networks Energy Management Strategy

To properly manage the system under a variable load demand, a frequency separation technique is used. This method allows to supply each source according to its power frequency spectrum. In this context, an NN based management routine is proposed, trained off-line via the previous technique, permits to handle multiple inputs to provide as a result the reference current amount of each support source. Neural Network technique is utilized for modeling,

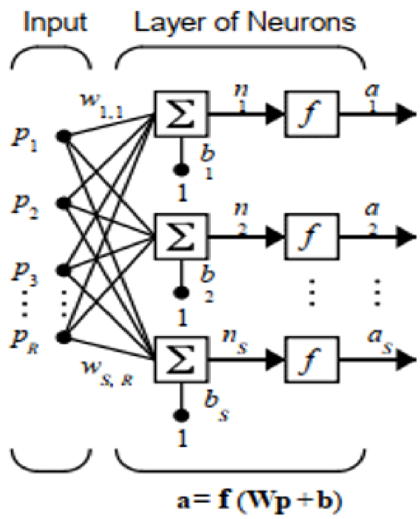

Figure 2.11: The principle of Neural Networks [26]

optimization, simulation and prediction of a system performance. Neurons are an artificial neural network component which are processing elements. They are connected by joining links called weights. A simplified NN model has an input layer, an output layer, and at least one hidden layer [25]. Fig.2.10. illustrates the principle of the neural network.

The neural network structure, showed in Fig.2.11, has 4 input nodes, 10 hidden nodes and 2 output nodes. The inputs are: the voltage of the DC-Bus (Vdc), the load current demands (Iload) sensed at the dc link, the battery and the SC states of charge (SOCbat, SOCsc). Regarding the changing of these inputs, the algorithm provides the reference current of the storage devices, Ibat-ref, and Isc-ref, to cover the load current demand.

There are 3 steps to realize this controller: create a data set of the four inputs (ILoad, Vdc, SOCbat, SOCsc) and the two outputs (Ibat-ref and Isc-ref) for the specific desired load profile using PI controller and the frequency-separation based technique. Afterword, Train the Neural Network on this data set. Then finally, implement the NN in the scheme of the hybrid sources. This steps will be explained in details in the appendix A.

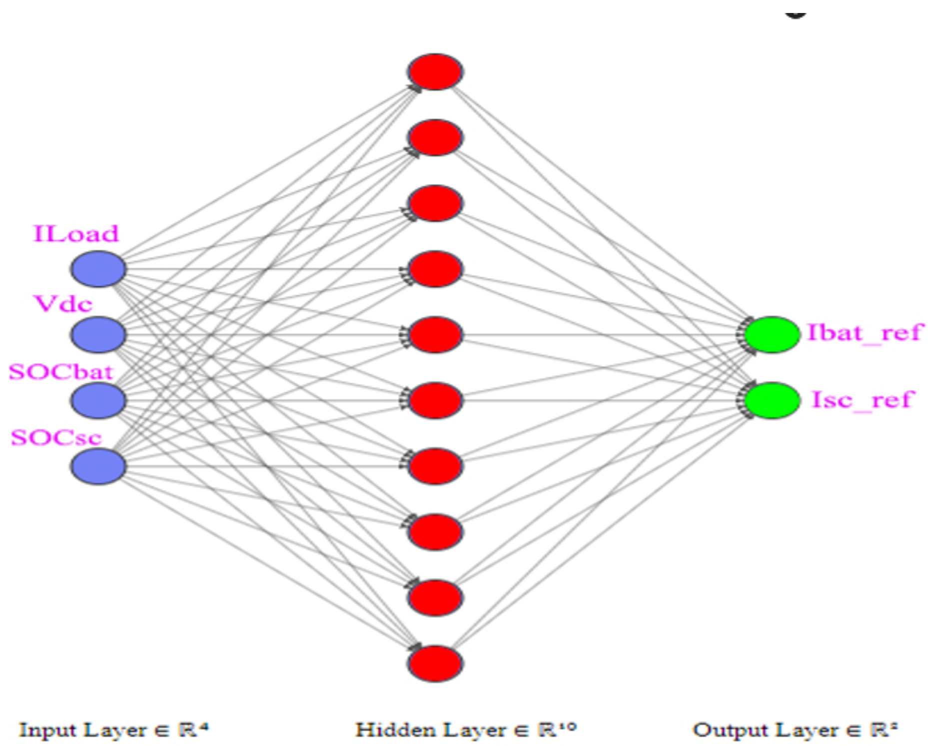

Figure 2.12: The Neural Network structure

Chapter 3

Simulation And Results

The diagram and its components (sources of energy, converters, filter...) had been simulated under the Matlab/Simulink Software.
The main parts of the Simulink diagram are as following:

1) Power sources (battery + supercapacitor)

2) The two chopper

3) The load image

4) Currents, voltages & SoCs visualizing

5) DC-BUS Voltage regulation & currents' refernces generating

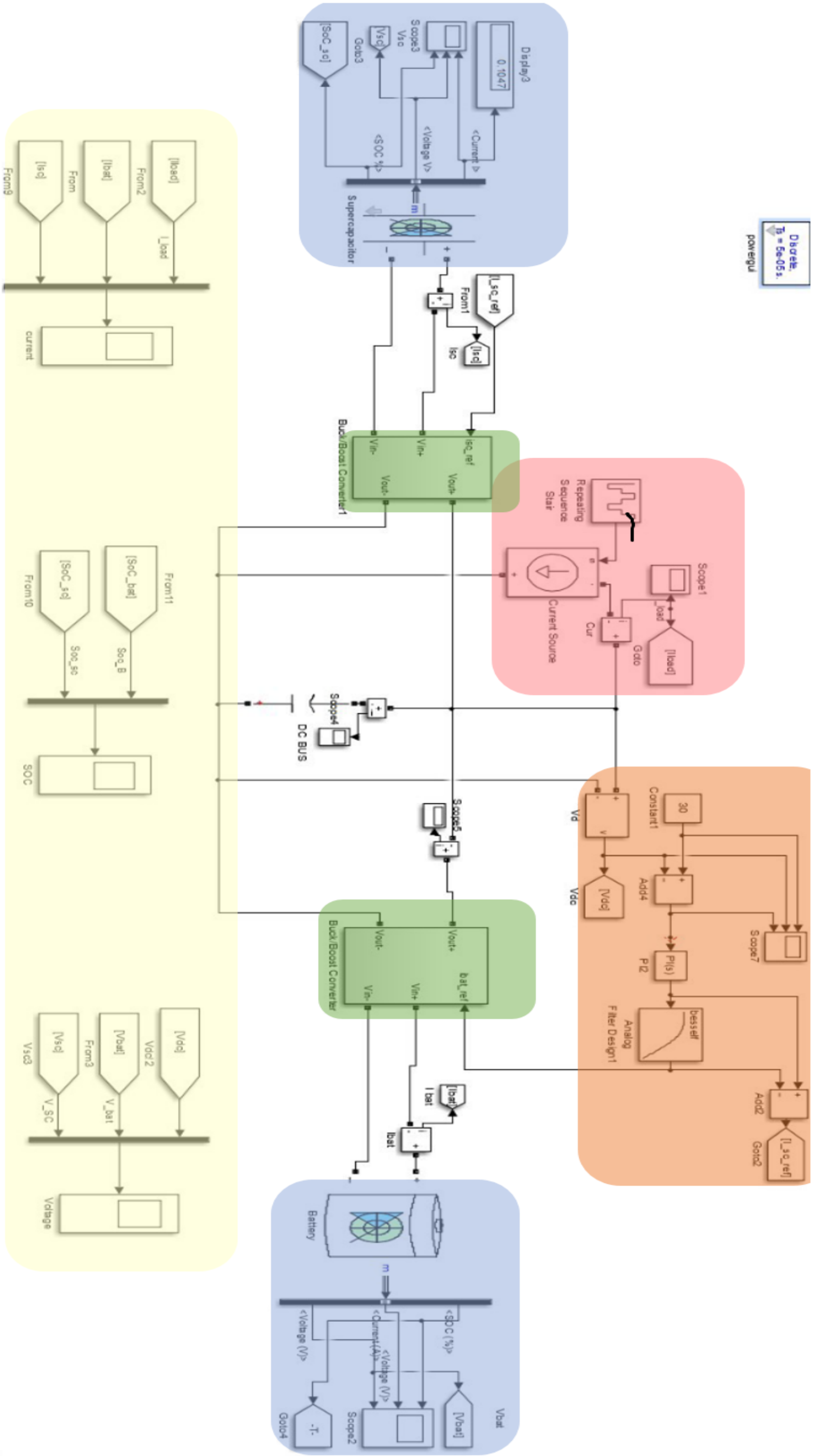

Figure 3.1: The schematic diagram of FBS

3.1 Diagram description:

The diagram and its components (sources of energy, converters, filter) had been simulated under the Matlab/Simulink Software.
As is shown above, the energy management strategy (EMS) by frequency separation is what was based on to manage multi-source (battery and super capacitor) contribution on this particular system, using current source to generate a simulation of vehicle on the track (accelerating and braking): :

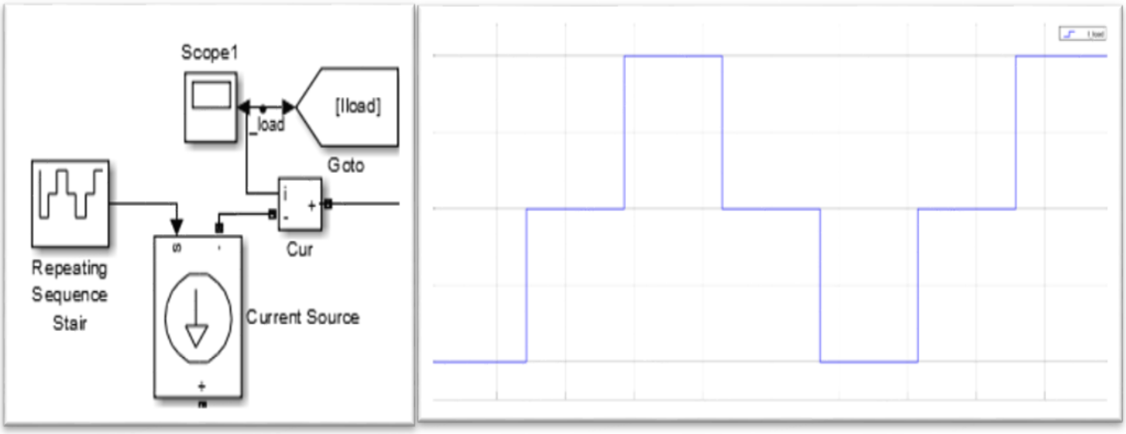

Figure 3.2: load image on accelerating and braking state

Then, we use a low pass filter to separate the frequencies which generate the references current that the converter needs (I bat ref & Isc ref) Then the two converters controls the battery and the super capacitor to deliver the proper amount of energy that it is needed each moment :

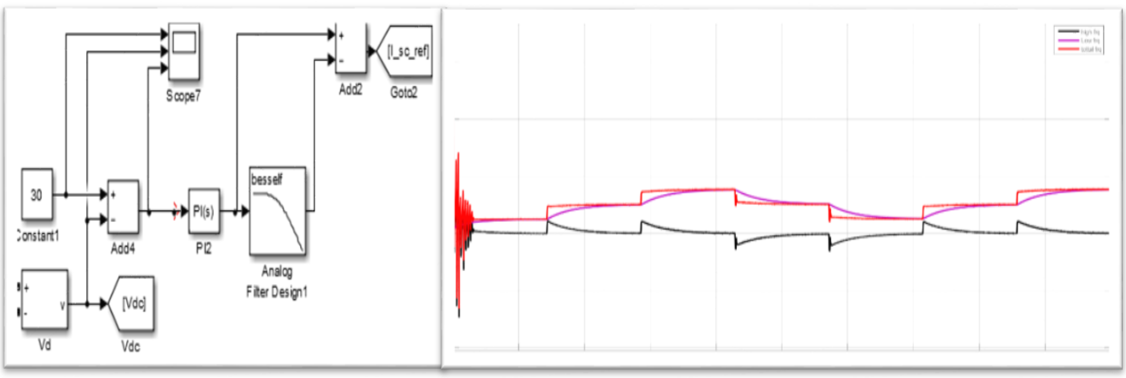

Figure 3.3: Voltage regulation & refernces currents generating

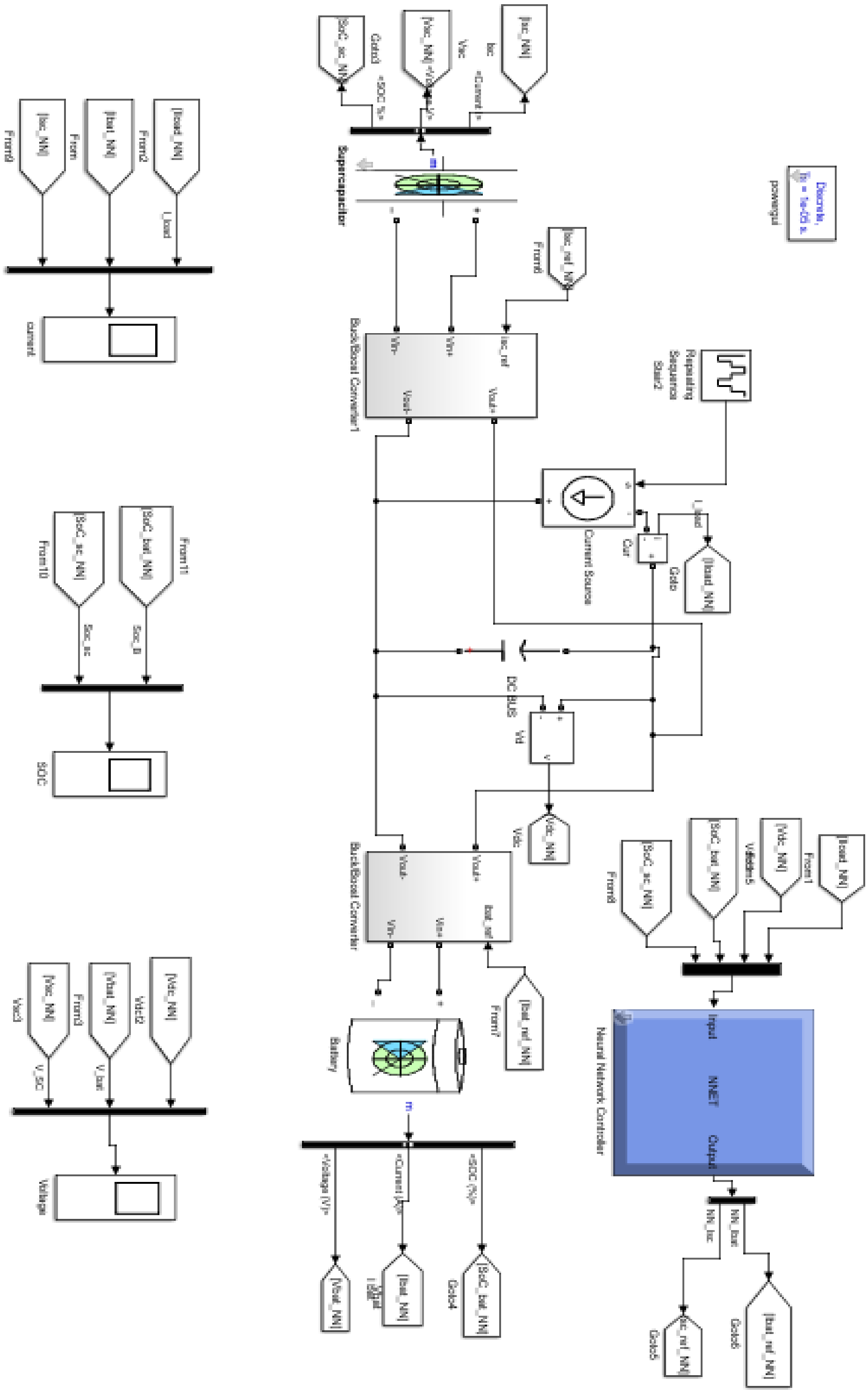

Figure 3.4: The schematic diagram of Neurel Network EMS

The rest of details and demonstration will be added on Appendix A

3.2 Results & interpretation:

The table 3.1) shows the parameters associated to the system:

Parameters	Names and values
battery	Lead-Acid
Nominal voltage	12 (v)
Rated capacity	100(Ah)
Initial state of charge	80% values
Battery time response	30s
Super capacitor	
Rated capacitance	58 (F)
Equivalent DC series resistance	2.2e-3 (Ohms)
Rated voltage	12
Number of series capacitors	6
Number of parallel capacitors	1
Operating temperature	25c
Filter Passband edge frequency	2*pi*0.5 (rad/s)
DC bus capacitance	2200e-6 (F)
Inductance values	10e-3 (H)
Converter-PI parameters	Kp=0.01 ki=10
DC-BUS-PI parameters	Kp=1 ki=50

Table 3.1: The parameters associated to the system

Currents visualization and Interpretation: Currents:

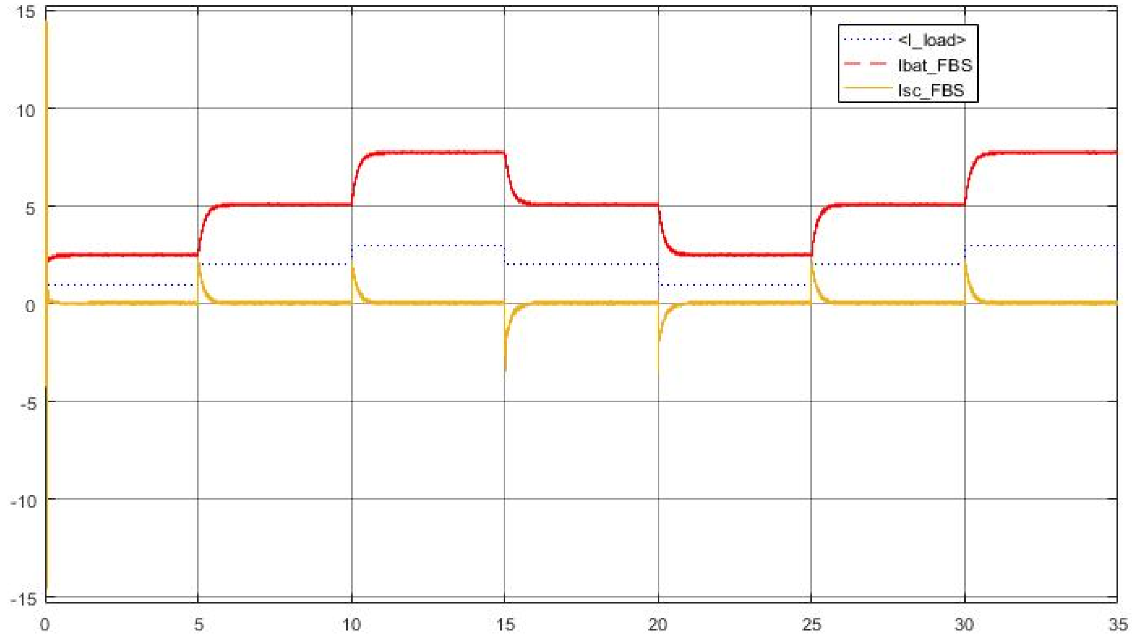

Figure 3.5: Currents of the battery and the SC with FBS

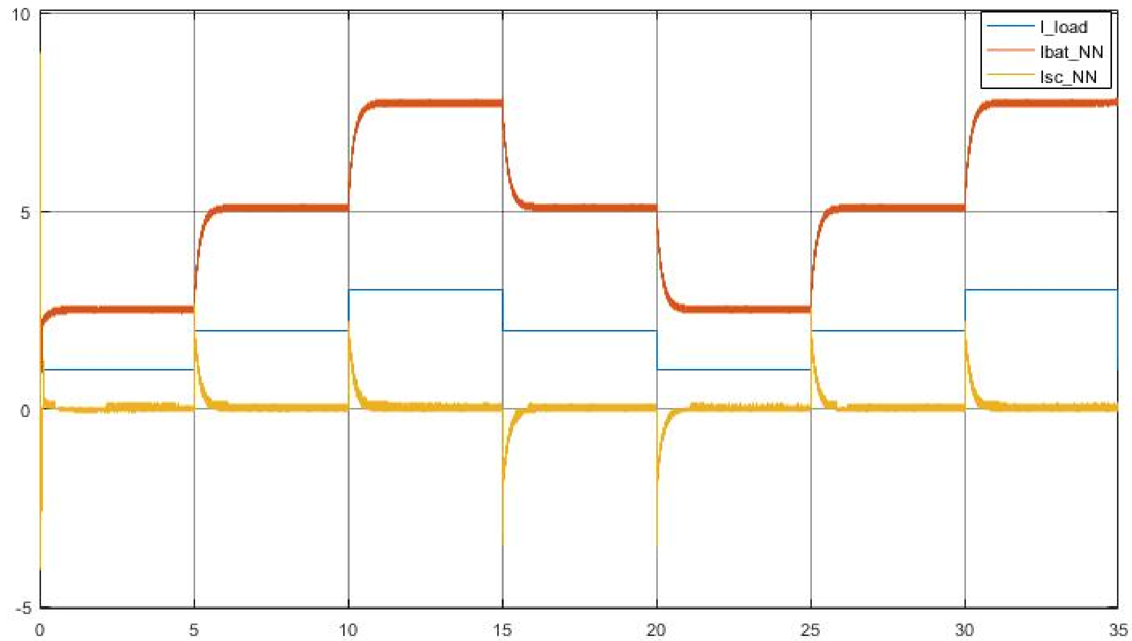

Figure 3.6: Currents of the battery and the SC with NN

comparing I bat and Isc using Neural Network and Frequency based strategy

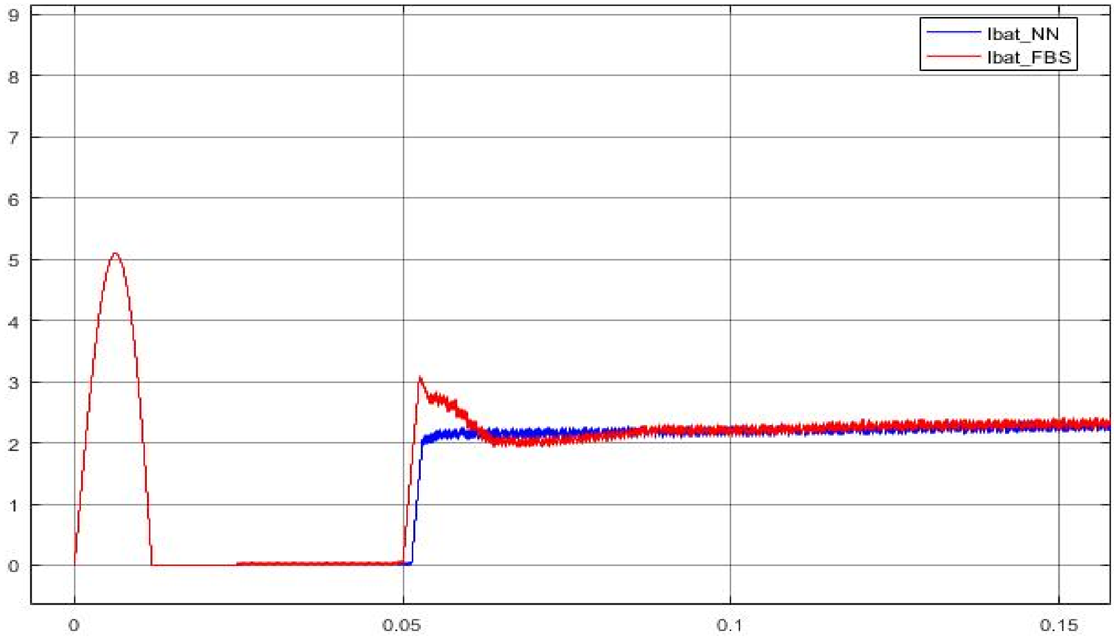

Figure 3.7: comparing I bat using NNk and FBS

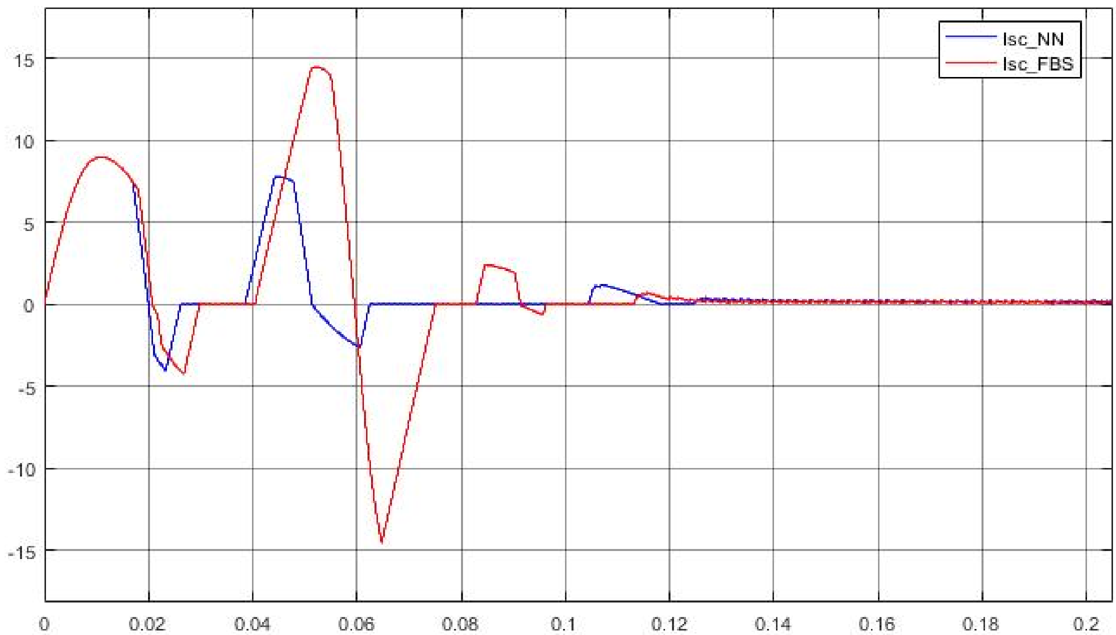

Figure 3.8: comparing Isc using NNk and FBS

Interpretation and Comparition:

As it is shown on the currents curve, the battery keeps feeding the system by current in every moment but when there is more power demand (at acceleration moments), the supercapacitor responds immediately and provide peak current given its ability and its dynamics, that is illustrated on both fig 3.6, 3.5 in cases of NN or FBS

Now we move to comparing the two methods and ravel out the deference, so by and large there is no big deference especially on responding time, but the deference is manifested on tiny details such as the oscillations are smaller on Neural Network as it is shown on Isc 3.8, also more stability comparing to FBS as its also illustrated on I bat comparation 3.7, with no oscillation at all.

What makes the system preform butter and smoothly and more efficient.

Voltages:

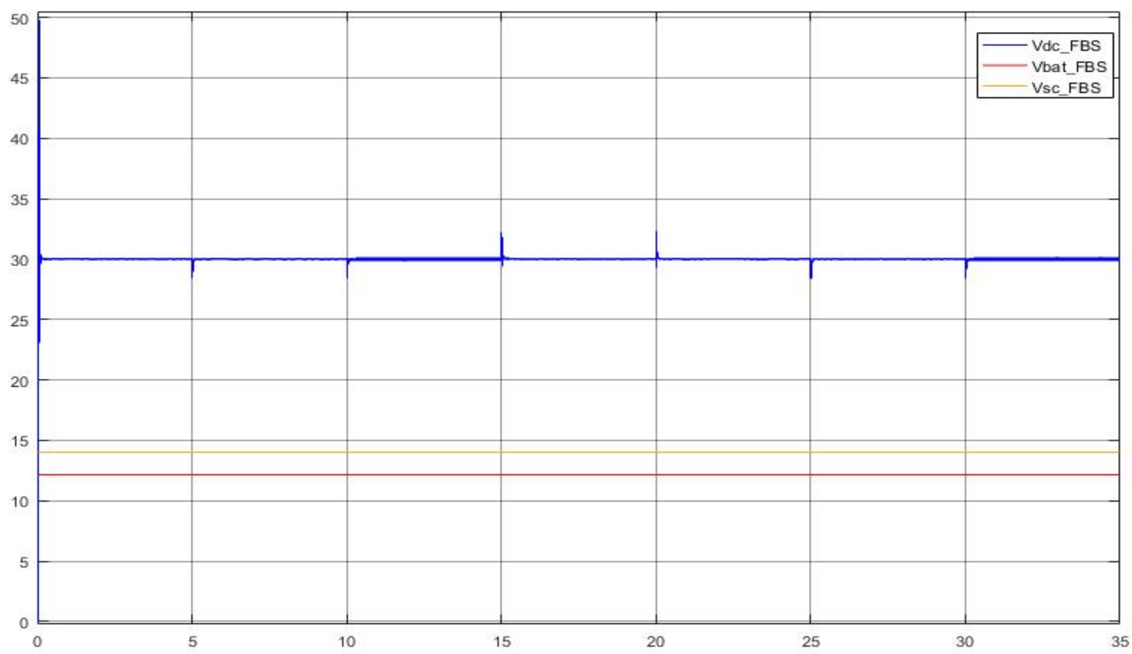

Figure 3.9: Voltage of the battery and the SC with FBS

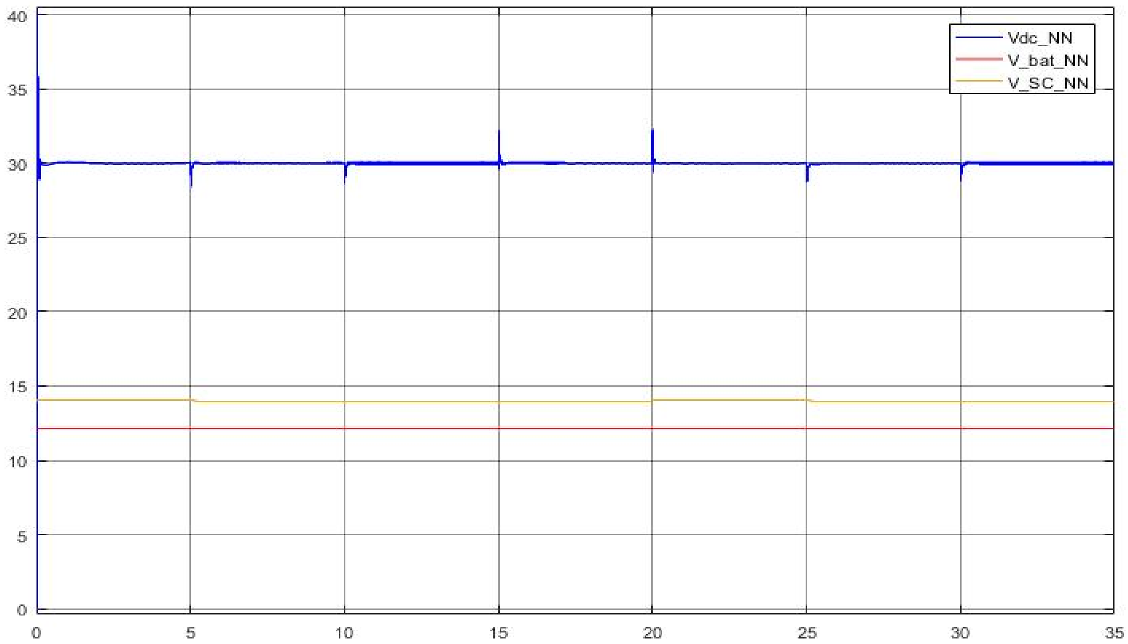

Figure 3.10: Voltage of the battery and the SC with NN

comparing Vdc using Neural Network and Frequency based strategy

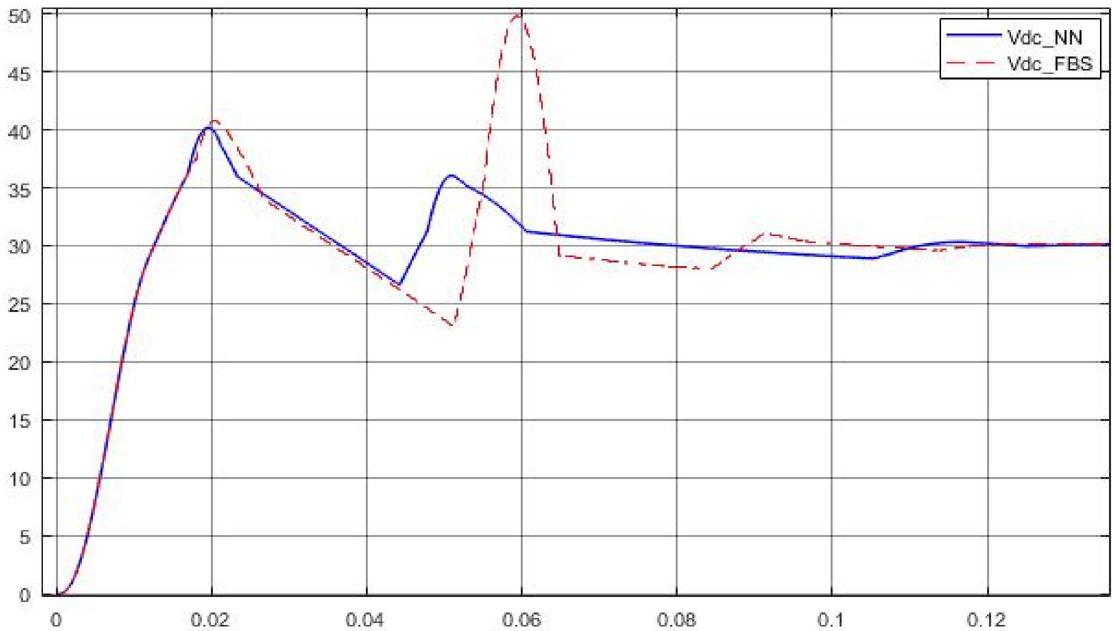

Figure 3.11: comparing Vdc using NNk and FBS 1

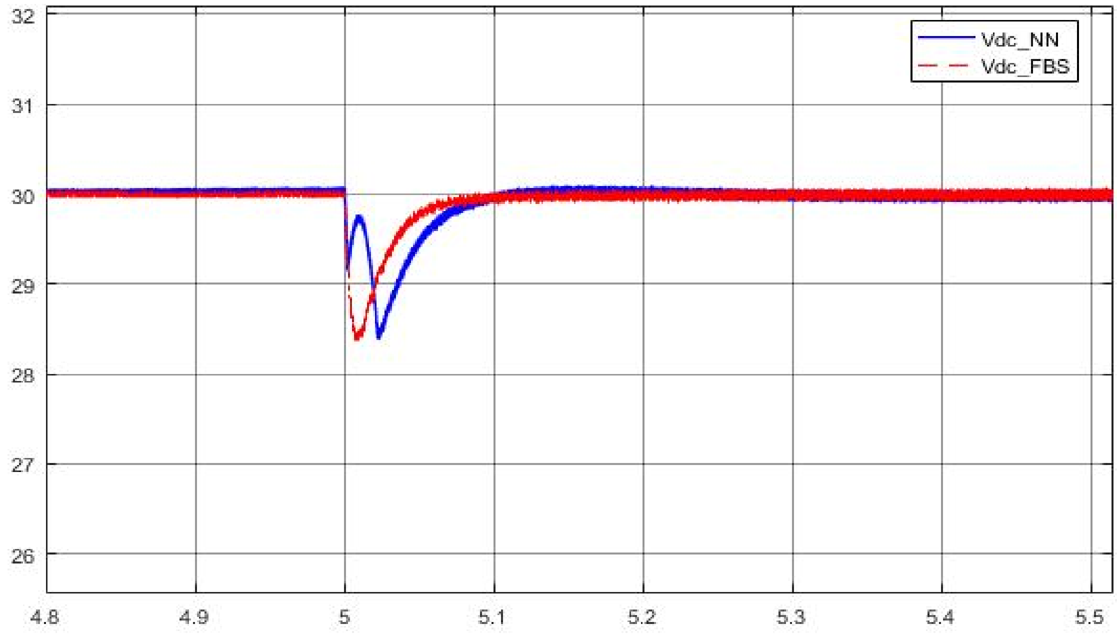

Figure 3.12: comparing Vdc using NN and FBS 2

Interpretation and Comparition:

Its noticed that dc voltage maintained at its reference with certain over passing during the variations moment (acceleration) but remains in permissible interval, thought it overshoot on beginning of FBS comparing to NN as we proved previously that is more stable and more efficient, where there are less oscillations and more smaller fig 3.11

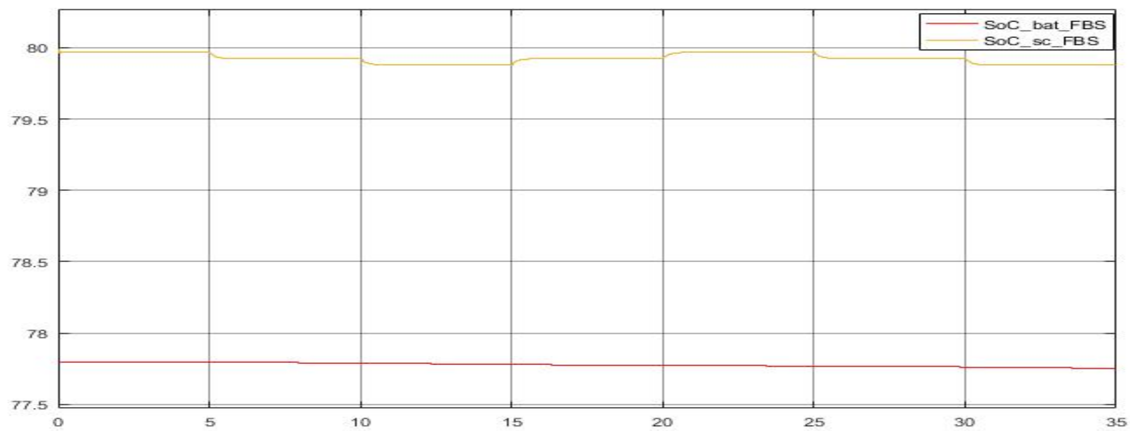

Figure 3.13: FBS SOC

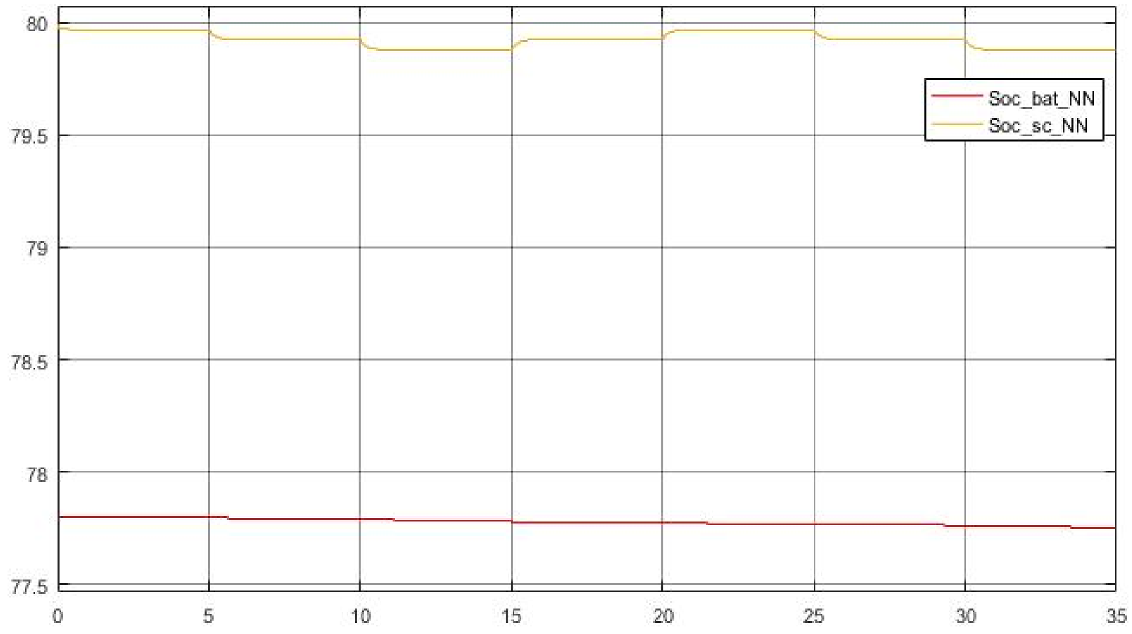

Figure 3.14: Neural Network SOC

Fig 3.14 ,3.13 show a decrease in state of charge of the supercapacitor and the battery when they deliver current, what is noticed that the supercapacitor recover amount of current on deceleration phase given to its fast dynamics of charging and discharging.

General Conclusion

On this thesis we have seen an overview of electric cars, the challenging and future alternative of fuel car that becoming the major threats to human beings. causing serious problems for society and human life by Deterioration in air quality, global warming, and a decrease in petroleum resources? However, the complexity of EVs or even HEVs as electro-mechanical-chemical systems implies the use of Energy Management Strategies (EMSs) that we?ve been through them along with a state of art, knowing the most used methods. Moving to the case studied, we choose a Frequency-decoupling strategy, to manage two power sources, (battery and super capacitor) that feeds the system, going back to the simulation results it worked perfectly given the intervention of super capacitor on each intense demand of current by the load (presenting the acceleration phase) which preventing the overload on the battery and extend its life to guarantee a long life term also longer travel range to meet the required autonomy. then we integrate artificial intelligent to Energy Management of EV to increase the efficiency of performance and improve the quality of control and that what was noticed above all we attribute with new tech on this new field of cars and green transportation For future work we aiming for improving this method and seeking for perfection with more real and complex drivig cycle to match as possible the reality considering the hit and all other paramrters so we could produce our EMS that will help building the first Algerian Electric Car.

Appendix A

Creating and implementing NN using MATLAB/Simulink

In this appendix, we will explain in details the 3 steps to implement a neural network controller for the energy anageent of our system. The three steps are: create data set; train the neural network; implement the NN controller in the system.

1 Create a data set:

In this step, we use the system with frequency-separation based EMS (FBS), to create the data set of the Inputs of the NN : load current (ILoad), DC-BUS voltage (Vdc_FBS), SoC of the battery and the supercapacitor (SoC_bat_FBS & SoC_sc_FBS). And the Outputs (known as targets): the reference current of the battery and the SC (Ibat_ref & Isc_ref).

To create the data set, we send the Inputs and the Outputs as matrixes to the workspace using (To workspace) block, as it is illustrated in fig 3.15

Then we transpose the two matrixes to have the columns as the features and the rows as samples.

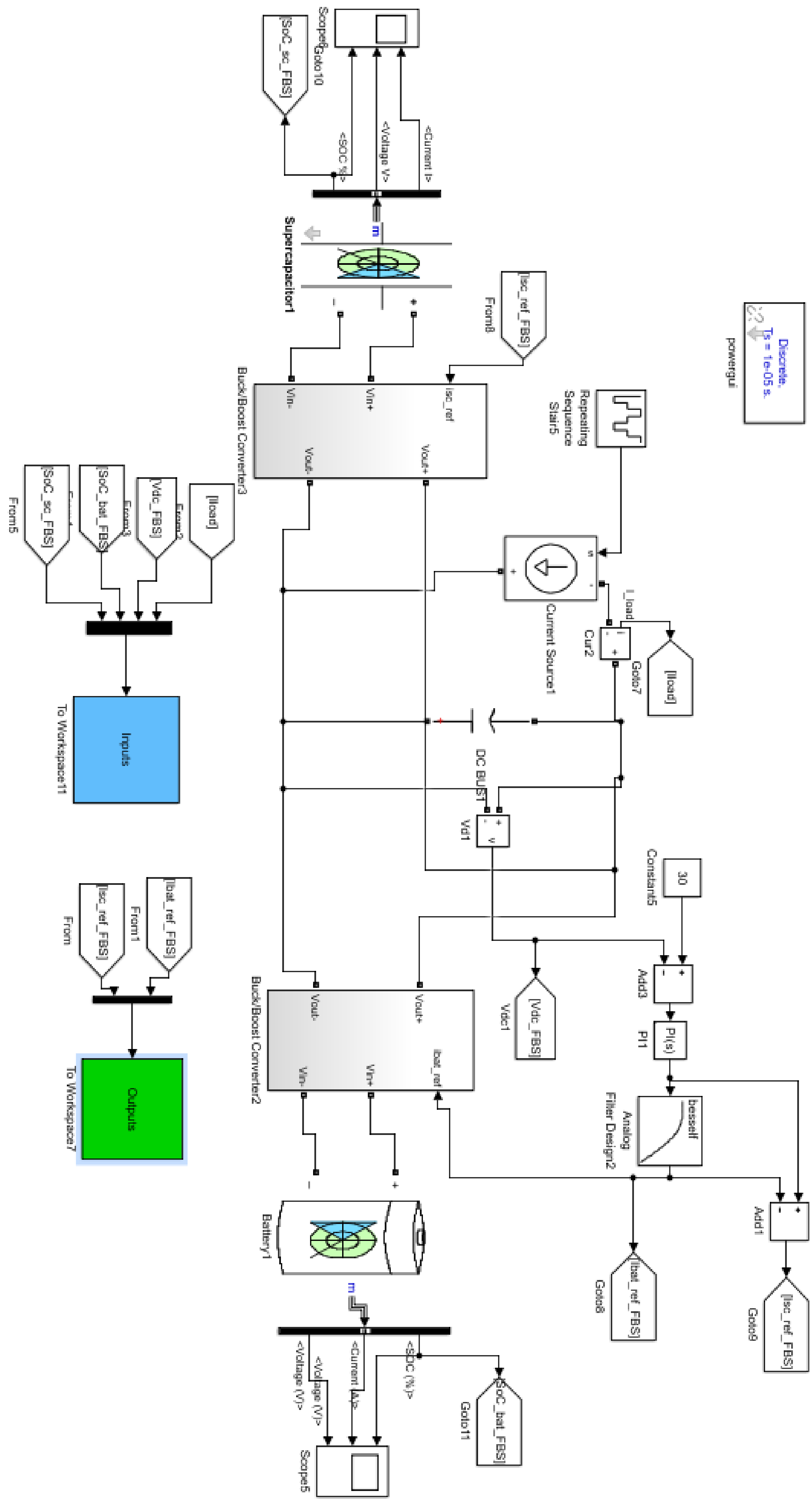

Figure 3.15: Create data set of inputs and outputs from FBS

2 Create and Train the NN:

After getting the data set, we create and train the NN using the Neural Network Start with the nnstart instruction in MATLAB, then follow the steps shown in the following figures:

>> nnstart

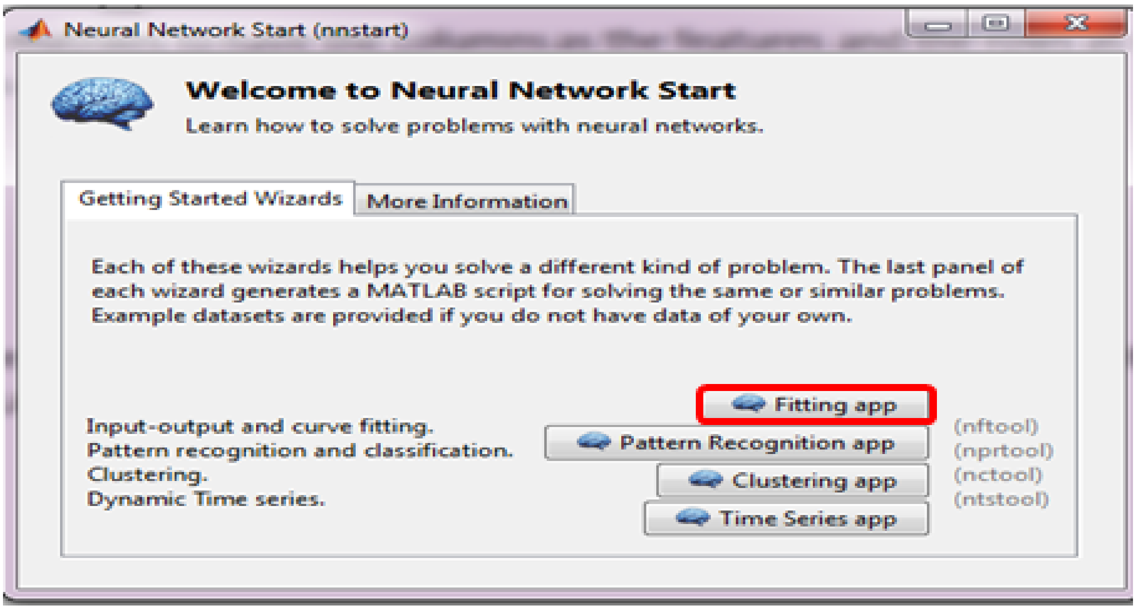

Figure 3.16: Neural Network Start

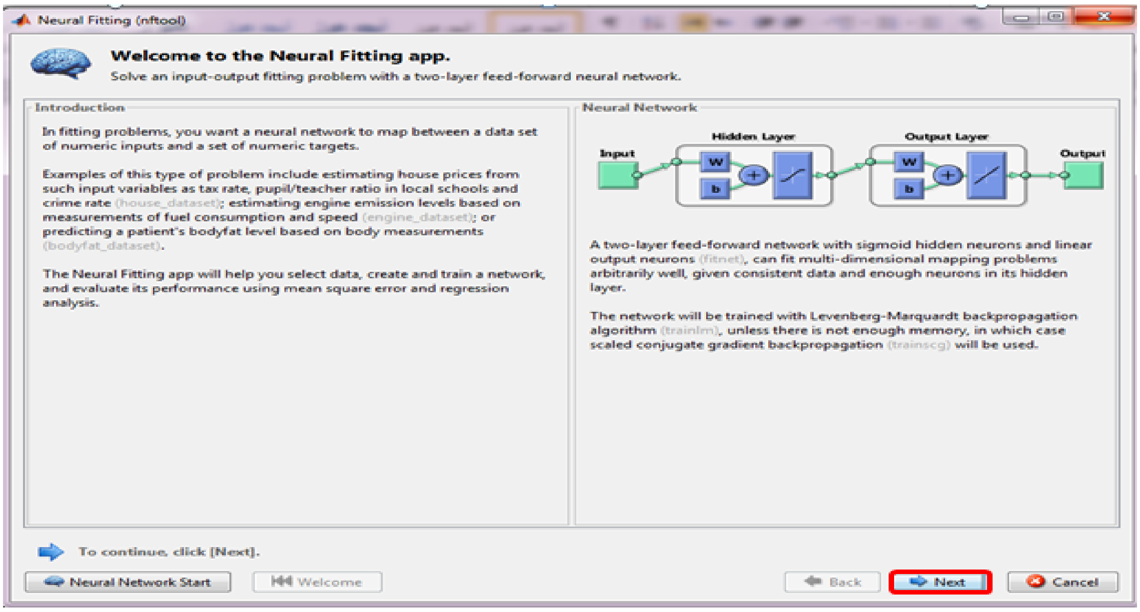

Figure 3.17: Neural Fitting app

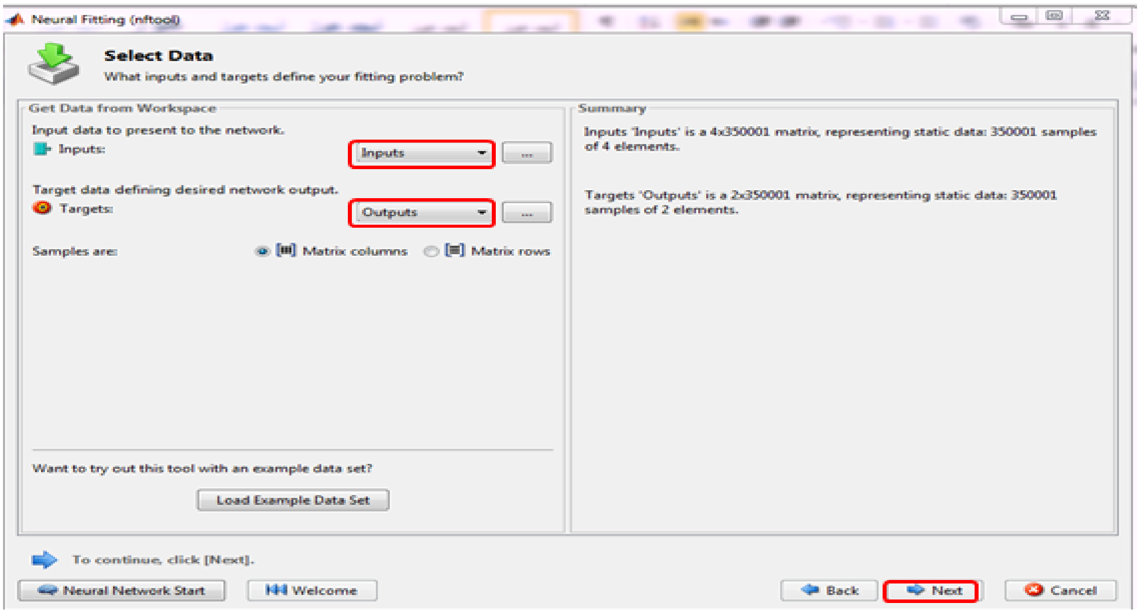

Figure 3.18: Select Inputs and Outputs

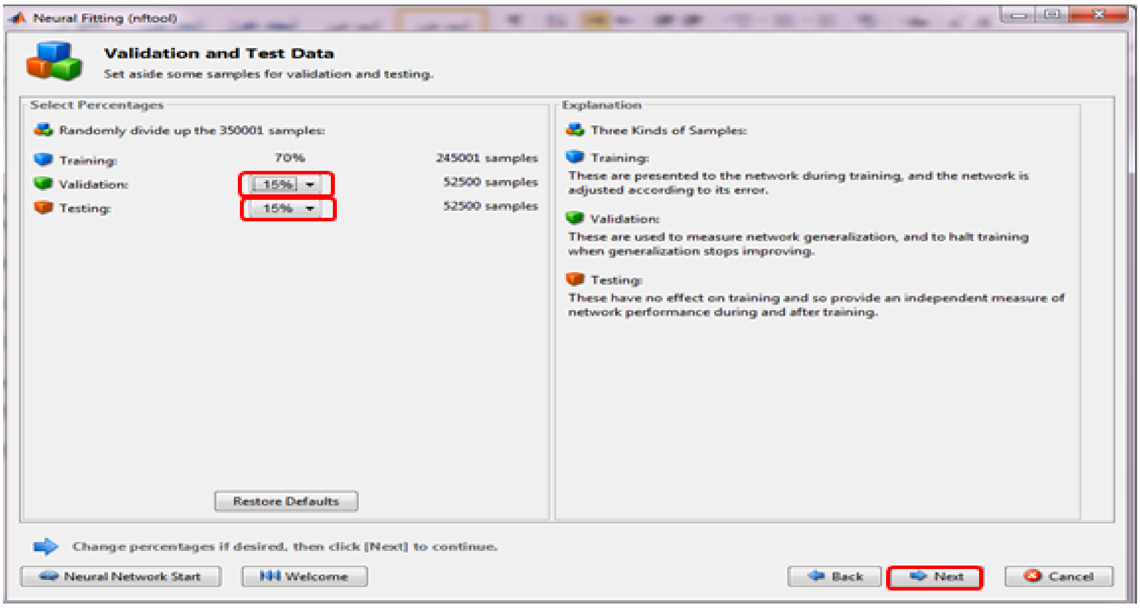

Figure 3.19: Validation and Test Data

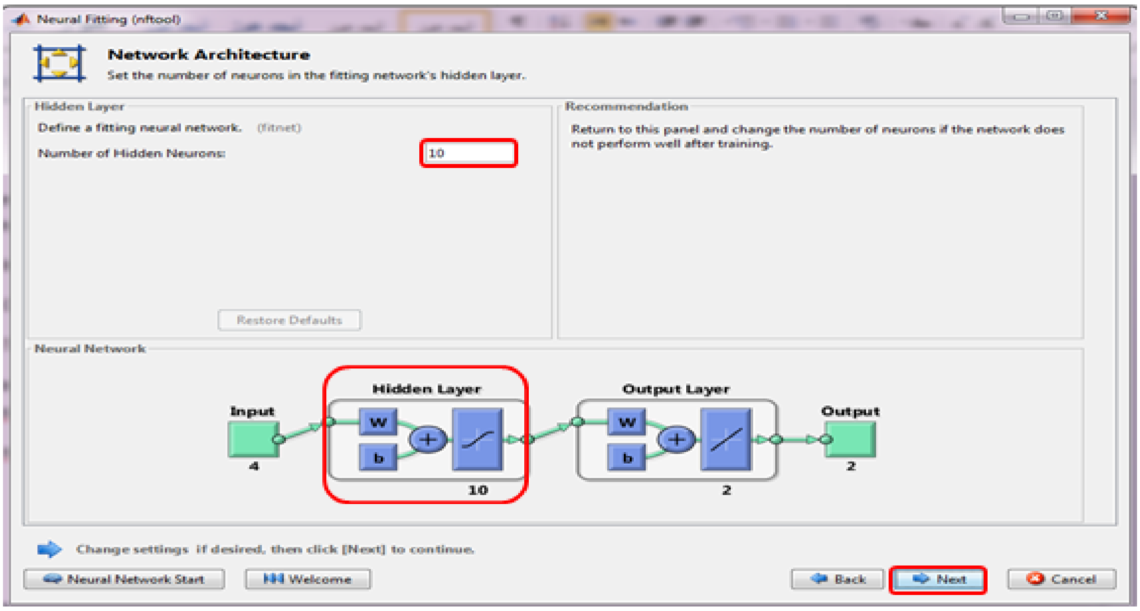

Figure 3.20: Network Architecture

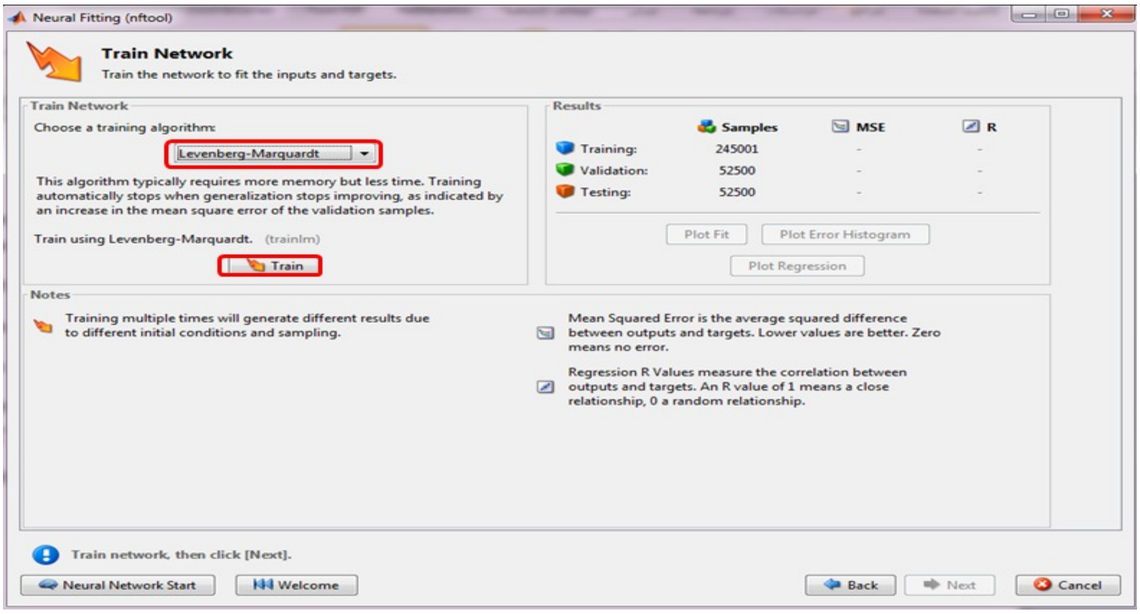

Figure 3.21: Train Network

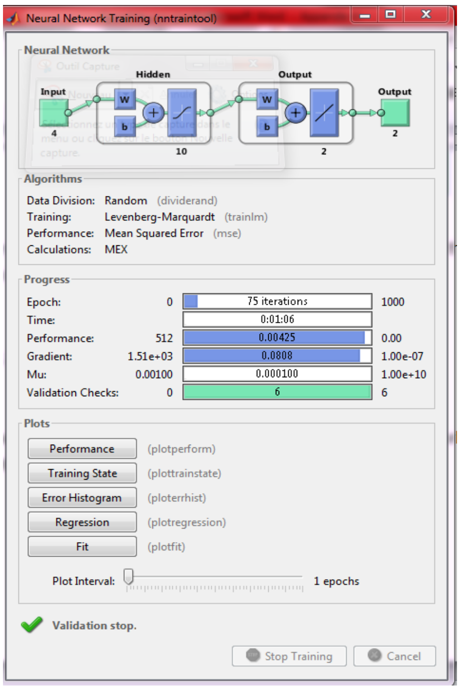

Figure 3.22: Neural Network Training

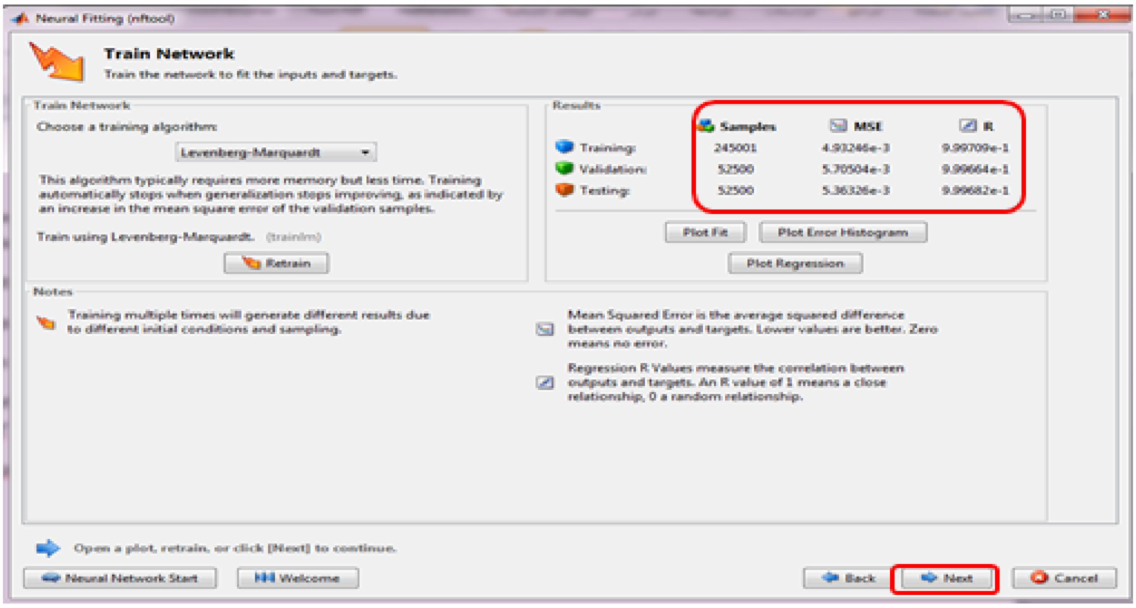

Figure 3.23: NN Training Results

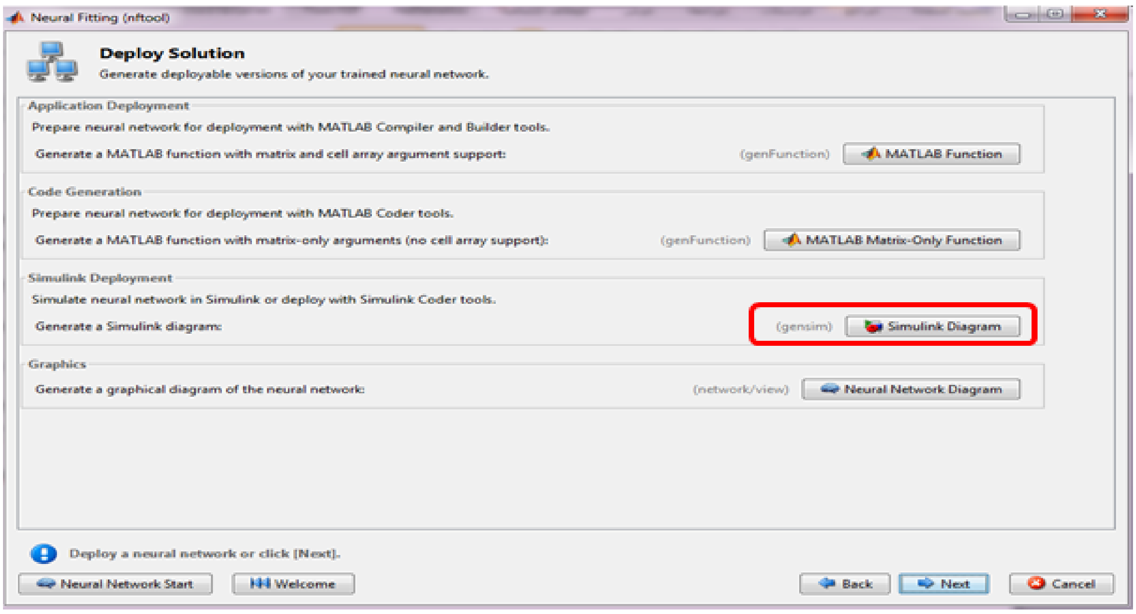

Figure 3.24: Display Soulutions

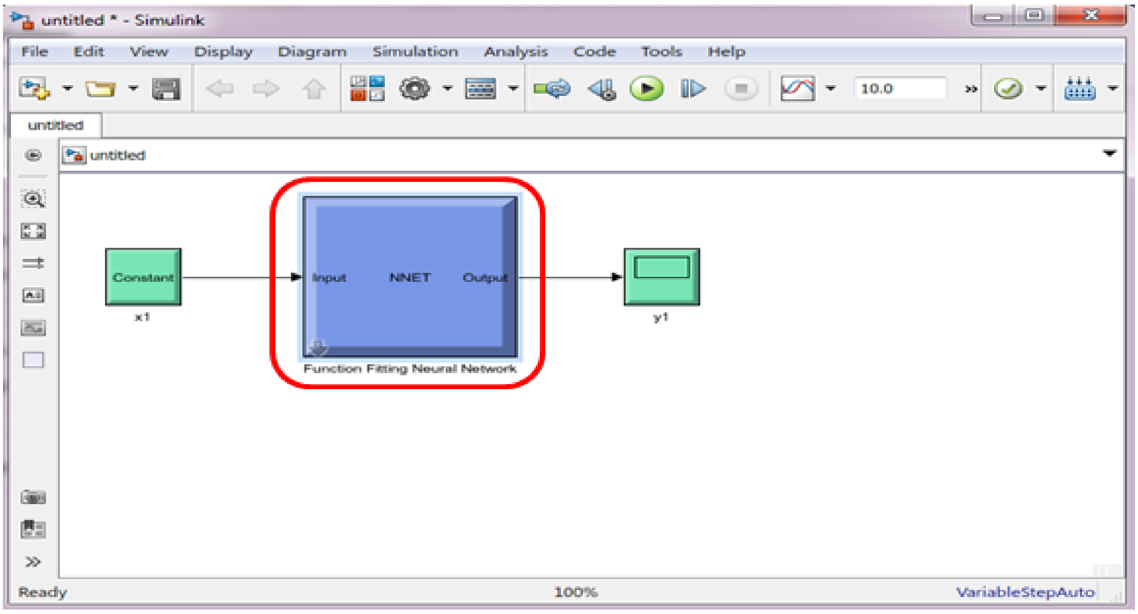

Figure 3.25: NN Simulink Diagram

3 Implementation of the NN Controller:

After the generation of the NN Simulink block, we copy it to our block diagram system and implement it as it is shown in the following figure (Fig 3.26) :

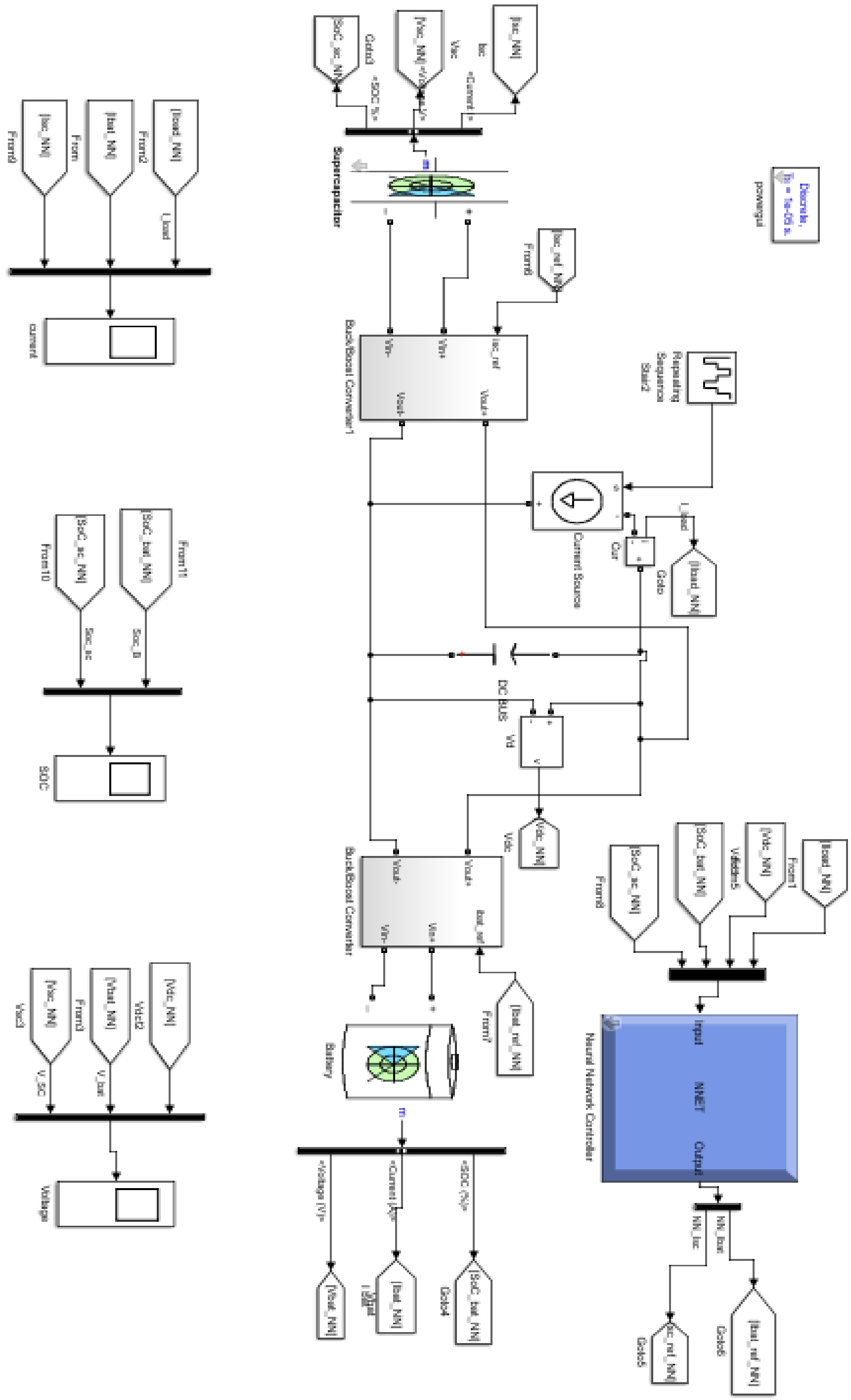

Figure 3.26: The schematic diagram of Neurel Network EMS

Bibliography

[1] "L'hydrogène électrolytique comme moyen de stockage d'électricité pour systèmes photovoltaïques isole." Julien Labbé. PhD Diss. École Nationale Supérieure des Mines de Paris, (2006).

[2] "Fast Facts: U.S. Transportation Sector GHG Emissions 1990-2018". Office of Transportation and Air Quality, EPA-420-F-20-037, (2020).

[3] "Energy management strategy design based on frequency separation, fuzzy logic and Lyapunov control for multi-sources electric vehicles". B. Traoré, M. Doumiati, C. Morel, J. Olivier and O. Soumaoro, IECON 2019 - 45th Annual Conference of the IEEE Industrial Electronics Society, Lisbon, Portugal, pp. 2676-2681, (2019).

[4] "Fundamentals of Engineering Thermodynamcis". Moran, M.J. and Shapiro, H.N, 3rd ed., John Wiley & Sons, New York, (1995).

[5] "ELECTRIC And HYBRID VEHICLES Design Fundamentals". Iqbal Husain, CRC PRESS page 1. CRC PRESS Boca Raton London New York Washington, D.C.. edition published in the Taylor & Francis e-Library, (2005).

[6] "Thorough state-of-the-art analysis of electric and hybrid vehicle power-trains: Topologies and integrated energy management strategies", Dai-Duong Tran, Majid Vafaeipour, Mohamed El Baghdadi, Ricardo Barrero, Joeri Van Mierlo, Omar Hegazy. Renewable and Sustainable Energy Reviews, Volume 119, 109596, ISSN 1364-0321, (2020).

[7] "Electric and Hybrid Vehicles: Technologies, Modeling and Control - A Mechatronic Approach " Khajepour, A.; Fallah, S.; Goodarzi, A.; John Wiley Sons: Hoboken, NJ, USA, (2014).

[8] "Control and Energy Management of an Electric Vehicle" O. Kraa, Ph.D. Thesis, University of Biskra, (2015).

[9] "Energy management strategies of connected HEVs and PHEVs: recent progress and outlook" Zhang F, Hu X, Langari R, Cao D. . Prog Energy Combust Sci 2019;73: 235-56. (2019).

[10] "Hybrid Electric Vehicles: Energy Management Strategies" Onori, S., Serrao, L., Rizzoni, G.; (pp. 25-28). London: Springer; (2016).

[11] "Modélisation des supercondensateurs et évaluation de leur vieillissement en cyclage actif à forts niveaux de courant pour des applications véhicules électriques et hybrides" Walid Lajnef; Thèse de Doctorat; Université Sciences et Technologies - Bordeaux I; (2006).

[12] "A comprehensive analysis of energy management strategies for HEVs based on bibliometrics" Zhang, Pei, Fuwu Yan, and Changqing Du; Renewable and Sustainable Energy Reviews 48 (2015), pp: 88-104. (2015).

[13] "Multi-mode control strategy for fuel cell electric vehicles regarding fuel economy and durability". Xu, Liangfei, Jianqiu Li, Minggao Ouyang, Jianfeng Hua, and Geng Yang. International Journal of Hydrogen Energy 39, no. 5 (2014), pp: 2374-2389. (2014).

[14] "Handbook of flywheel systems" Documentation NASA 16/92/FL, Washington (1992).

[15] "Caractérisation et modélisation de composants de stockage électrochimique et électrostatique" Nathalie Devillers. PhD Diss. Université de Franche-Comté, (2012).

[16] "Lithium-Ion Batteries: Modelling and State of Charge Estimation." Farag Mohammed. PhD Diss.(2013).

[17] "What Are Batteries, Fuel Cells, and Supercapacitors?" Winter, Martin, and Ralph J. Brodd. "What are batteries, fuel cells, and supercapacitors?(vol 104, pg 4245, 2003)." Chemical reviews 105, no. 3 (2005), pp: 1021-1021. (2005).

[18] "Fundamentals and energy storage mechanisms overview" M. Aulice Scibioh, B. Viswanathan, Chapter 2 - Editor(s): Materials for Supercapacitor Applications, Elsevier, 2020, Pages 15-33, ISBN 9780128198582. (2020).

[19] "Modélisation, dimensionnement et optimisation des systèmes d'alimentation décentralisés à énergie renouvelable - application des systèmes multi-agents pour la gestion de l'énergie." Jérémy Lagorce. PhD Diss. Université de Technologie de Belfort-Montbeliard, (2009).

[20] "Fixed electric double-layer capacitors for use in electronic equipment - Part 1 : Generic specification, International Electrotechnical Commission"; (2005).

[21] "Control strategy of fuel cell and supercapacitors association for a distributed generation system" P. Thounthong, S. Raël et B. Davat. IEEE Transactions on Industrial Electronics, vol. 54, pp. 3225-3233, (2007).

[22] "Hybrid supply for automotive application using supercapacitors." Rizoug, G. Feld et B. Barbedette. IEEE Vehicle Power and Propulsion Conference (VPPC), Lille, France, (2010).

[23] "Commande et Optimisation d'un Système Energétique Hybride (SEH)" Said Khoudiri, Application à l'Énergie Renouvelable, Thèse de doctorat, Université de Biskra, (2018).

[24] "Gestion optimisée des flux énergétiques dans le véhicule électrique" Adrian Florescu. PhD Diss. Université de Grenoble, (2012).

[25] "Neural network power management for hybrid electric elevator application" Maamir, M., Charrouf, O., Betka, A., Sellali, M. and Becherif, M., 2020. Mathematics and Computers in Simulation, 167, pp.155-175. (2020).

[26] "Neural network toolbox for use with MATLAB" Beale, Mark, and Howard Demuth. The MathWorks, Natick, pp: 42, (2002).