HYBRID ENERGY STORAGE SYSTEM FOR ELECTRIC VEHICLES

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CERTIFICATE

I, Shalu Yadav, Roll No. 2K18/PSY/13 student of M.Tech. Power systems (PSY), hereby declare that the dissertation/project titled "**HYBRID ENERGY STORAGE SYSTEM FOR ELECTRIC VEHICLES**" under the supervision of Prof. Mukhtiar Singh of Electrical Engineering Department, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology has not been submitted elsewhere for the award of any Degree.

Place: Delhi
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ABSTRACT

Hybridized storage energy system has now become a necessity of electric vehicle. Two or more energy sources are operated in conjunction to meet the load requirement. This facilitates with electric vehicle with long distance endurance. Inclusion of hybridized sources further increases the battery life by minimizing stress on battery, providing a cost optimal solution for the electric automobiles. Taking in consideration aforementioned advantageous features, the idea is to develop a modern hybridized storage structure topology. The optimal control methodology supervises DC_DC converter operations, which holds in the responsibility of regulating the power flow between battery pack, ultra-capacitor and the vehicle load.

This research work undertakes collaboration of batteries and ultra-capacitors along with magnetic integration which also acts as a filter and offers current smoothing along with additional weight saving advantages. Firstly, the control methodology is implemented using conventional controller i.e. PI controller. And in second phase, the control mythology is executed using an ANN controller. The ANN controller harnesses Levenberg Marquardt algorithm for weight training in order to achieve optimal weight parameters. Finally, the responses achieved using both the controllers are compared by validating the results using MATLAB/Simulink simulation which shows superior performance of A-NN controller on the projected topology over the PI controller.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

SC	Super-capacitor
UC	Ultra-Capacitor
HEAS	Hybrid energy accumulation system
HEV	Hybrid electric vehicle
BEV	Battery electric vehicle
PHEV	Plug-in hybrid electric vehicle
PI	Proportional-Integral
SEV	Solar electric vehicle
BLDC	Brushless DC motor
DC	Direct current
A-NN	Artificial Neural network
ELDC	Electric double layer capacitor

CSA-HES	Capacitor semi-active hybrid energy storage
BSA-HES	Battery semi-active hybrid energy storage
SA-HES	Semi-active hybrid energy storage
FA-HES	Full active hybrid energy storage
SOH	State of health
SOC	State of charge
BP	Backward propagation
LMA	Levenberg Marquardt Algorithm
PWM	Pulse width modulation

LIST OF SYMBOLS

W_L	Inductor energy
Q_C	Capacitor charge
L_1	Primary inductance
L_2	Secondary inductance
M	Mutual inductance
V_{UC}	Ultra-capacitor voltage
C_{UC}	Ultra-capacitor magnitude
β	Parameter vector
W_n	Nth weight
t_K	target output at kth epoch
O_k	System output kth epoch
J_k	Jacobian matrix at kth epoch
x_i	Independent variable
y_i	Dependent variable

μ	Marquardt factor
e_k	Error output vector

CHAPTER 1

INTRODUCTION

1.0. BACKGROUND

Electric vehicle is am eco-friendly technology for automobile users as they powered by fuel as well as batteries which falls under the category of clean energy source. The batteries alone or along with fuel can effectively use to power the wheels of the electric vehicle with reduces carbon emission to reduce the pollution level which is actually what the world needs as per current pollution level scenario.

The use of electric vehicle was first evoked by California Air Resource Board, as a big opportunity for the automobile users to contribute to reduce down pollution level by exploiting electric energy for their vehicle. The utilization of electric vehicle was first evoked by California Air Resource Board, as a major open door for the car clients to add to diminish down contamination level by misusing electric vitality for their vehicle.

But also, electric vehicles could not perform as required due to various limitations posed by batteries used in electric vehicles. This further pushed the researchers to optimize the battery design are thereby improving factors such as power density, life cycles, chemical stability etc. With the battery usage, various performance parameters tend to degrade over time because of various properties associated with chemical stability, conductivity etc. as well as other factors like operating temperature and other environmental conditions.

Although researchers are continuously working in past decades in order to improvise battery performance, still challenges are faced during peak usage time since battery deterioration occurs during its sudden usage. In EVs, sudden usage situation is faced considering variable driving cycle, road condition, traffic situation etc. During acceleration period in EVs, sudden load demand poses limitation as the battery pack cannot discharge that quickly as required by driving load. Same applies during deacceleration period in EVs, as high current flows in braking condition These high current flow into or from the battery pack tend to have detrimental effect on battery performance. These conditions in long run results in reduction in life span of the battery.

1.1 OUTLINE OF CHAPTERS

The thesis consists of following chapters:

Chapter 1: This chapter gives a brief review on electric vehicles, challenges faced by them and how these challenges can be overcome.

Chapter 2: This chapter gives the literature review done in related for the present work "HYBRID ENERGY STORAGE SYSTEM IN ELECTRIC VEHICLE". The literature review is done to understand various types on electric vehicles, charging standards of electric vehicles and understand types and working of various elements employed in EVs.

Chapter 3: This chapter gives a detail understanding of various energy storage elements exploited for the purpose of driving the EVs and various topologies related to arrangement of these energy storage elements. Thereon, the projected energy storage topology is being explained along with the modelling of its elementary components.

Chapter 4: In this chapter detail analysis id done on artificial neural network which is being utilized for designing the controller for our hybridized energy storage system.

Chapter 5: This chapter deploys the designed controller into the system in MATLAB/SIMULINK environment. The results are obtained by running the simulation using PI and ANN controller, and results are then compared.

Chapter 6: This chapter gives the main conclusion of the work done and also includes scope for future work.

CHAPTER 2

LITERATURE REVIEW

2.0. GENERAL

Although a wide range of batteries are available utilized as power source in EVs, but the most promising performance characteristics are obtained in lithium ion batteries, which are thereby most popular energy accumulat*i*ng device in EVs.
But the reason why electric vehicles are still not to conquer the transport industry is the limitations posed by the electric vehicle battery. Few major limitations are: Huge weight of the battery. With increased weight of the battery the load on electric vehicle also increases; Short lifespan of the batteries. Lithium experience the ill effects of maturing. A normal can withstand 500 – 1000 charge-release cycles. These henceforth should be supplanted every now and then and can turn into a headache whenever installed in the gear. Capacity in a cool spot at 40% charge, lessens the maturing impact.
Reduced efficiency under heavily loaded conditions. When the load on the battery increase their efficiency decreases. In order to overcome these limitations a technology is introduced which uses integration of batteries along with supercapacitors which give rise to a type of hybridized energy storage system for electric automobiles. Super-capacitors (SCs) are comparable electrochemical frameworks for energy, however the principle distinction is that they have high rate ability for quick charging/dis-charging [1]. They can't be utilized as the primary source of power for EVs since they have low energy dense in contrast to battery being primary power accumulator. By and by, they are acceptable alternatives to compromise with the high peaks, during brief timeframes when the power of battery isn't adequate[2].

The electrical attributes of SCs are a similar to that of the exemplary condensers, however as the name, the super capacitance is relatively a much greater. The word “super--condenser” was economically applied to define the primary twofold layered condensers, however in the logical setting, it was alluded to the electrochemical frameworks working dependent on capacitive or pseudo-capacitive nature. The presentation of the known pseudo-condensers is depending on the electro-chemical redox framework relatively than double layer charging. This offers an occasion for delivering an expressively higher specific capacitance, though., the cyclability is quite inferior. It has been decorated in numerous published literature that SC's can effectively and also function longer than any other kind of energy stockpiling framework(ESF)[2]. Introduction of super-condensers along with batteries in EVs offers various advantages such as:

- Reduces thermal stress on the batteries.
- Protecting from distractive current spikes to the
- Increases life cycle of the batteries.

Improves efficiency of overall system by storing the energy during the slowdown of the EAs.

2.1. TYPES OF ELECTRIC VEHICLES

Before analyzing any deeper let's begin with categorizing the electric vehicles Electric vehicles based on power source available in the vehicle to drive the power train.

2.1.1. Battery Electric Vehicle (BEV)

BEVs are the EVs which operate solely with batteries as their power source to drive the wheels. Since batteries are only the power source therefore the mileage of these vehicles is straightly proportional to the capacities of batteries used. Typically, BEVs cover a range of 100 km to 250 Kms in one charge. This range may also go up to 300 Kms to 500 kms when top model batteries are used. Further, this range also depends on other factors such as driving cycle, road condition, climate, vehicle configurations etc. Once the battery is empty it requires some time investment respective to refueling fuel tank of a conventional ICE vehicles which hardly take a minute while BEVs may take as long as 36 hours to get full [3].

Charging span relies upon charger arrangement, its framework and supplying power level. Because of their straightforward development and operation BEVs are exceptionally advantageous to utilize. The major advantage BEV offer is these do not emit greenhouse gases. Also, these are noise free. Electric propulsion gives instant and high torque, even at lower driving speed. Combining the advantages and disadvantages offered by BEVs, BEVs are found suitable for urban driving vehicles as urban driving requires running at slower speeds. Tesla and Nissan leaf are key players in BEV market. Fig 1. shows essential structure of BEV where electric motor(s) drives the wheels; and motor is controlled by pack via

DC_DC converter.

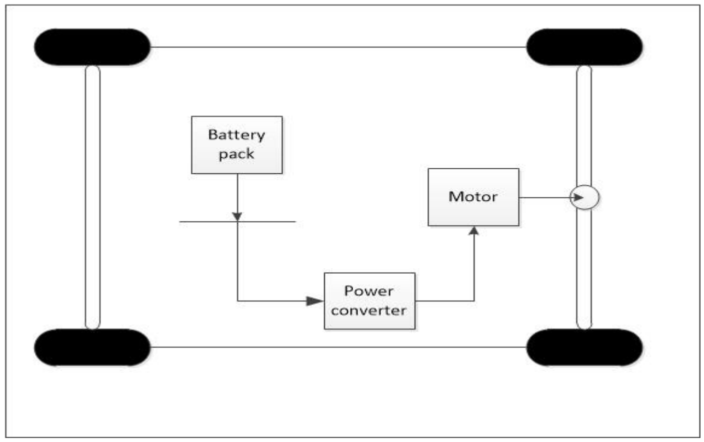

Fig. 1. Drivetrain architecture for Battery electric vehicle

2.1.2. Hybrid Electric Vehicle (HEV)

As the name suggest HEV is combination of internal combustion engine (ICE) and electric power supply to drive the wheels. When power demand is lower, HEV utilizes electrical propulsion system. It reduces fuel ingestion since the engine remains off when vehicle is in idle condition e.g. traffic jams etc. which cuts down carbon emission. During higher speed, internal combustion engine is turned on. The ICE and battery pack works combinedly to improve overall vehicle efficiency[4]. In turbocharged vehicles, similar to the Acura NSX; hybridized power structure is utilized comprehensively to chop down or to completely dispose of turbo slack. It additionally improves execution by filling the gap between gear moves and giving higher speeds when required. Further, HEVs use engine to power up the batteries when batteries are drained below certain level. So basically, HEVs are ICE driven vehicles where electrical power is used optimize performance characteristics. To exploit all these features HEVs are widely adapted by automobile users [5].
Fig.2. shows a conventional HEV. The ICE can optionally run the motor runs generator in order to charge the battery pack, while starting the vehicles. When speed boost is required, ICE and motor both supplies power to drive the wheels.

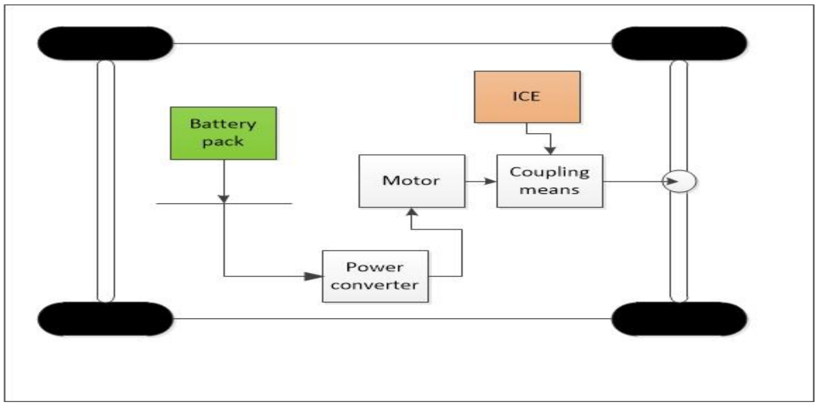

Fig. 2. Drivetrain architecture for hybrid electric automobile and Plug-in electric vehicle

2.1.3. Plug-In Hybrid Electric Vehicle (PHEV)

A Plug-in hybrid electric automobile uses ICE and the electric power train both but unlike the hybrid electric vehicle PHEV utilizes electric force as the chief driving force. Since the electric power source is the main energy supplying force therefore battery capacity requires in PHEV is much more than in HEV and so is the size of battery. PHEV starts in all electric phase, also works in electric mode and when batteries are to drained up it reaches ICE engine to power up the battery pack. So, ICE engine is basically used to extend the range of PHEVs. Also, PHEV can have additional functionality to utilize the grid power to power up the battery pack, which is absent in HEVs. The ability of PHEVs to get driven merely on battery packs most of journey makes carbon emission quite low and fuel requirement is also low. The main market players in case of PHEVs are Chevrolet Volt and Toyota Prius[6].

2.1.4. Fuel Cell Electric Vehicle (FCEV)

Fuel cell electric vehicle as the name suggest runs on fuel cell producing electricity through chemical reaction, illustrated in Fig.3. They are frequently called hydrogen energy unit vehicles as hydrogen is primary option. FCVs holds the hydrogen in unique high-pressure tanks, another element for the power generation is oxygen; which FCEV secures from the air captured from nature. Power created from the energy components goes to an electric engine which drives the wheels. Overabundance energy is accumulated in frameworks like or super-condenser. A major advantage of such vehicles is that these vehicles can generate electricity of their own through the chemical reaction process. This enables FCEV to have lesser carbon imprints than any other type EV. Extra available electric energy is being stored in batteries and supercapacitor. Another advantage of such EVs is lesser refilling time which further increase adaptability in the market for FCEV in near future. The biggest challenge currently faced by these vehicles is scarcity of hydrogen fuel station.

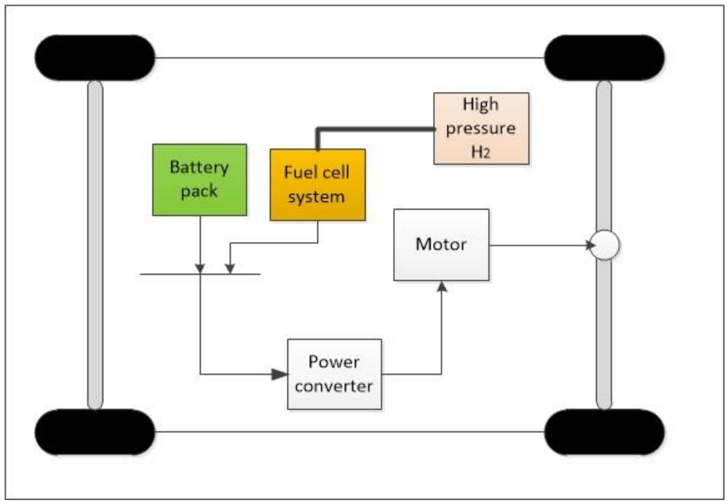

Fig. 3. Drivetrain architecture for fuel-cell electric vehicle

2.1.5. SEV Solar electric vehicle (S-EV)

Solar electric automobiles are the transportation means energized by solar energy. For that solar arrays are being attached to the top of vehicle. The photovoltaic cells present in array converts solar energy directly into electricity which is to be used to drive the wheels. Solely using solar energy can cause irregularity in energy availability therefore battery is made available to store the energy when present in excess. Practically, SEV appears to be a better choice when vehicle running time is much lesser than its parking time wherein the parking is in sunlight.

Illustrating the Table 1 to demonstrate advantages and disadvantages of various technologies being employed in electric vehicle domain[3].

Electric automobile Technology	Advantageous features	Disadvantageous features
Hybrid electric vehicle	• Reduced fuel	• Higher initial cost

(HEV)	consumption • Possible energy recovery from regenerative braking	• build in complexity due to two power trains
Plug-in electric vehicle	• Grid connection available • Possible energy recovery from regenerative braking	• High initial cost • Added weight due to battery and associated components
Battery electric vehicle	• Cleaner energy source available	• Short distance range • Public improved recharging infrastructure needed.
Fuel cell electric vehicle	• High productivity contrasted with ICE vehicle	• High initial cost • Accessibility and price reasonableness of hydrogen refueling stations
Solar electric vehicle	• Ready to use full power at any speed	• Lower speed compared to ICE cars • Can't operate in sunlight only, unless battery operated

Table 1. Advantages and disadvantages of various type electric vehicles

2.2. CHARGING SYSTEM FOR ELECTRIC VEHICLE

In grid integration, architecture development and usage, charging gear in EVs plays a critical role. A charging station regularly incorporates charge line, charge stand, connection plug, electrical plug, vehicle connector and furthermore a security framework so as to shield the automobile from undesirable surges and possible short-circuits and other different issues. The arrangement of the charging station may differ from region to region, further depends on frequency, voltage, electrical grid connectivity and standards applicable in the particular region. In any case, charging period and expected life of an EV's battery are linked to the characteristics of the charger that first must guarantee a right charging of the battery. After charger is able to provide good charging characteristics its further expected for the charger to be efficient and reliable, with higher power density, lower price and lower weight and volume.

Plus, the EV charging framework, that can be sorted into off-board and on-board types with uni-directional or bi-directional power movement. The advantage of using a unidirectional power flow charger is that it limits hardware requirement for the system and simplifies connection related problem. On the other side, a bidirectional charging unit supports energy dosage to the grid from the vehicle battery. Whenever, charger is located inside the vehicle, called on-board chargers and it permits holders of vehicle to charge their vehicles everywhere a appropriate power supply is available. Be that as it may, on-board chargers typically have limited power because of their volume or weight, space requirement and expenses. They can be incorporated with the electric drive for staying away from these issues. The accessibility of a charging foundation diminishes on-board energy storing needs and expenses. High charging rates are intended for an off-board charger and is less compelled by size and weight. and load on the battery is lower therefore energy requirement to drive the vehicle is also low.

2.2.1 Charging levels for EV

There are three levels which are undertaken to portray the charging intensity of EVSE: Level 1, Level 2 and DC Fast Charging. The charging level used decides amount of time a vehicle will take to charge and the range. The measure of range accommodated each of these is illustrated in Fig.4. beneath with extra subtleties in the accompanying segments.

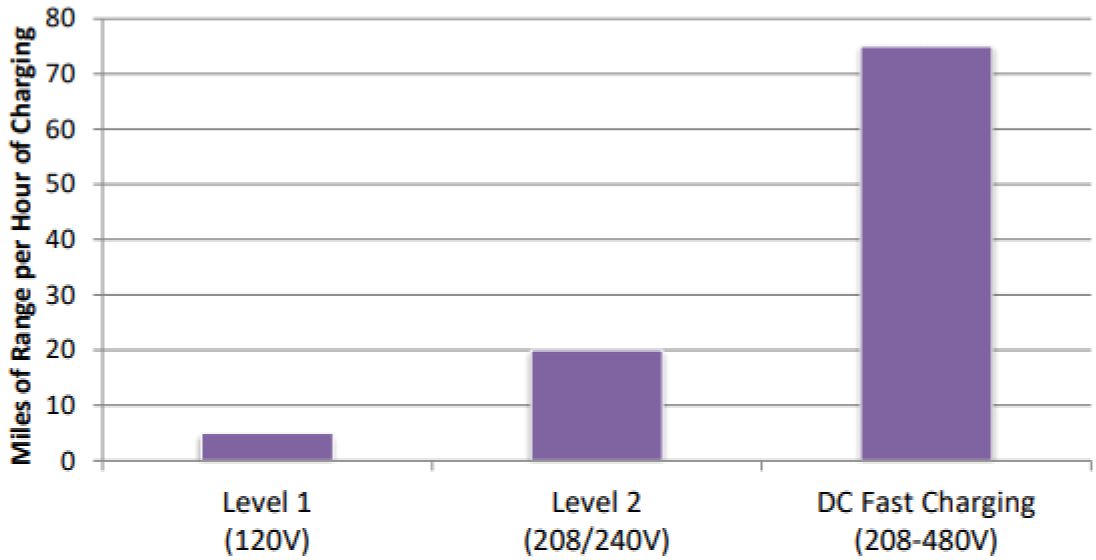

Fig. 4. Charging range added per four of charging

1.2.1.1. 120 Volt Charging; Level 1

The easiest charging form is level 1 charging. It makes use of an AC supply, 120 Volts connection at a standard uptown and/or commercial electrical outlet proficient of passing a current of amount which is 15-20 amps, draws power of usually around 1.4 kW while charging. Electric automobiles are furnished by portable Level 1 chargers. Around, 10-14 hours are required to full charge an EV with range of 60-80 miles, which is quite a big amount required by level 1 charging.

Pros for level 1 charging:

- Lesser installation cost.
- Lesser effect on electric utility peak demand prices which are frequently imposed to business accounts.

Cons:

- Charging is sluggish wherein approximately 3-5 miles of range is being supplemented per hour of level 1 charging.

1.2.1.2. 208/240 Volt Charging: level 2

Moving on to another charging standard which is charging "Level 2", requiring a 208/240V AC power assembly. Since it using a higher voltage level than level 1 charging, here the charging time is meaningfully reduced. A 208/240V supply is readily available to a user since commonly 240 V power is used in some household appliances such as electric heater appliances etc. Also, business customers mostly have 3ph electric power supply with 208 V power which can used easily for level 2 charging. Any of above voltage 240V/ 208 V works adequately fine for "Level 2" charging standard. A J1772 connector employed widely by electric automobiles, which can theoretically furnish up to current of 80 amps (19.2 kW), although most vehicles presently available only use up to 30 amps for 3.3 to 6.6W charging. The J1772 connector is manufactures to operate for a 1ph electrical system with 240 V or 120 V such as those used in North America and Japan. The J1772 connector comprises a circumferential body of 43 mm i.e. 1.7 in diameter having five pins, with three different pin sizes (starting with the largest), for each of: AC line 1 and line 2. AEVs (every electric vehicle) with 60-80 miles of range will normally take about 3-7 hours for a full charge utilizing Level 2 hardware, contingent upon the limit of the EVSG (Electric vehicle supply gear) and the vehicle charging framework. Likewise, EVs with minimal, for example, a PHEV with 10 miles of range for example Toyota Prius Plug-in, and so forth may require not exactly an hour to achieve full charge.

Advantages

- Charge duration is noteworthy faster than Level 1. A 10-20 miles is being added to EVs by an hour of level-2 charging.
- Speedy charging and efficient as well than a level-1 charging infrastructure.
- Variety of makers provides differentiated equipment's for separate business sector and prerequisites for level-2 charger.

Disadvantages

- Establishment prices are more than Level 1 and are exceptionally factor contingent upon gear and establishment issues related with this charging standard.
- Conceivably higher effect on electric utility peak demand's charges than level-1.

1.2.1.3 DC Fast Charging/Level 3 charging

Regularly alluded to as Level 3, DC quick charging apparatus infuses high power straight into arrangement of the EVs, which empowers speedy charging. Traditionally, a 80% charge can be feed into the in only a period range of 30 minutes or even less for some electric vehicles. DC quick charging can't utilize same J1772 plug connectors as Level 2 due to higher voltage and current level which can't be handles by J1772 plug connector. There are three

discrete connectors for quick charging gear by different market players:
i) CHAdeMO utilized by Nissan, Mitsubishi and Kia;
ii) SAE Combo utilized by American and European creators, for example, Chevrolet, BMW and Mercedes Benz; and
iii) Tesla's Supercharger utilized only on Tesla Model S and later tesla vehicles. Tesla has additionally declared a connector permitting their proprietors to utilize CHAdeMO gear. Lately, ABB India installed its first public DC fast charger in New Delhi with EV Motors India, the major charge point operator for BSES Yamuna Power Limited. The Terra54 CJG charging station, which caters to multiple charging protocols of CCS2, CHadeMO and AC Type 2.

Advantages

- Charge time is dropped down radically – typically to a duration of 30 minutes for an 80% charging state to be achieved.

Disadvantages

- Gear and establishment prices are than level 1 and level 2 charging, \$20,000-\$100,000 relying upon hardware and power accessibility at site.
- Scope for expanded peak power demand charges from electric utility.
- Contending norms are puzzling to EV purchasers and furthermore to charging station administrators.
- Expected problems with chilly climate activity which prompts expanded charging time.

2.3. Motor in EVs

Presently, the type of motor used in electric vehicle in majority are DC motors. Among AC motor there is induction motor being used in EVs. Usually, advanced power EV (more than 5kW), utilize Induction Motors. Directly, BLDC motor finds applications in low power EVs. Electric motors utilized in electric vehicle must possess imperious properties as in easy setup model, high vitality, low maintenance cost, and precise control. Motors generally employed by electric vehicle manufacturers are DC motors, Induction motors, Synchronous motors, Switched Reluctance motors and Permanent magnet brushless motors. AC induction motor and DC brushless are two of the most innovative and best-performing motors to chosen.

Product Name	Manufacturer	Type of motor used	Year
Chevrolet Bolt EV	Chevrolet	PMM	2018
Focus electric	Ford	PMM	2018

Mitsubishi i-MiEV	Mitsubishi	PMSM	2017
Nissan Leaf	Nissan	PMSM	2017
Volkswagen Golf Electric	Volkswagen	PMM	2014
Fiat 500e	Fiat	PMM	2014
Tesla model S	Tesla	IM	2012
Toyota Pirus	Toyota	PMM	1997

Table 2. Recent electric vehicles manufacturers by top producers and electric motor used in them

2.3.1 Direct Current Motors

DC brushed motors can achieve at low velocities the high torque, influencing them to be suitable for traction framework. However, lower power density is a downside of brushed DC motor for accounting in electric vehicles. DC brushless motors in the contrary provide better efficiency and have less maintenance. Truly, a DC (Direct Current) drive has been utilized evidently in the EV's on consideration of the fact that they provide speed regulation and flawless torque speed characteristics. Excursion motors for electric vehicles are aligned in two sections, switching motors and motors without commutation. Switching motors are essentially conventional DC motors, including, series and shunt excitation. DC motors have been the subject of attention since these offers straightforward control and decoupling of motion and torque. Obviously, DC motor is still great competitor for lower power requirements. DC motors are robust and allow simple control. The permanent magnet motor utilizes rare-earth elements into its magnets, which makes it exclusive. Part of vehicle delivering organizations prior utilizing AC engine presently have begun to change from induction motor to permanent magnet motors since it has a size and weight advantage that is huger as cars are getting generally littler. They are likewise being utilized in practically all electric vehicles around the world. One organization that took a major leap in its engine utilization is Tesla. The famous California-based corporation applies an AC induction motor to all its model vehicles, yet when Model 3 EV was exhibited, it was found that they modified its motor to DC permanent motor. As per reports, the purpose behind the change is that it needn't bother with an extra power, dissimilar to the AC engine. They additionally uncovered that utilizing the permanent magnet has settled their cost-minimization work.

2.3.2 Induction Motors

3ph induction motors are usually utilized in electric vehicles as they facilitate enormous proficiency, efficient speed control and no commutator requirement as in case of DC motors. 3ph AC supply is associated with stator winding, thus building up the spinning magnetic field. AC Induction Motor Drive is ideally utilized then in EV. They are largely acknowledged these days due to being the commutator less arrangement. This leads to their high reliability and a low upkeep necessity.

- Induction motor contains no collector and no brushes, so it requests fewer supports.
- Price of Induction Motor is not as much as cost of DC motor for a similar rated power.
- Weight of Induction motor is under weight of DC motor for a similar rated power
- IM is much sturdy than DC motors and can works better in unusual surrounding conditions.
- IM could be made to work for rated voltage till 25 KV.
- IM could be fabricated for greater power and can arrive at a pivot of 50000 rpm.

2.3.3 Permanent Magnet Synchronous (PMS) Motors

In synchronous motor, rotor shafts at synchronous speed. The rotor is supplied from a DC power supply while the stator is provided with an AC 3ph supply to generate a 3-phase rotating magnetic field. PMS motors are also acknowledged as brushless AC motors. Regarding the vitality productivity, the most effective motor is the Permanent Magnet (PM) Brushless Motor Drive, pursued by Induction Motor having relatively comparable effectiveness. As a matter of fact, numerous vehicle giants, for example Honda, Nissan, Toyota etc. have effectually exploited these motors. These motors stay ahead in sense that they have higher power thickness, higher proficiency as well as, they possess more powerful propagation of warmth into the condition. Machine profits by the enormous energy thickness of the magnets, on grounds that the permanent magnet excitation requires restricted space. As no excitation current is required, the PMSM gives a colossal capability in the extent of apparent speed. The commanding misfortunes in setting with PMSM are the iron losses, occurring in stator, and could be successfully reduced by a cooling structure. From this time forward, the PMSM outperforms the IM in thickness and profitability. Its huge obstacle is the high cost of uncommon earth magnets like NdFeB.

2.3.4 Permanent Magnet Brushless DC and AC Motors

Another category of motors in possibility to employ is the permanent magnet brushless dc motor. These are accessed by for all intents and purposes transforming the stator and rotor of the permanent magnet dc motor. Despite the fact that their setup is relative to the PMS motors, the BLDC motors are fed by an AC supply that is rectangular in nature as opposed to a sinusoidal supply. Another advantage of PM-BLDC motor is their potential to produce a larger torque when contrasted with other motors at similar apex amount of current and voltage. Permanent magnet brushless dc motors give a higher power thickness and a substantially more remarkable productivity, that's why it holds a decent ability for getting employed in automobile impetus framework.

2.3.5 Switched-Reluctance Motors (SRM)

SRMs use rotor location changes to strengthen the different phase coils in sequence. A wide speed expand is possible. Rotor intends to continue to a position of smallest reluctance along these lines inciting torque. SRMs have characteristics viz., huge beginning torque, and incredible inborn variation to non-basic disappointment capacity, in this manner being sensible for EV use. Activity in steady power is shaped conceivable by the phase progressing of current in stator conduction edge down to the point that covering between the progressive phases happens.

CHAPTER 3

HYBRID ENERGY STOARGE SYSTEM

3.0. INTRODUCTION

There are various preferences offered by electric and hybrid vehicles with respect to their low discharge, comfort factors, high trustworthiness, dynamic angles and some more, in spite of all these profitable factors yet there is one significant challenge looked by electric vehicles and that as execution of energy stockpiling arrangement of electric vehicles. In present situation, practically all pure electric vehicles (PEVs) are outfitted with galvanic electrochemical batteries, which have much lower vitality thickness (J/m3 or J/kg) contrasted with petroleum [1]. Indeed, even in very good quality EVs like Tesla model X which is giving in excess of 450 km travel go, the normal cost electric vehicles can drive far not exactly customary vehicles [2]. There is even an extraordinary term called – "range anxiety", relating the fear that electric vehicle can run out of charge before arriving at its objective or reviving point [3], [4]. This issue is decently settled with traditional internal combustion engine, hydrogen engine or fuel cells being outfitted in hybrid electric vehicle(s) (HEVs).

3.1. TYPES OF ENERGY STORAGE SYSTEMS IN EVs

The following energy storage systems are used in HEVs, PHEVs, and EVs.

3.1.1. Batteries in Electric vehicle

Battery is a heart of electric vehicle. Evolving a high performing battery in multiple aspects is term of power, high energy density, low resistance, safety in operation, higher life expectancy, low cost, less environment affected is what a major obstacle in emergence of electric vehicle is greatest technology in automobile market vanishing fuel run vehicles from everywhere. Lead-acid batteries Lead-acid batteries were initially utilized in before hybrid electric vehicles (HEVs) and EVs. In any case, the driving extent was not exactly agreeable because of the lacking energy thickness, which had likewise restricted its market adequacy. Since the time at that point, mounting research has been centered around the advancement of higher explicit vitality NiMH immediately turned into the innovation of decision for the

developing HEV market [6].
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Lithium SBs (storage battery) are most guaranteeing for vitality stockpiling in EVs, due to their standout qualities offering high vitality thickness, high specific vitality, high torque, and light weight. Moreover, lithium battery has no memory effect and no destructive effects dissimilar to mercury or lead. Nonetheless, this type is pricier than other types; it ordinarily costs around $150 for 1300/kWh and furthermore needs insurance for innocuous activity and a cell balancing framework to guarantee unswerving execution at a similar voltage and charge level.

3.1.2. Supercapacitors for electric vehicles

A form of electrochemical capacitor i.e. super-capacitor, is also mentioned as the ultra-capacitor. They constitute different electrolyte and electrode properties as compared with traditional capacitors. There is no traditional solid dielectric present in the supercapacitor like that of traditional capacitors. On the contrary, in super-capacitors electric-energy accumulation is attained by the electrostatic double-layer capacitance and electrochemical pseudo-capacitance. The previous is a consequence of splitting of twofold layer charge at the interface between a conductive cathode and an electrolyte when the voltage source is suggested, while the working instruments of pseudo-capacitors are redox responses, intercalation and electro sorption [14]. Supercapacitors are a lot quicker to charge than battery. It beats batteries likewise because of their stable electrical properties, more extensive range and longer lifetime [7].
A SC is similar to an ordinary capacitor in terms of construction and functioning [7]. Nevertheless, a SC tends to comprise high energy accumulating capacity typically 10 to 100 times energy per unit mass or volume than an electrolytic capacitor, when the magnitude ranges in kilo farads but have lower voltage holding capability, that conduits the difference in electrolytic capacitors and rechargeable batteries. The specific power of SC is nearly 1000–2000 W/kg with 95% energy efficiency. SC has the lengthiest life-time of almost 40 years, in class of all ESSs. SC is recognized in automobiles requests because of its higher-power accumulation features; it requires little care, and it showcases temperature in-sensitivity and a much longer operating duration. With fast charging and discharging profile of SCs, the SCs are being employed in EVs as energy accumulators during the period of electric braking and as an energy source while swift acceleration required for steep running in EVs. SCs are present in three categories, namely, an electric double-layer capacitor (ED-LC), a pseudo

capacitor, and a fusion capacitor. (ED-LCs) use carbon electrodes or derivatives and has greater power density than other type capacitors. Meanwhile, specific energy is 5–7 W h/kg which is quite low, self-discharge is higher, and price is higher as well. Metal oxide or conducting polymer electrodes with a high amount of electro-chemical pseudo-capacitance additional to the double-layer capacitance is used in Pseudo-capacitors

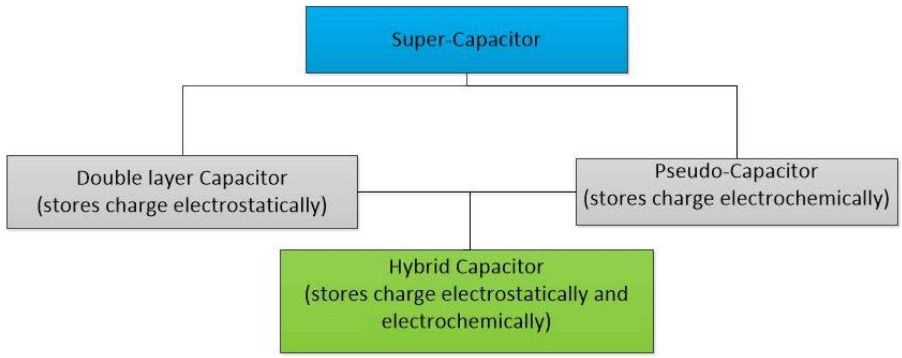


Fig. 5. Capacitor types

SCs exploits dielectric materials of higher permittivity, permeable dynamic carbon surface-edged anodes, or aqueous type electrolyte, and a slender permeable separator. SCs have higher vitality thickness and terminal voltage than aqueous SCs [9]. SCs are regularly utilized for driving EVs. Particles move in the middle of the cathodes through the electrolyte in SCs. The energy accumulated in the capacitor is in direct proportionate to its capacitor magnitude and squared proportionate with the voltage along terminals, and the capacity surges with the increase of the surface area of the electrode and the permittivity of dielectric materials, and with the abatement of the separation between anodes, as delineated in Eq. (1.1)

$$W_c = \frac{1}{2} CV^2 = \frac{1}{2} QV \tag{1.1}$$

Fig.6 and Fig. 7 show voltage and current qualities while charge absorbing and releasing of a supercapacitor. In charging, the voltage rises straightly and the current drops of course when the capacitor gets fully charged. It does not need a full-charge recognition circuit as well. This is valid with constant current flow and voltage limit that is reasonable for the capacitor rated voltage; surpassing the voltage could harm the capacitor. The voltage increments straightly during a steady charge, when the capacitor is full current drops of course as appeared in Fig.6. Voltage drops straightly on release, the dc-dc converter can keep up wattage level by higher current with dropping voltage.

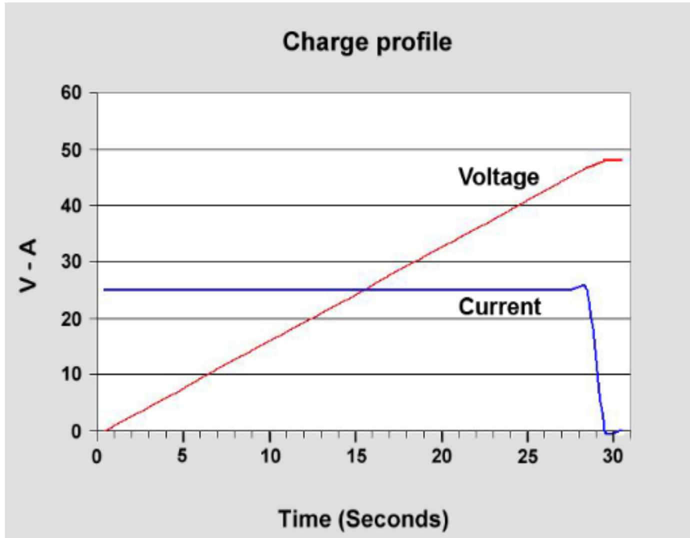


Fig. 6. Charge profile of a Super-capacitor

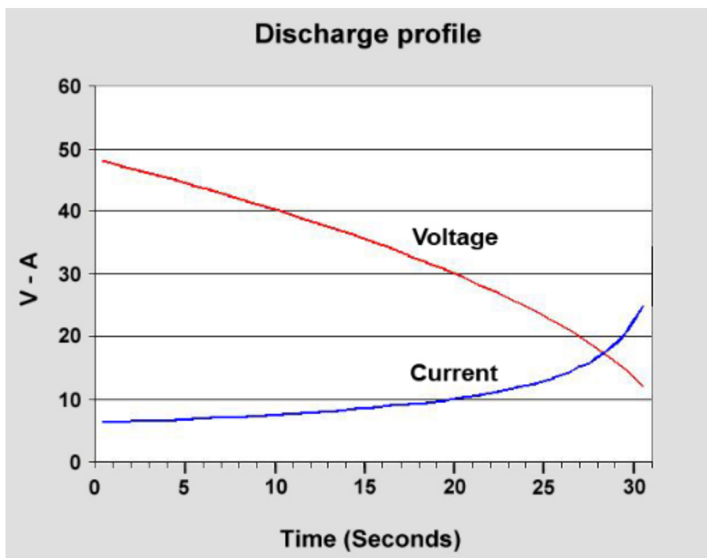


Fig. 7. Discharge profile of Super-capacitor

The common charging time of a super condenser is 1–10 sec. The charge attribute is practically identical to an electro-chemical battery and the charging current is, to an enormous degree, restricted by the charger's ability. The underlying charging can be made quick, and the filling the charge will need additional time. Course of action must be made to bound the inrush current while charging an unfilled or void supercapacitor as it attempts suck in everything it can. The super capacitor isn't inclined to overcharge and doesn't need full-charge detection; the current basically quits streaming when filled in.

The super-capacitor can be filled in and out frequently limitless number of times whereas an electrochemical battery has a definite life cycle. A supercapacitor goes from 100 percent to

80 percent capacity during a 10 years span, under normal operating condition. When operating voltage is higher it tends to curtail the life span of supercapacitor. Supercapacitor are forbearing in hot and cold climatic conditions, which is a big advantage over batteries, as batteries cannot meet this equal superiority.

Self-release behavior of a super-condenser is extensively higher contrasted with that of an electro-static capacitor and marginally higher than an electrochemical battery; the organic electrolyte adds to this. The supercapacitor releases from 100 to 50 percent in around 30 to 40 days wherein lead and lithium-based batteries, in examination, self-releases at the pace of around 5 percent for each month.

Table 3 demonstrates typical performance comparison between lithium ion battery and SC. Comparing the supercapacitor with a battery has merits, but considering the similarities between two, makes digging deep in this distinctive device superfluous. Focusing on the unique differences the following points are being made.

The chemical features of a battery determine its operational voltage; charge and discharge electrochemical reactions while in the case of super-cap which is non-electrochemical in nature and its maximum allowable voltage is being governed by the type of dielectric material utilized as separator in between the plates.

Function	**Super-caps**	**Li-on battery**
Charging time	1-10 seconds	10-60 min
Life-time	1 million cycles	500 or higher cycles
Voltage of cell	2.3 to 2.75 V	3.6 V
Specific energy	5 Wh/kg	120-240 Wh/kg
Specific power	Up to 10,000	1,000-3,000
Cost per kWh	$10,000	$250-$1,000
Service period	10-15 years	5-10 year
Range of charging temperature	_-40 to 65^{o}C	0 to 45^{o}C
Range of Discharging temperature	_-40 to 65^{o}C	-20 to 60^{o}C

Table 3. Performance comparison between Li-ion and super-caps

Advantages	Almost infinite cycle life; can be used million times
	Higher specific power and lower resistance permits SC to feed high load current
	Charging period in seconds
	Simple charging; draws only needed current i.e. it's not subjected to overcharge
	Safe
	Brilliant lower temperature charging and discharging

	performance
Disadvantages	Lower specific energy; grips a portion of conventional battery
	Linearized discharge voltage averts using the full energy spectrum
	Higher self-discharge rate
	Lower voltage of cell, requires series connection along voltage balancing
	Higher price per watt

Table 4. Advantages and disadvantages of Ultra/capacitor

3.1.3. Superconducting magnetic ESSs

Super-conducting magnetic ESSs (SMES) accumulates energy in the form of magnetic field. SMES frameworks have a high vitality putting away efficiency of roughly 97%, full vitality release capacity, a long-life pattern of 100000, and fast reaction of milliseconds. However, the primary prices are high, which is 205–340 $/kW for a characteristic SMES, although still costs lower than that of electric double layer capacitor. The typical power rating of SMES is in kW to MW, and for further power rating improvement R&D is going on. The superconducting electromagnetic coil, which is constitutes niobium titanium alloys at liquid helium temperature, i.e., 2–4K. However, for maintaining the low temperature SMESS needs a cooling system. Super-conducting materials for high-temperature operation, are being established with a cheaper coolant. Thus, a hybrid SMESS system could be formulated between low and high temperatures for conducting ingredients for higher accumulation capacity. Commonly, SMESS is employed in Uninterrupted power supplies, power quality improvement applications, and in grid systems. SMESS is presented in hybridized electric automobile applications with batteries [8]. The energy accumulated by SMESS is reliant on the coil's internal inductance value and squared current that circulates through coils, as stated in Eq. (1.2).

$$W_L = \tfrac{1}{2} LI^2 \tag{1.2}$$

where W_L: energy accumulated inside inductance coil, L: internal-inductance, and I: current magnitude in the coil.

3.2. BATTERY AND SUPERCAPACITOR HESS

Super-capacitors, considered by high power density in range 5-10kw/kg [17], can deliver huge demand current (up-to 100Amps) that too rapidly and with very higher efficiency, which evokes acceleration and regenerative-braking [9] and further contributes in reduction in charging time appreciably [18]. Using super-caps, appears to be a quite good methodology to tame the power shortage and charging in-efficiency of batteries. However, due to the fact that super-capacitors cannot store much energy, it cannot operate as a primary power source

means in any electric vehicle system. Contrarywise, the battery can store bulk energy to act as primary power source. But then again, without extreme consumption or over-sizing of system components, a battery package can’t generate as much instant power as super-capacitors can. Therefore, a propitious solution seems to integrate batteries with super-capacitors resulting a HEAS, which can stream a large burst of current and further accumulates plenty energy to guarantee a suitably long running span for a vehicle [10].
Owing to the high specific power of super-capacitors, hybridizing super-capacitors and batteries contributes in diminishing the tension on the battery package and prospectively improves acceleration and exceeds slope mounting performance. Super-capacitors also facilitate the battery in trapping energy during regenerative braking. In industrial applications, energy efficiency, automobile performance, structural sizing and money value of energy storage apparatus are presently the major problems.
Taking a scenario all-electric automobile for instance. Tesla Roadster model is 2690 pounds wherein battery pack weight more than 900 pounds [19]. Coordinating an ultra-capacitor bank can make up for such misfortune and makes accessible the greater adaptability in dispersing size and weight for every energy stockpiling instrument in the planning stage, so the foreseen storage and peak current qualities could be practiced. With all of this expressed, it has been implied that a HEAS gathered from two 18650-cell lithium-particle and two 100 F ultra-condensers attains a peak power of 132W, it is a seven times upgrade when contrasted with the lithium-battery cells alone [12]. There is going on a mounting research on looking at the ideal topology of the HEAS. Existing arrangements fluctuate regarding cost, intricacy and adaptability. As a rule, the gathering of the current HEAS can be described into two kinds, which are the passive HEAS and the active HEAS, every one of which has various further sorts of topology.

3.3. TOPOLOGIES OF BATTERY AND SUPER-CONDENSER HES

The energy source is chief part of any electric automobile. All things considered, battery remain the prime vitality hotspot for electric vehicles, as a result of its generally high energy thickness, as appeared in Table I. In any case, even the serious innovation every now and again doesn't permit adequate power densities to fulfill the need of huge power pulses at a generally low fiscal, volumetric and weight cost [15]. They don't bring as momentary charge/release abilities as supercapacitors. The colossally long charging span will in general be a basic issue. Moreover, the life span of battery is shorter, particularly when they are exposed to moderately high charging/releasing rate. Such extraordinary misuse of could prompt a potential wellbeing issues because of overheating caused in the battery. In this manner, battery packs are popularized electric vehicles are ordinarily larger than usual so as to modify the huge force request and are likewise utilized with dynamic cooling innovation to guarantee adequate life is kept up.
At present, the dimensioning of this sort of energy accumulation system bargains for a predetermined operating point, and the structure is a trade off in the middle of a several

necessities. Different activity of such an electrical energy accumulation apparatus can direct to fractional utilization of the stored energy. To satisfy the necessities in better manner, hybridized energy accumulation system (HASSs) have been built up to blend at least two distinctive energy storing hardware. Regularly, these capacity frameworks are created with target of consolidating high-energy (HE) and high-power (HP) storing components. The advantage of such a energy framework is a general increment in specific power as well as specific energy. HP stockpiling permits quickening or de-speeding up of power and it typically utilizes electrical twofold layer capacitors (EDLCs) or even different high-power . On the opposite side, HE stockpiling affirms the long-term supply, which is for the most part accomplished by utilizing a HE Li-particle cells. The incorporation of HP and HE stockpiling units to shape a HASS can be accomplished in various manners. Rather than the hard wiring of vitality stockpiling components which have the comparable cell science, an enhanced association topology wins for HASS. Comprehensively, the topologies analyzed are isolated into passive hybrid storage (P-HS) topology, and the active hybridized energy storage (A-HES) topology [13].

3.3.1. Passive HESS

The illustrative feature of a passive HASS is the straight forward connection of a battery and a super-condenser into parallel configuration. As revealed in Fig.8, the battery bank is first connected to the super-condenser, and following that it is tied up with the traction motor. Because of this direct connection, the terminal voltage at the battery end and the super-condenser end are moderately constant, and thus high risk of the battery getting damaged is imposed, in case when an immediate power is required from the traction motor by the vehicle. In order to resolve this matter, a DC_DC converter is implanted in-between the energy accumulation bank and the DC_AC inverter, to guarantee safe operation [21].
This is the simplest way achieving the hybridization i.e. by connecting the different HP and HE elements in parallel way. Fig. 8 illustrate an instance of this passive hybridized energy storage (P-HES) topology using grouping of battery accumulation bank and UC. The coupling of two storage means is done passively i.e. without adding any midway converter [14]. The voltage of HP and HE element (VBAT1 and VEDLC1) is equal to the voltage of the rated traction motor (Vload) [15]. The voltage level of both energy accumulation systems must therefore be similar to the load. In automotive applications, the load is the power train. Likewise, the operating voltage levels of the corresponding storage technologies must have the largest probable joining with one other.

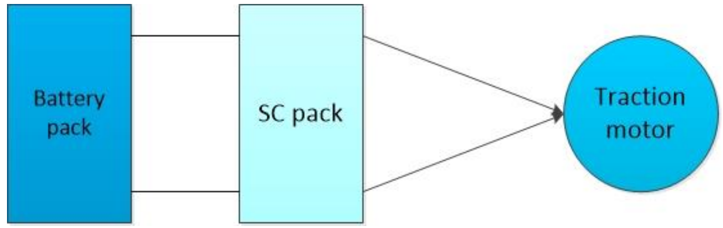


Fig 8. Basic passive configuration

Now, the foremost advantageous features of the above described passive topology is the comfort of implementation in hybrid energy system, without the requirement of intricate control devices. Also, this structure is price-effective, require lesser space and is weight volume saving with simple wiring required. The battery and the supercapacitor are secured parallelly and are having the similar voltage, therefore the power dispersal proportion in-between the battery and ultra-capacitor is entirely depending on their internal resistances ($Ri_{,BATT1}$ and $Ri_{,EDLC1}$) [7] wherein the in-built resistance depends on factors for example cell design, the current state of charge (SOC_{BATT1}, SOC_{EDLC1}), temperature (T_{BATT1}, T_{EDLC1}), and aging. So, power flow management could not be carried out at an effective rate. As a consequence of which, the superiority of the battery and the supercapacitor are not being successfully exploited. And thereby, passive assembly is not valid in case adjustable and effectual power management is required.

The working lifespan of a hybridized merger of lithium-ion batteries and ED-LCs, in the instance of a discharge profile with high dynamics, is greater than that of a battery-only operation. The voltage drop in a hybrid structure is also lower than that in a pure battery system [14]. This can be portrayed by considering that the batteries naturally have a higher inner resistance than the ED-LCs, accordingly follow-on is a lower ohmic resistive element for a P-HES geography. The battery conveys just a small amount of the current while the significant current goes through the ED-LC [24]. A theoretical examination has indicated that in hybridized operation, battery warming is decreased enormously, as a result of the peaks current are being conveyed by the ED-LC, in this manner diminishing the inside misfortunes of the battery. The degree of the advantage came to relies upon the pulse width proportion, the pulse amplitude, and the quality of the ED-LC [18].

passive hybridization is used to lessen pressure in light of the fact that the ED-LC can give and devour peak current during increasing speed and de-acceleration. The ED-LC associated parallelly acts as a low pass filter that smoothens out rapid voltage changes. A bigger capacity of the ED-LC brings about better filtering properties. Besides, exploratory tests represent that an extra ED-LC upsurges the power quality and source effectiveness. Nonetheless, due to the immediate coupling, the usable limit of the ED-LC is restricted, as the working voltage window is normally restricted by the battery accumulation or the power train. Regardless, because of the prompt coupling, the usable furthest reaches of the ED-LC is limited, as the working voltage window is typically confined by the accumulating or the force train. As the power distribution can't be influenced, it is ludicrous to hope to achieve a high utilization of stored energy content even at low temperatures. To update the show of the imperativeness amassing structure, a functioning circulation of intensity is crucial [10]. To upgrade the exhibition of the energy accumulation framework, an active spreading of power is vital [10].

3.3.2. Active HESS

Equated with a passive HES topology, an activated HES topology demands much sophisticated power electronic converters as well as controllers for batteries and super-caps. The regulator can be modified by specific methodologies or calculations, permitting the HESS to work with greater adaptability. Differing from the immediate connective battery and the super-capacitor as in the inactive HES topology, a DC_DC converter is embedded in the middle of as an interface, this allows the super-capacitor to work in extended of scope of voltage. However, the battery voltage yet remains fixed as a result of the immediate connection with the DC_AC inverter. Plainly, there is the same anxiety for the battery as on account of P-HES topology, since it isn't secured suitably by any DC_DC converter. With the super-condenser and the battery pack being traded in substitute topology, might resolve the difficult articulation. The power stream in battery could be maintained inside the more secure range by the DC_DC converter while super-condenser going to act as energy buffer [20]. In any case, the working scope of the super-caps is limited as an outcome of the immediate connection with the DC_AC inverter.
The expense and distribution attributes of energy accumulation gadgets vary generally, contingent upon the energy storage innovation utilized. So as to permit the energy storing structure to act in the most ideal manner and as per its highlights, energy accumulation gadgets must be detached [11]. This has been alluded to as a functioning hybrid energy accumulation (A-HES) topology, wherein energy accumulation units are conceivably isolated, for instance by a DC_DC inverter.

3.3.3. Semi-active hybrid energy storage topology

A SA-HES topology may comprise of at least two distinctive energy accumulation means, in which a bit of the energy accumulation gadget is isolated. This topology structure is hence known as a power isolated configuration. Isolation is done utilizing a DC_DC converter. Despite the fact that fusing a converter into the framework adds to the expense and requires extra establishment zone, this geography class has numerous preferences. Specifically, isolated energy accumulation can work preeminently dependent on its charge and release attributes. Scientists have inspected the conclusion of a storing and an ED-LC [11,12]. Contingent upon the decayed energy storage, the semi-active and half equal energy storing topology (PSA-HES topology), the battery semi-active hybrid energy storing (BSA-HES topology), and the semi-dynamic mixture topological vitality protection (CSA-HES) topology [8]. These sub-topologies are talked about in the accompanying areas.

3.3.4. Parallel semi-active hybrid energy storage topology

Here, the isolation between the storing gadget and the load is done utilizing a DC_DC converter, and the power accumulation gadgets are legitimately associated in parallel. Because of this disintegration, the working voltage scope of the force outline is free of the heap voltage extend. This eliminates the shared requirements and settles on energy hardware and burden choices a lot simpler. DC_DC converters focus on the most extreme force and greatest burden current required by the heap [8]. While the energy gadget is legitimately associated, the voltage of the two force supplies will be equivalent. The working voltage window is typically dictated by and restricts the usable limit of the EDLC. Like the P-HES, the genuine distribution is controlled by the interior opposition and balance voltage of the two energy units. In this manner, the results from the immediate association of the energy gadget is equivalent to the P-HES. Fig.9. illustrates arrangement of system elements in parallel semi-active topology.

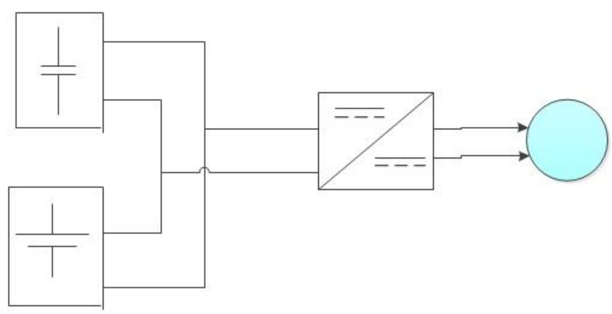


Fig. 9. Parallel semi-active HEST

3.3.5. Battery semi-active hybrid energy storage topology

BSA-HES topology (Fig. 10) eliminates battery storage in ED-LC and load, which makes the battery less charged for a short period of time taking place after a change in lighting [10]. The power between the battery and the load can be adjusted utilizing a DC_DC converter. The battery can be used regardless of the working capacity, which supports to increase the size of the BEV. By using a suitable maintenance method, the short-term power output can be attracted by the ED-LC to accelerate the deceptive process. This is useful during the use of Li-ion battery packs due to their non-linear voltage profile. The immediate installation of the ED-LC on the power train means that the latter will be intended to accommodate different load voltages. If acceleration and motion are constant, the load voltage may alter snappishly [10]. The DC_DC converter is also modelled to handle extensively varying load voltages. When the DC_DC converter fails, the load must be handled by the energy stored in the ED-

LC. In a BEV, the capacity of the ED-LC is quite small as being compared to the capacity of the battery, which makes EL-DC as emergency backup means, somewhat impractical.

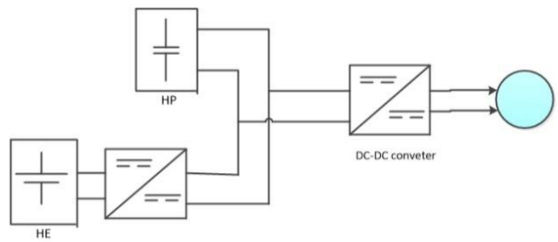


Fig 10. Battery SA-HEST

3.3.6. Capacitor semi-active hybrid energy storage topology

Assessing the BSA-HES topology in the CSA-HES topology differs battery location and ED-LC. The situation is reversed, as shown. The ED-LC disconnects from the load and battery storage via a DC_DC converter. The DC _DC converter regulates the power flow and supplies the EDLC with a wide operating voltage. For inequalities with passive composite or direct binding structure, the full power theory of ED-LC can be used here. In this structure, the ED-LC allows the maximum load to be captured. However, the DC_DC converter is designed to accept maximum power and maximum voltage level converters, and the cost of the system increases. The direct combination of battery storage and power with battery storage capacity reduces the load voltage significantly less than BSA-HES [10].

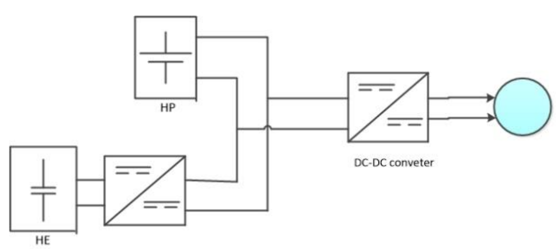


Fig. 11. Capacitor SA-HEST

3.3.7. Full-active hybrid energy storage topology

The fully functional hybridized Energy Accumulation Topology (Topology FA-HES) consists of two or more dissimilar energy accumulation devices and each accumulation unit is separated by power electronics. This category of topology is known as a fully integrated framework as well. Separation is usually performed using two-way DC_DC converters. Compared to a semi-active hybrid energy accumulation (SA-HES) topology, system losses are higher here because the number of DC_DC converters exceeds the required installation space for electronics and it will be more costly and complexity. While more and more challenges create problems with each DC_DC extension, the above categories have some advantages. If a good operating procedure is used, this HEAS ensures that all the power accumulation modules work properly depending on their charge and output. This high control system has the advantage of having to distribute power evenly to each energy accumulation, increasing the efficiency of the accumulation as well as helping to extend the life of the battery [10].

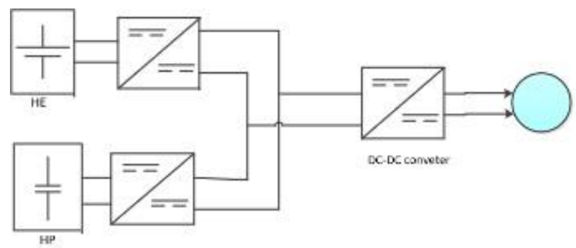


Fig. 12. Full active HEST

3.2.8. Modular multilevel full-active hybrid energy storage topology

MMFA-HES is a subtype of FAHES topology in which several energy accumulation modules are connected in series (Fig.13.). The module includes energy accumulation devices and electrical related electronics in the form of a DC_DC converter that acts as a charge / discharge unit. Integrated DC_DC converters permit each energy saving appliance to operate according to its optimal profile and discharge. Upgrading and incorporating power electronics into each module allows the energy accumulation space to be quickly adapted to different voltage and power points [12]. Each energy accumulation device can have a different capacity, cell chemistry, intranasal resistance, self-discharge rate, health status (SOH) and aging behavior, making this topology and PFA-HS topology suitable for use in a second life. The time model of the external contact interaction model makes it important to ensure that each DC_DC switching device can control the maximum train current. On the input side, each DC_DC switching device must reach the maximum rated voltage or control unit. This should increase visibility, and in addition, DC_DC conversion increases system costs. The solution of the system is larger than the above-mentioned point, which increases the problem and implementation costs [12]. Another drawback is the oversized shaft on the DC / DC fiasco, as one switch can cause the system to overheat.

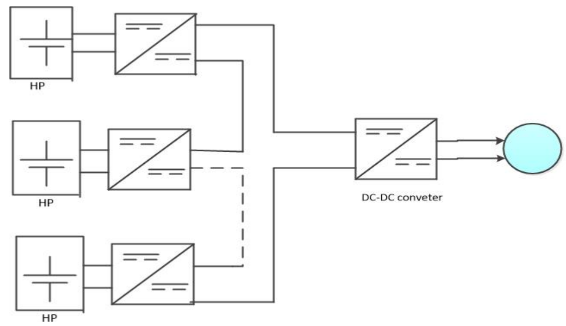


Fig. 13. Modular HEST

3.4. PROJECTED HYBRID ENERGY ACCUMULATION SYSTEM TOPOLOGY

In Fig.14, a projected hybrid energy accumulation system comprises a DC_DC converter, super capacitor, an integrated magnetic structure and Li-ion battery pack. DC_DC converters consists T1, T2, T3 and T4 the four IGBT switches and D1, D2, D3 and D4 its feedback diode D1, D2, D3 and D4 and L1 and L2 self-inductances of primary and secondary coil, and M mutual inductance sharing the same core. The battery bank supplies smooth power to the BLDC traction motor. The ultra-capacitor serves the rapid surge power requirements[11][12]. The power supervision system of automobile regulates the movement of energy in accordance with the traction demands [13].

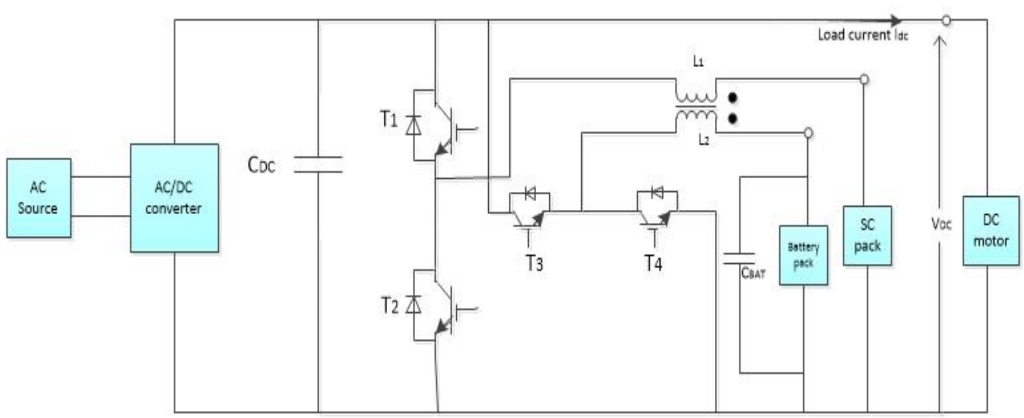


Fig. 14. Proposed topology of hybridized system

3.4.1. Designing a Dc-Dc Converter with Magnetic Integration

The function of the DC-DC dual converter is to control the flow from the load source to the field and from the load source during regeneration. Also controls power transfer between battery and UC. Current converters must have high efficiency, low current from the source, be able to amplify and amplify despite changes in input voltage, and control the two-way power flow [16]. Magnetic energy storage apparatus, such as inductors, are essential in energy conversion, filtration, electrical insulation, and energy storage. The size of the magnetic element is a major factor in determining the size and weight of the transformer [17]. In order to attain the incorporation of magnetic elements, electronic type magnetic cores can be produced in practical applications. Coupling inductance (L1 and L2) is used here. As shown in the Fig. 14, L2 as the output filter inductor, L1 as an external inductor, and Cb as auxiliary power connected to the battery. In design mode, the voltage Cb is equal to the output voltage L2 and L1 regardless of the output voltage. The DC_DC switch in Fig.14. contains 4 IGBT switch numbers, T1 ~ T4, and 4 input lines, D1 ~ D4. If the transformer operates as a transformer, there are two energies L1, T4 and D4, and the other has L2, T2 and D1; When working as a money changer [15] there are also three types available as L1, T3 and D4, and others having L2, T1 and D2. Table 5 provides a comparison of the variables of the two transformations of the DC_DC transformer [13]. The mass and volume of the DC_DC conversion and the magnetic field decrease. In these electric vehicles, the use of alternating current in direct current [18] in combination with a comparative electrical structure can reduce the amount of volume and mass of the storage system [19]. A great way to increase the weight of the car. Furthermore, the combined structure magnets can reduce the waves of these waves [14].

3.4.2. Modelling of System Component

The system comprises various key elements like battery pack, super-capacitor pack, dc-dc converter, dc motor etc. For analysis purpose where. these elements are modelled taking in consideration their electrical characteristics.

Modelling of Li-Ion Battery

A suitable Li-ion battery model is important to predict the behavior of the battery under different operating conditions and to evaluate the characteristics of the batteries and performance parameters, such as charge status and the health of the battery. The equivalent Li-ion model as shown in Fig.15. The battery model comprises the open current voltage of the battery, VOCV. The series resistor, RO, which represents the ohmic resistance and the storage capacitance, is represented by a series capacitor CS [20]. The parallel RC branch takes into account the diffusion charge, where Rd represents the diffusion resistance and Cd represents the diffusion capacity. Nb indicates the number of lithium ion cells arranged in serially. Vt being the edge voltage of the battery is determined across its terminals, and is represented by

$$Vt=V_{OCV}-V_1-V_2-V_3 \qquad (2.1)$$

The battery's SOC can be designed by following integral equation,

$$SOC_= SOC_{ini} - 1/3600\int I_{batt}(t)\, dt \qquad (2.2.)$$

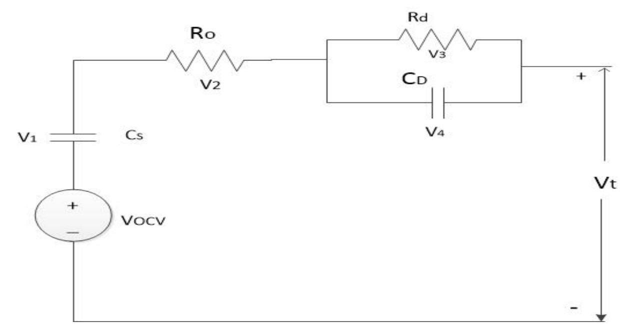


Fig. 15. Equivalent electrical circuit based li-ion battery model

A 144V terminal battery is connected directly to the motor drive. The batteries work with 30% to 100% SOC, and the original SOC is considered 100%. The required battery power in a hybrid system is reduced compared to a non-hybrid system. This is because the allowable drop depth (DOD) is 70%.

Modelling of Super-Capacitor

UC is shown as an RC series circuit consisting of equivalent capacitance Cs and series resistance Rs. This series resistor, Rs, simulates energy loss during capacitor charging and discharging. The interference effect of cell equilibrium and energy loss due to the self-discharge characteristics of the capacitor are denoted by the equivalent resistance Rp in parallel with the circuit of the RC series [20]. The minimum UC capacity required for the maximum vehicle speed can be calculated using equation [21].

$$½ C_{uc}\{V^2{}_{uc\_max} - V^2{}_{uc\_min}\} \text{ X No. of series connected cells} = ½\, mv^2 \qquad (2.3)$$

where the C_{UC} is the stability of UC; V_{UC}_max is the maximum voltage of UC; and V_{UC} _min of UC low voltage [7].

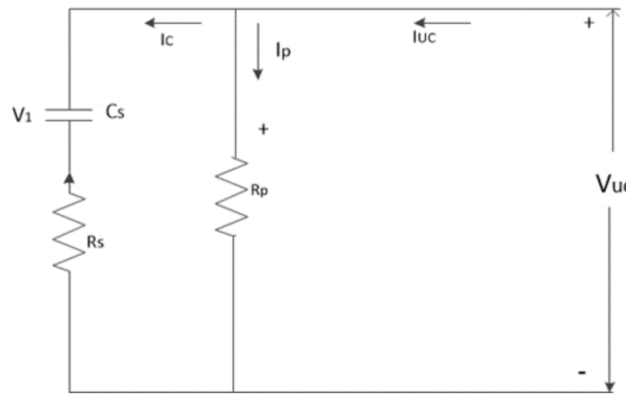


Fig. 16. Capacitor model

Modelling of Motor

The current study is selected when projecting a brushless DC (BLDC) motor on the LEV. Performance improves in various aspects such as efficiency, quick reply, simple assembly, high torque, and easy maintenance [24-26]. It must also be connected to the corresponding intermediate circuit of the frequency inverter. The IDC plot of engine torque versus engine speed and engine power versus engine speed delivers the required design information for a three-wheel EV engine. The maximum engine power is 5.5 kW. However, you are likely to overestimate the engine almost 1.75 or 2 times in seconds. Therefore, the 3 kW BLDC motor was selected to meet the braking and acceleration power requirements.

3.4.3. Advantages of Dc-Dc Converter with Magnetic Integration

Table 5 shows that an evaluation of the two DC _DC converter models shows that the volume and weight of a DC_ DC converter with an integrated magnetic structure have decreased. In electric vehicles, DC_ DC converters with magnetic association structures can be used to decrease the overall weight and weight of energy accumulation systems. In addition, the integrated magnetic structure reduces the ripple of the output current.

Features	**Non-magnetic integration structure /cm2**	**Magnetic energy storage system /cm2**
Surface area	79.15	60
Volume of core	104.19	79.60
weight of core	0.31	0.23
Wire weight	0.21	0.21

Table 5. Comparison of DC/DC converter with and without magnetic energy storage

3.4.4 Modes of Operation

There are broadly five operational modes for hybridized energy accumulation system[14].

Constant driving mode

The battery sends electricity to the load through the amplifier converter consisting of L1, T4, D3. As shown by the red line in Figs.1, the battery current when switch T4 is closed is charged via switch T4 to the inductor L1. When switch T4 is off, the battery power and induction L1 flow through diode D3 on the DC motor side [23].

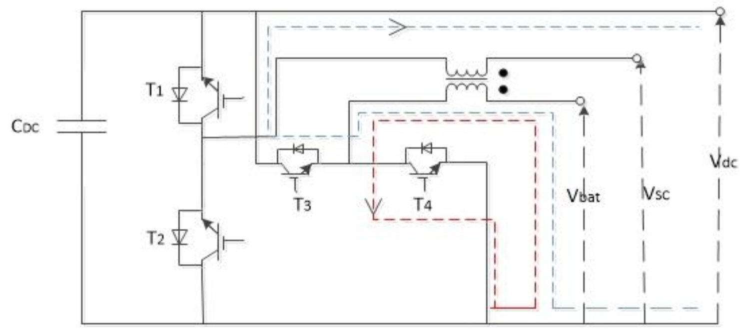


Fig. 17. Constant driving mode

Acceleration mode

A super-capacitor is used to deal with a sudden increase in load. An amplifier converter consisting of L2, D1, T2 transfers the power from the supercapacitor to the load side. As shown in Fig.18, when the switch T2 is closed, the current coming from the supercapacitor charges the inductor L2 to the value T2. When switch T2 is closed, the supercapacitors and the electrical energy stored in inductor L2 flow to the DC motor side through diode D1 [11].

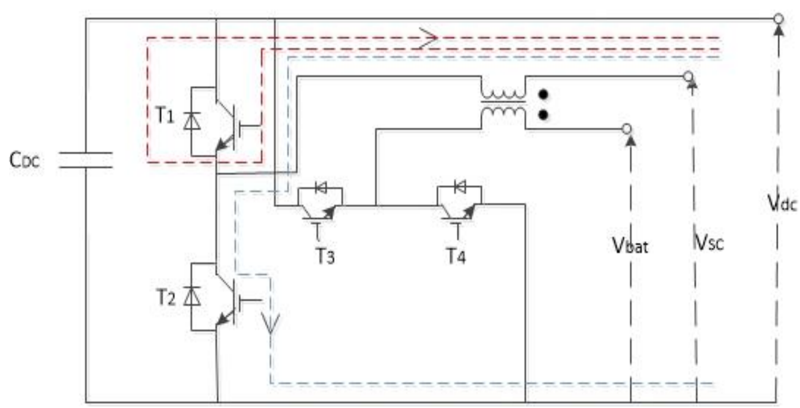


Fig. 18. Acceleration mode

Braking mode

When the load drops sharply, the buck converter supercapacitor, consisting of T1, D2, L2, is used for energy recovery and charge storage. This mode of operation is similar to mode 1, in which the supercapacitor is charged as shown in Fig.19. The supercapacitor is charged by a buck converter consisting of T3, D4, L1 and T1, D2, L2, respectively [20]. The blue line in Fig. 19, is the direction of the current. When T3 is closed, current flows from the DC bus side to L1 to charge inductor L1. When T3 is off, the electrical energy stored in inductor L1 charges the battery through D4. Also, when T1 is closed, current flows to L2 through the DC bus, the L2 load coil. When T1 is off, the electrical energy stored in inductor L2 charges the supercapacitor UC through the circuit formed by D2.

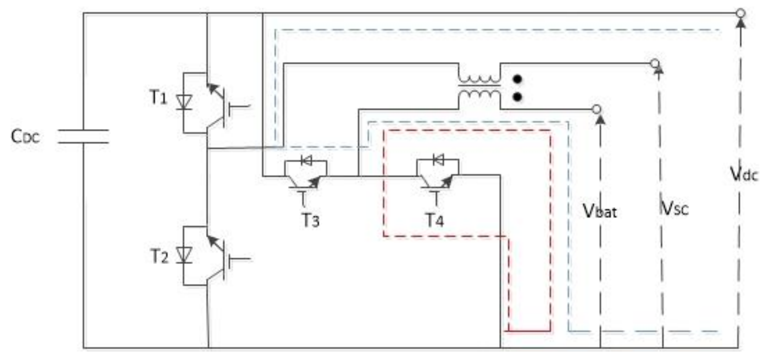


Fig. 19. Braking mode

Parking mode

The battery is charged by the AC power source when the driving cycle of vehicle is in parking mode. The main charging of battery is done from the available single phase AC supply.

3.5. CONCLUSION

The following chapter discusses the types of hybrid storage system used in electric automobiles. It also discusses standard topologies for arranging the energy storage elements in the system which helps in understanding the various advantageous and disadvantageous features associated with the topologies which father helps in developing the superior topology of enhancement of the system. Modelling of various storage elements is done for supporting the implementation of system in MATLAB/Simulink.

CHAPTER 4

ARTIFICIAL NEURAL NETWORK

4.0. INTRODUCTION

Neural networks have been stated as a revolutionary technology of the modern era. Neural controller is being widely used in every field and is also gaining lot of attention in power electronic domain as well. Conventional controllers like PI controller [15]etc. used in controlling of inverters and converters in power electronic circuits have certain unavoidable shortcomings. Therefore, there is huge requirement to shift to implementation of advanced controllers such as artificial neural network controllers.

The neural network is a circuit of neurons or processors which works on parallel processing. These processors are arranged in tiers. The key to the effectiveness of neural controllers is that they are highly adaptable in nature and are quick learners. The inputs that corresponds to the accurate output are being given higher weights and likewise is done to the whole system. In order to implement neural controller in our hybrid energy system to achieve improved performance, prior understanding of the controller is needed. Therefore, it is imperious to first understand various ANN architectures, learning methods and some its applications in power electronic and other domains.

4.1. HISTORICAL BACKGROUND

The first research study on neurocomputing was started in 1890 when William James printed his work on brain activity. The first simple neural network based on arithmetic and logical calculations was presented by McCulloch and Pitts in 1943. The major step towards the artificial neural network was the development of learning rule for biological neurons. The primary artificial neural network was developed in year 1958 by psychologist Frank Rosenblatt. He called it Perceptron, and it was proposed to model how the human brain processed visual data and learned to distinguish characters. Nowadays, one layered network of Rosenblatt is called Perceptron. Other researchers have since used similar ANNs to study human cognition[16]. Then in 1969, drawbacks of perceptron were highlighted by Minsky and Papert and the emergence of neural network went into near eclipse. In the 1980,the neural networks gained tremendous popularity due to rapid development of new theories and concepts on many fronts. During the year 1986 the backpropagation (BP) learning method for multilayer perceptron was introduced by Rumelhart, Hinton and Williams. Radial Basis Function Neural Networks were introduced in 1988.

Summarizing evolution of ANN during 1940s to 1960s:

• 1943 - Based on the work of physiologist Warren McCulloch and mathematician Walter Pitts, the idea of a neural network is believed to have originated in 1943 when they used electrical circuitry to model a network, simple neural circuits to determine how brain neurons might function.

• 1949 - Donald Hebb's Behavior Organization introduces the fact that repeated activation of a neuron by another neuron increases its efficiency with each use.

• 1956 - Taylor introduces the ANN Associative Storage Network.

• 1958 - Rosenblatt develops a learning method for the McCulloch and Pitts model of neurons called the perceptron.

• 1960 - Bernard Widrow and Marcian Hoff invent the ADALINE and MADALINE models.

The development of ANN in the 1960s and 1980s.Some of the key developments during this period are listed below

• 1961 - Rosenblatt tries unsuccessfully, but proposes a system of "backpropagation" of multi-layered networks that makes significant progress.

• 1964 - Taylor builds a win-win round with blocks between starting units.

• 1969 - Minsky and Papert invent the multilayer MLP perceptron.

• 1971 - Kohonen develops associative memories at ANN.

• 1976 - Stephen Grossberg and Gail Carpenter develop adaptive resonance theory.

ANN from the 1980s to today. Some of the most important developments of this time are:

• 1982 - Hopfield's approach to energy was expanded considerably.

• 1985 - Ackley, Hinton and Sejnowski develop the Boltzmann machine.

• 1988 - Kosko developed the binary associative BAM memory and also introduced the concept of fuzzy logic in ANN.

The historical review demonstrate that substantial progress has been made in this domain. Neural network-based chips are evolving and applications to complex problems are being developed. Surely, neural network technology is further evolving till today and new depths will be explored in future also.

4.2. APPLICATIONS OF NEURAL NETWORK

Major applications of ANN comprise controlling of dc as well as ac drives, uninterrupted power supplies (UPS), Switch mode power supplies (SMPSs), High voltage direct current (HVDC) transmission, Flexible alternating current transmission systems (FACTS), fuel cells, Electric vehicles [17], Active power filters [18], signal processing etc. ANN has shown promising results in all above fields in power electronic domain.

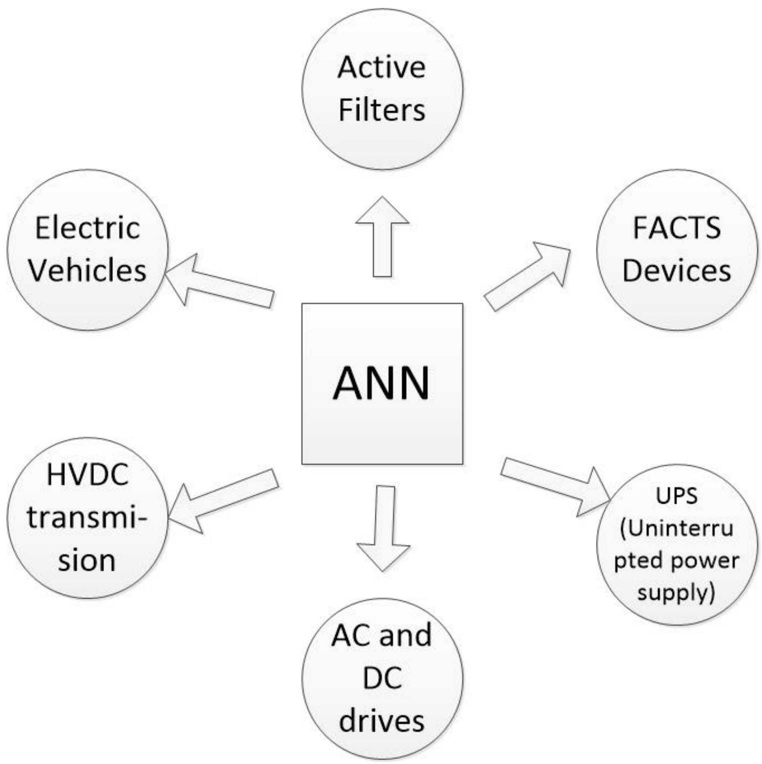


Fig. 20. Applications of ANN in field of power electronics

4.3. MODEL OF NEURAL NETWORK

A neural network a grid with connections of artificial neurons. An artificial neuron, like its biological counterpart, is a basic computing element. An elementary structure of neuron is as revealed in Fig.21. below. A neuron first achieves a weighted sum of input p by multiplying the weight w with it. This sum along with bias b is gives activation, referred as neural net n. On the neural net n, transfer functions or activation function f performs operation to achieve

output a. Therefore, the artificial neuron is basic unit of neural network which is modeled with bias, weights and activation function. Neuron may simply be called as node.
Here, relationship between input and output is given as:

$$a= f(n)= f(wp+b) \tag{3.1}$$

where a and p are scalar input and output respectively.

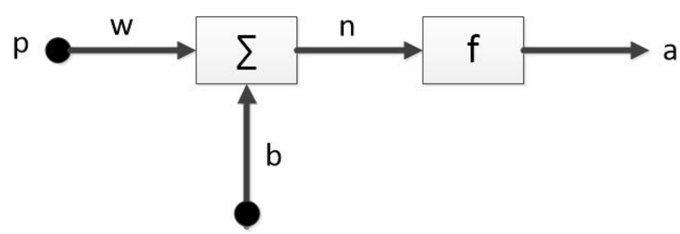


Fig. 21. Single input artificial neuron

The neuron with multiple input is as shown in Fig. 22**.** The inputs are p1, p2….pn and their corresponding weights are w_1, w_2…..w_n. For example, when 4 inputs are given to neuron, it will have corresponding weight values which can be tuned while training session. An artificial neuron may collect various inputs p_1, p_2….p_n. but provides only single output.

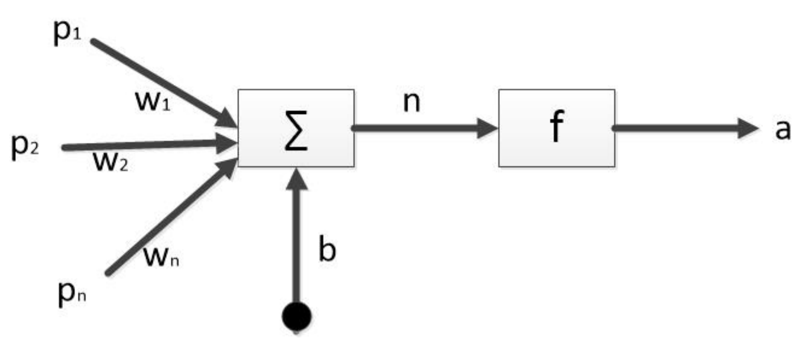


Fig. 22. Multiple input artificial neuron

Bias- b is bias or offset. It's an additional input for neurons and always equal to 1, and it has its own joining weight. This ensures that even if not all inputs are (all 0), the activation takes place in the neuron.

Activation Function-- Activation functions are used to increase the non-linearity in neural networks, but there are also linear transfer functions. Place the values in a smaller area, i.e. a sigmoid activation function divides the data value amongst 0 and 1. The activation functions should be explained in more detail as in the next section.

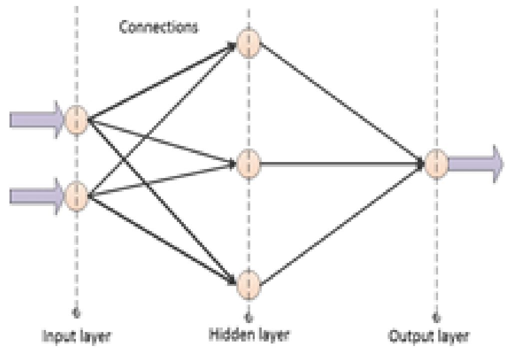


Fig. 23. Structure of A-NN network

Connections—It connects a layer of a neuron with another layer or with a neuron in the same layer. There is always weight in connection. The purpose of exercise is to maintain this weight to reduce the loss (failure).

Input Layer—It is the initial layer of the ANN. It picks up the input signals (values) and transmits them to the layer followed by this initial layer. It does not perform any function on the input signals (values) and is not associated with weights and deviations. Our network has 4 input values x1, x2, x3, x4.

Hidden Layers—The hidden layer contains neurons (nodes) suitable for various processing of the input data. A hidden layer collection of vertically loaded neurons. Suppose, there are 5 hidden levels. A first hidden layer of four neurons (nodes), a network of five neurons, a third network of sixth neurons, four four neurons, and a network of five three neurons. The final hidden layer transfers the value to the board layer. All hidden neurons of the nervous system overlap the nerve endings of each subsequent layer, so there may be a separate hidden layer.

Output Layer—This layer is last member of the layer, which gets its input from last input layer. What has been described as such above is subject to a product value analysis. In this case, 3 neurons are used in the ring and produced by y1, y2, y3.

Weights (Parameters)—Weight is the strength of the bond among devices. If the weight value in between node 1 to node 2 is higher, it means that neuron has a greater effect on the nervous system 2. Weight reduces the significance of the input value. A weight close to 0 means that varying that input does not brings corresponding variation in the output. Negative weights imply that raising this input will lead to a decrease in production. Weight determines how a input value is going to effect the output.

4.4. ACTIVATION FUNCTIONS OF NEURAL NETWORK

The activation function, also called the transfer function, implements the output of the neuron. It can be linear or non-linear in nature. Fig.24 shows the most common activation function of neural networks with corresponding mathematical equations.

In organic neurons, the activation function can be assessed as a surmised threshold function. In artificial neural networks, which are more complex, we outdo this biological behavior with generally nonlinear functions that are comparable to the threshold function but are both continuous and separable. Separability is an important and necessary feature in the formation of complex neural networks. Two common activation functions are sigmoid function and the hyperbolic tangent function, commonly employed in A-NN network. Note that the two functions are very similar and only differ in their respective starting areas. In some cases, the respective output unit can employ a linear activation function when the output of the system does not have a predetermined range[16].

Activation functions [26] calculate the weighted sum of inputs and deviations in order to adopt whether a neuron could be triggered or not. It operates the information presented via processing the gradient, typically gradient descent, and then generates a neural network result that includes data parameters. The activation function is linear or non-linear depending on the activity it represents and is used to control neural devices in various fields, object recognition and classification for speech recognition, segmentation, fingerprint recognition, weather forecasts, cars [27] and the like. By selecting the correct activation function, the calculation results for the neural network are improved.

For a linear model, a linear mapping of an input function to an output, performed in the hidden layers before the final prediction of the class score for each label, is given by the affine transformation in most cases. The transformation of the input vectors x is given by

$$f(x) = w^T x + b \qquad (3.2)$$

where=input, w= weights, b=biases. Furthermore, neural networks produce linear results from the maps of equation (1.1), and there is first need for an activation function to convert these linear outputs to non-linear outputs for computation, especially for learning models of data. The edition of these models is indicated

$$y = (w1\ x1 + w2\ x2 + \ldots. + wn\ xn + b) \qquad (3.3)$$

These outputs from each layer are used in multilayer networks such as deep neural networks, passed to the next layer until the final output is reached, but they are linear by default. The expected output determines the type of activation feature to activate on a particular network. However, because the output is linear in nature and non-linear activation functions are required to convert these linear inputs to non-linear outputs. These AFs are transfer functions that are used to generate non-linear outputs that are converted to linear model outputs and are ready for further processing. The non-linear output occurs after using

$$y = \alpha(w1\ x1 + w2\ x2 + .. + wn\ xn + b) \qquad (3.4)$$

Where α is the activation function. The need for these AFs involves the conversion linear inputs and models into nonlinear outputs, allowing higher-order polynomials to be studied for networks more than one degree deeper. A special feature of nonlinear activation functions is that they are separable, otherwise they cannot unction during the feedback of deep neural networks. A deep neural network is a neural network with multiple hidden layers and an output layer.

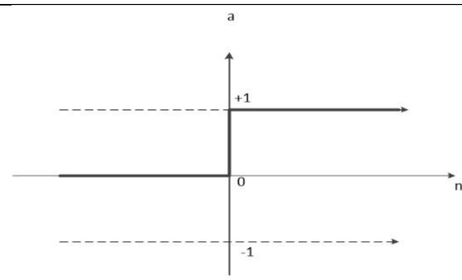
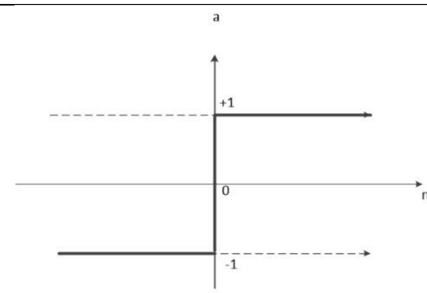
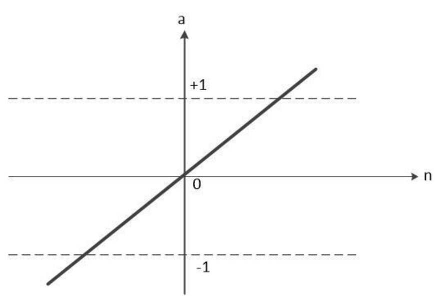
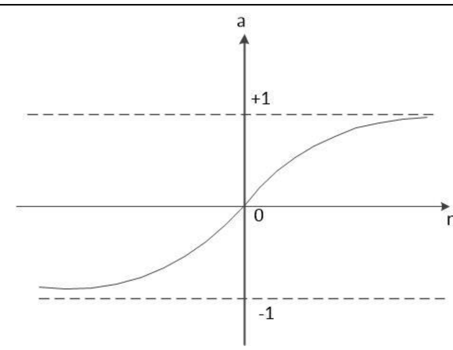
	
Hard limit activation fuction	Symmetic hard limit activation fuction
	
Linear Activation function	Log sigmoid activation fuction

Fig. 24. Types of activation functions in A-NN training

4.5. NEURAL NETWORK ARCHITECTURES

The neural network architecture defines the pattern of the network i.e. how many neurons are there and how they are connected. These neurons are inter-linked with neurons in different layers of the network which operate in parallel. The artificial neural network is classified into two forms recurrent or feedback neural networks and feed-forward neural networks. Feed-forward neural network (FFNN) are can be single layer or multilayer types [19].

Fig.25 and Fig.26. shows typical arrangements of units in artificial neural networks. In both figures, all the joints are forward and layered; Such neural networks are commonly referred to forward multilayer perceptron (MLPs). Units that do not belong to the income level and entry level are hidden units. This is because their output triggers cannot be monitored directly by the neural network outputs, and this reason the name Hidden is derived. Also, each neural network unit receives a connection from the polarization unit as an input. The neural networks of Fig. 24 are typical neural networks in which hidden units are arranged in layers that are completely connected between successive layers. However, MLPs are not the only suitable or acceptable neural network architectures. For example, it is often advantageous to have direct input and output connections; Which unit level hidden jumps are sometimes referred to as link links. Also, hidden drives don't necessarily have to be layered. For example, a waterfall learning architecture, an adaptive architecture that organizes hidden units on a specific, non-layered continent. There are also neural networks that allow for cyclic connections. In other words, connections from any neural network unit to any other unit, including self-connections. These repetitive neural networks present many additional challenges, so we only use forward or acyclic neural networks in our system.

4.5.1. Recurrent Neural Network

The basic feature of Recurrent or feedback neural network is that it comprises at least one feedback loop. The existence of this feedback loop makes these networks appropriate for the application in signal processing and modeling of the nonlinear systems. Another important advantageous characteristic of these recurrent neural networks is that, these types of network are free from the errors due to over-fitting and under-fitting. The outputs of neurons may circulate back by the via feedback loops through unit delay elements to inputs as illustrated in Fig.25. The functionality of the delay elements is to hold-up the signal propagating backward till the next time step. So, in the network the data flows in both forward direction and backward direction and thus provides ANN a dynamic memory. The complexity in the architecture and operation poses main setback for this type of network.

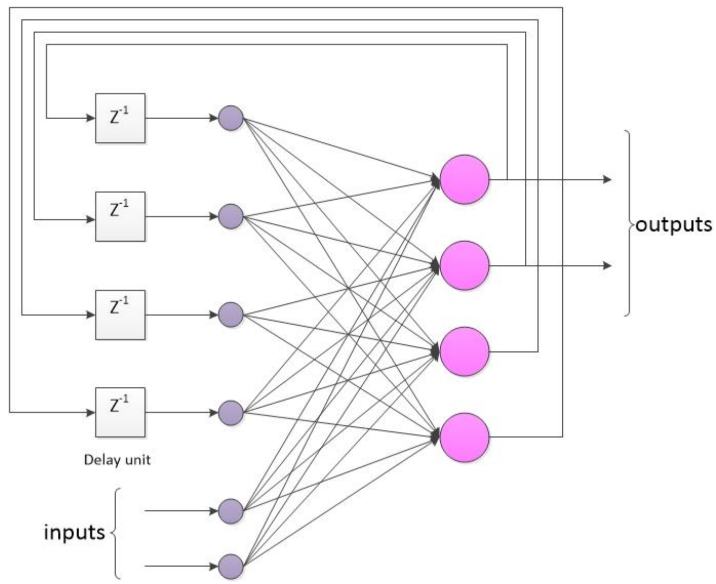


Fig. 25. Recurrent Neural Network

4.5.2. Single Layer Feedforward Neural Network

This architecture of ANN is simplest of all and the most widely used architecture. In feedforward NN, the data passes unidirectionally to all the layers until it reaches the output layer. This is also called as front propagated wave, achieved by using a transfer function. In contrast to other type of networks in FNN, there is no back-propagation and data flows unidirectionally in forward path. The FNN can have single layer or multiple layers i.e. hidden layer may be or may not be present in the network.

In FNN, weighted inputs are calculated and then propagated toward the output. Below in Fig.26 is the example of single layered feed-forward neural network architecture having 3 neurons.

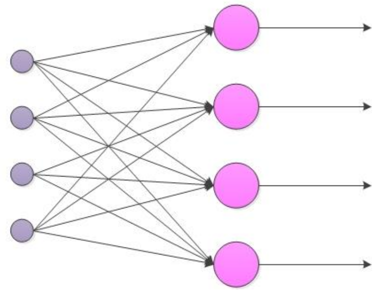


Fig. 26. Single layer feed forward neural network

This is simplest type of network which consists of only single layer. In this feed-forward network there is no feedback loop and input signals are always transferred in forward direction. A simple feedforward neural network is equipped to deal with signals which contains a lot of disturbance. Feedforward neural networks are also relatively simple to maintain.

4.5.3. Multilayer Feedforward Neural Network

When in FNN multiple layers are present, it is called MLFNN. This type of network is further classified into two main categories: (i) Radial basis function network (ii) Multilayer perceptron network

(i) **Radial Basis Function Neural Network:**
This network is also a forward-facing nonlinear multilayer NN which utilize the masked radial base activation function. The reliability output is a linear grouping of radial functions and input parameters. The number of hidden layers of the radial function NN is largely lost by one and this hidden layer is defined as a feature vector. The RBNN manages the size of the feature vector. We don't need a hidden layer to distinguish the non-linearities we are defending. The RBNN converts the input signal to another format, which can then be fed into the network to provide linear separability. RBNN is structurally inactivated by the perceptron (MLP) [29].
The RBNN contains Gaussian control functions in the hidden layer, the ratio of which is relative to the gap/distance from the center of the neuron. The elementary idea is that the foreseen target value of one element is definitely the same value as other elements that have values close to the predictor variable. The RBF network looks for one or more RBF networks in a state defined by the predictor variables. This space has as many meanings as there are predictive attributes. The Euclidean distance improves from the point to be evaluated at the center of each neuron, and at a distance a radial function (RBF), also understood as a central function, is assumed to increase the weight of each neuron. The name is radial basis function

because the radial distance is an argument of the function.
Weight = RBF
Radius-based function: There are several types of radius bases, while the much popular is the Gaussian function: if there are several predictive variables, the RBF function has as many variables as there are. The basic radial function of a neuron has a center and a radius. The beam is also reported missing.
A radial-based RBF network has only one hidden layer, many multilayer forensic neural networks have one or more hidden layers.
(ii) **Multilayer Perceptron Network:**
The multilayer perceptron network is commonly referred to as a forward nerve network.
The forward input layer of the neural network contains only inflatable elements. This layer collects the signal or data and sends it to one or more hidden layers in the network, where the signal or data is processed and finally read into the output layer. The choice of the number of hidden layers and the number of neurons in the different layers depends on the system in which the network is used.
Each perceptron of the left (first level) input level sends an output to all observations of the hidden level (second level), and all second level observations send the output to the last right side of the level (Output Level). Each perceptron sends a signal to each perceptron in the next layer. Perceptron uses different weights for each signal. Each path that leads from the perceptron at one level to the coming level represents a unlike output. Every layer can have a several illustrations and can have multiple layers, so that a multilayer perceptron could result in complexed system. The multilayer perceptron has another title, which is just a neural network. Three-level MLP is called flat or flat neural network. MLP with four or more levels is called a deep neural network. One difference between MLP and neural network is that in the classical perceptron, decision-making is a phase-to-phase function while output is binary. In neural networks developed from MLP, other trigger functions can be used that result in true value outputs, usually between 0 and 1 or between -1 and 1. This allows predictions based on the probability or classification of additional element entries.

This neural network architecture has been widely used in power electronics transformers in recent years because of its enormous advantages. It is easy to implement and also allows learning to be tracked. When the FNN receives a signal, it transmits only from one layer to another on the forward path. It uses the same activation functions at a certain level and can use different transfer functions at different levels. The feedback learning algorithm is mainly used to train this network. Because all the interesting features of the multilayer forward neural network are taken into account, this type of NN architecture is used in the design of the controller for a hybrid energy storage system.

4.6. BACK-PROPAGATION BASED ANN MODEL FOR HYBRID ENERGY SYSTEM

For achieving optimal power flow supercapacitor, battery and load, we are exploring ANN controller because for its excellent features and advantageous offered by it over other types of controllers. Since ANN technique appears to be very promising tool for function fitting, nonlinear system estimation and control, a typical ANN network is composed of an input layer, hidden layers and an output layer is supplement in the proposed hybrid energy storage framework. The number of hidden layers and their neurons present in any system are case-oriented. Although, even single hidden layer comprising a substantial count of neurons holds the ability to prove the ANN system sufficiently influential to examine any nonlinear system, but at times more than one hidden layer are being employed in the training network.
The projected A-NN structure consists of inputs and outputs: the input is the error signal and the response are the reference current. Then network is skilled and authenticated by entering a database that can be mined from experimental tests at an established test site. Training data should cover the full range envisaged. Therefore, the values of the test base vary widely and cover all possible margins. The backpropagation (BP) algorithm is used in the context of an early shutdown strategy to train the projected ANN model to ensure a sufficiently precise estimation while avoiding overly perfect conditions. The efficiency of the model is confirmed by experimental outcome using a randomly selected test data set [17].

4.7. BACK-PROPAGATION TRAINING

ANNs are extensively and fruitfully functional in many areas, most of them uses a feed-forward ANN with a backpropagation (BP) as the training procedure. The weights are calculated at each epoch by using BPA, wherein the epoch refers to one cycle through the full training dataset. Typically, training a neural network consumes more than a few epochs. Alternatively, we can say, by feeding a neural network the training data for more than one epoch in varying patterns, we expect an improved generalization when network is fed with a new "unseen" input (test data). An epoch is frequently misunderstood, considering it same as an iteration. Iterations is the number of steps or batches through segregated packets of the training data, required to complete one epoch. Heuristically, one inspiration is that (particularly for larger but finite training data sets) it provides the network a chance to look the preceding data to readapt the model parameters so that the model is not influenced towards the last few data points while on-going training [20].

During training, the error between the outputs of the A-NN system and the target in the foreground must always be reduced by using derived information. The error is characterized by the root mean square error (mse), which can be expressed as follows:

$$MSE= 1/N\sum(t_k-o_k) \tag{3.5}$$

Where, N signifies the count of patterns, t_k signifies the kth target output, and o_k denotes the kth network output.
During learning, the Levenberg-Marquardt algorithm [30] is activated to estimate the weights

updated in each epoch. A search direction is used which represents the cross between the descent direction and the Gauss-Newton direction, which is the steepest. Another numerical optimization algorithm, the LVM algorithm, is also an iterative method. The problem of fitting a curve of at least a square with a set of m empirical points (xi, yi), where xi are independent variables and yi are dependent variables, is the main application of LVM.
In every iteration step, β the parameter vector is being substituted by its new calculation β+δ. For determining δ, the function given by Ƒ(x_i, β+δ) is then approximated by its linearized version given by

$$f\,(x_i, \beta+\delta) \approx f\,(x_i, \beta) + J_i\,\delta_i \tag{3.5}$$

Where,

$$J_i = \frac{\partial f(xi,\beta)}{\partial \beta} \tag{3.6}$$

This algorithm receives the speed advantage of the Gauss-Newton algorithm and the stability advantage of the method with the steepest descent. As a result, LM has higher reliability than the Gauss Newton method and faster convergence than the steeper descent method. It can be shown that the update rule for the Levenberg-Marquardt algorithm has the form

$$W_{k+1}=W_k- (J_k^T J_k + \mu I)^{-1} J_k e_K \tag{3.7}$$

where wk + 1 is the weight vector in the k + 1st epoch; wk is the weight vector in the k th epoch; Jk is the Jacobean matrix at kth epoch; µ is the coefficient of the positive combination, called Marquardt factor, and ek is the vector of the error of inference.
The Jacobian matrix contains firstorder derivatives of the total weight error function in the kth epoch.
It can be calculated, where m is the number of neurons in the output layer; here m is 1; n is the number of weights in the network.
The Jacobian matrix contains first-order derivatives of the total error as a function of weight in the kth epoch. It can be calculated, where m is the number of neurons in the output layer; here m is 1; n is the number of weights in the network.

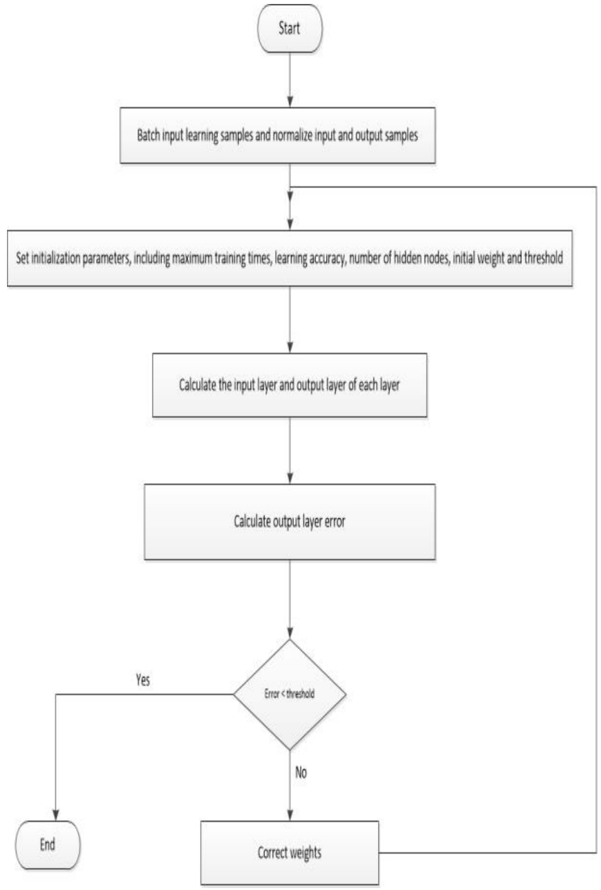


Fig. 27. Flowchart of Levenberg-Marquardt algorithm

4.7.1. Early Stopping Strategy

The error in training ANN models consistently diminishes as the training process advances. But, an issue with overdrive can happen when execution starts to decay, despite the fact that the training error keeps on diminishing, particularly in the later phases of training. An early stopping methodology is an overall measure to keep away from clog issues and is utilized in the present controller. In this technique, the preparation information base is isolated into preparing, approval, and testing subsets as indicated by the suitable proportion. Preparing doesn't end when the preparation error arrives at the minimum value. Rather, preparing is halted when the check error increments by a specific number of repetitions and the loads and deviations come back to the base blunder. It tends to be expected that the time of progressive increments in the validation error shows the event of extra matching [50][51].

CHAPTER 5

SIMULATION OF HYBRID ENERGY STORAGE SYSTEM

5.0. INTRODUCTION

The model of proposed topology for hybridized energy storing system is developed in MATLAB/Simulink. The aforementioned schematic of DC/DC converter is supplemented with two controllers, which supervises turning on and off the charging or discharging part of scheme, depending on the magnitude of DC-link voltage, and battery and Ultra-caps current limit. Two variation of controllers will be employed in the system and a comparative study will be done for both of them. Responses of both the controller will analyzed and superiority facts of one controller over other will be judged.

5.1. MODELLING OF SYSTEM USING MATLAB/SIMULINK

The Hybrid energy storage system is implemented using MATLAB/Simulink and has been shown in Fig. 29. A battery pack containing 12, 12 V batteries connected in series to provide rated voltage of 144V and a 125V, 0.2F Supercapacitor are simulated in MATLAB/Simulink using the components from Simscape toolbox. The parameters of battery and supercapacitor are displayed in Table 6.

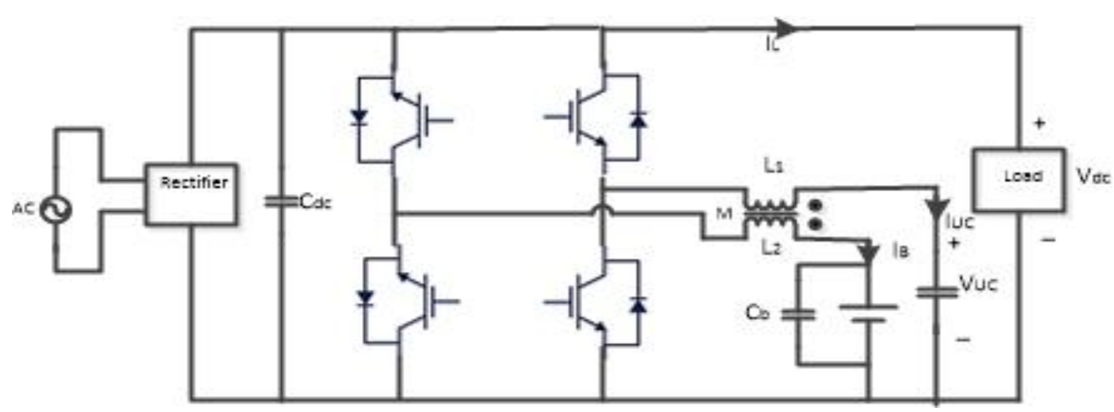


Fig. 28. Hybridized energy storage topology

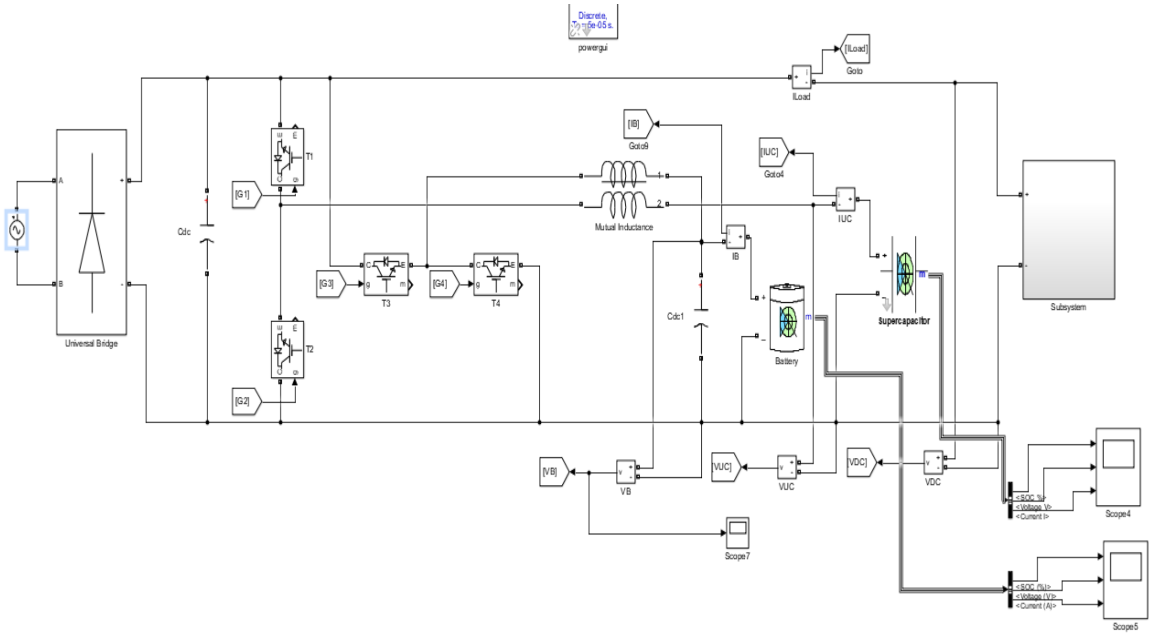


Fig.29. Hybridized energy storage topology Simulink model

At the input side, AC source is present to simulate the charging mode of the electric vehicle being used in the system. 230 V, 50 Hz AC supply is now rectified using a diode bridge carried from MATLAB Simscape library. Then DC/DC converter is lodged into the system. System, motor and battery parameters are illustrated in Table. 6, Table 7 and Table 8.

Parameters	Values
AC supply voltage	230V
Frequency	50 Hz
Cdc	4.4 mF
L1	10.12 mH
L2	0.59 mH
M	0.58 mH

Table 6. System parameters

Parameters	Values
Rated Voltage	144 V
Rated Battery Capacity	70 Ah
Initial SOC %	100
Response time of battery	30 sec
Cut-off voltage	108 V

Table 7. Battery Parameters

Parameters	Values
Armature resistance	0.4832 Ω
Armature inductance	0.006763 H
Field resistance	84.91 Ω
Field inductance	13.39 H
Field-armature mutual inductance	0.7096 H
Total inertia	0.2053 kg.m^2

Table 8. Motor Parameters

For implementation of rule-based strategy with which control parameters will be restricted in operational zone, following technique in used to generate controlled pulses for battery and ultra-capacitor operation. Fig. 30, demonstrate used control technique.

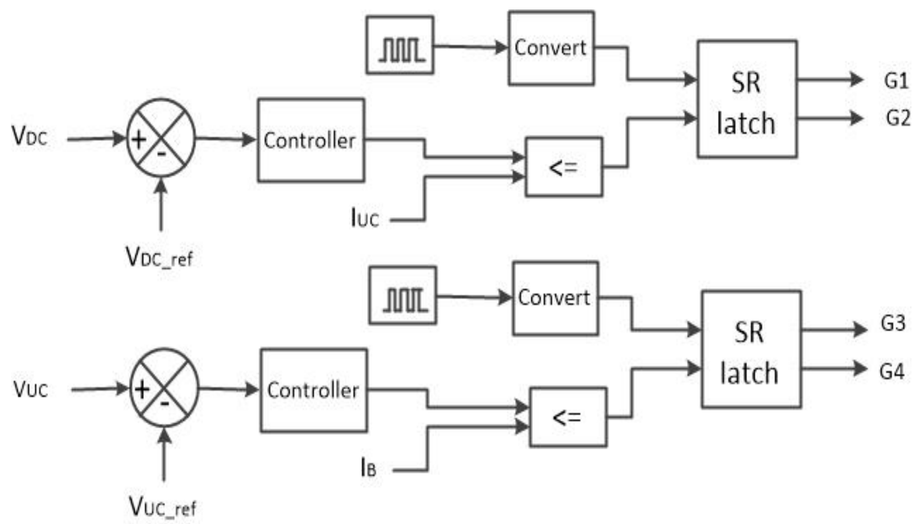


Fig. 30. Rule-based control strategy

For controlling the output voltage, PI controller is designed for generating controlled pulses for the converter. In the system, two PI controller is devised for executing the control strategy by generating G1, G2, G3 and G4. The PI employed control approach is as shown in Fig.31.

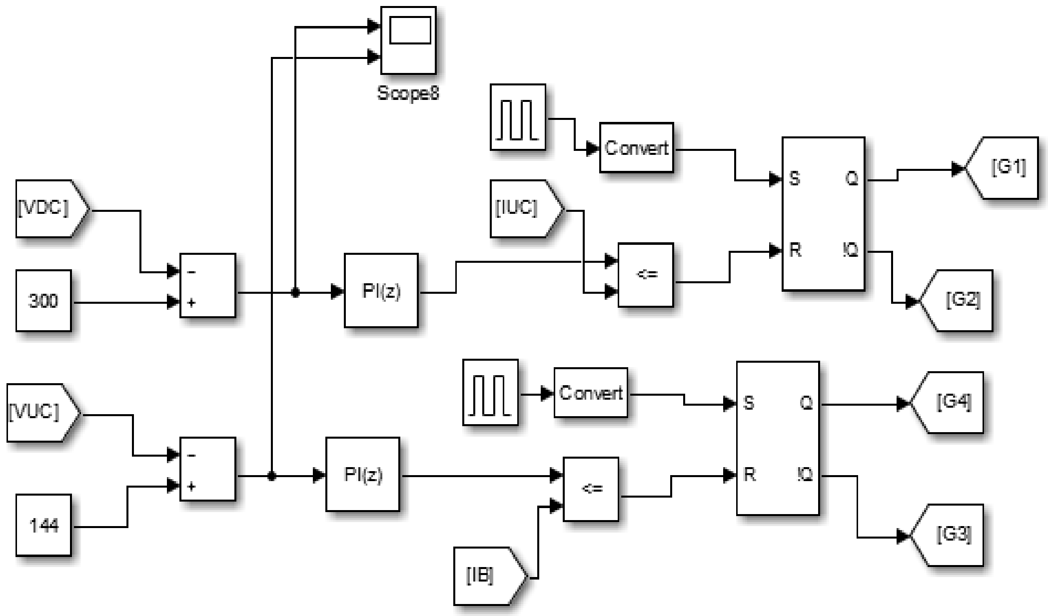


Fig. 31. Simulink model for pulse generation with PI controllers

Similarly, two ANN controllers are devised for operating the hybrid storage circuit by generating G1 and G2 corresponding to first controller and G3 and G4 are produces corresponding to second controller. The arrangement of two ANN controller is as shown in Fig.32.

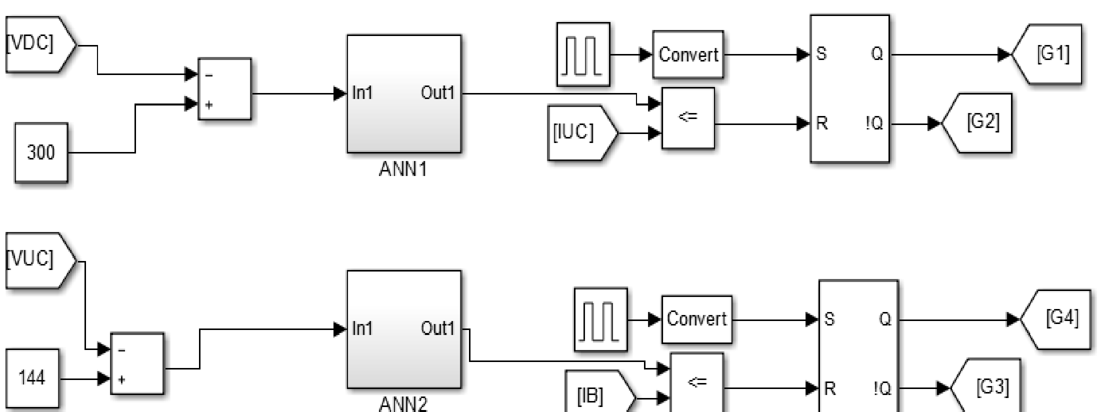


Fig. 32. Simulink model for pulse generation with ANN controller

To simulate driving cycle for vehicle, stair case generator is used as shown in Fig.33. The signal from staircase generator is fed to controlled current source through switches. The controlled current source transforms the input Simulink signal into a corresponding current wherein the generated current is driven by the input signal of the stair generator.

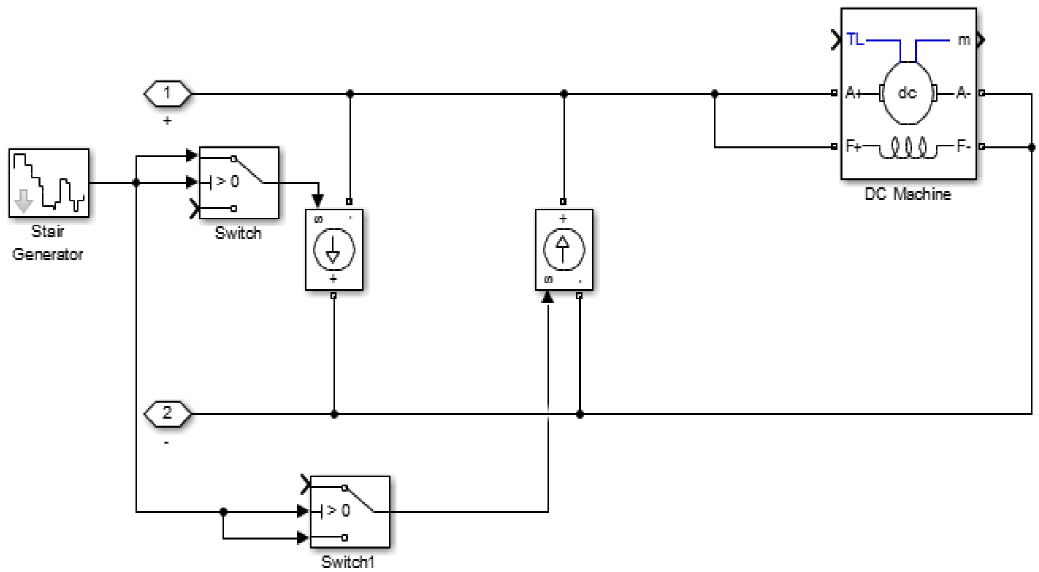


Fig. 33. Simulation model of motor load with a desired driving cycle

The error calculated by comparing the system voltage with threshold voltage, and derivative of error is fed to the function fitting neural network (shown in Fig.34) through a mux wherein the Mux block combines its error and its derivate into a single vector output. The function fitting neural network comprises two-layer network.

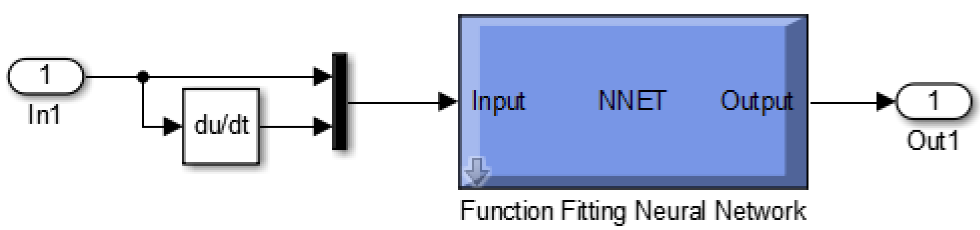


Fig. 34. Function fitting neural network

In the function fitting neural network, the input is processed in order to limit the value range since before training its advantageous to map/scale the input values and target value to make them fall within a specified range. This processing operation is performed at input and output of the network.

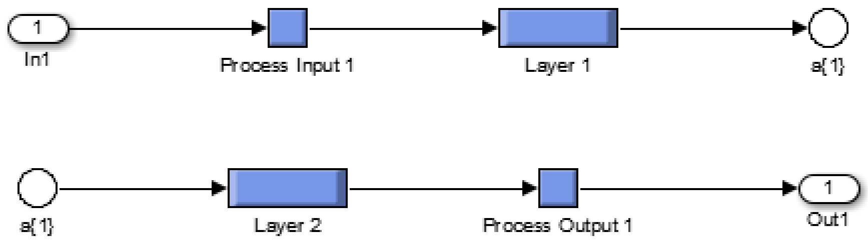


Fig. 35. Layers in neural network structure

Input error signal is first pre-processed are fed to the input layer. The output from the layer along with bias input is fed to output activation. Consecutively, the output of first layer is fed to second layer and output obtained from second layer is processed and corresponding control signal is being generated.

The basic structure of a neuron in as shown in Fig.36. The input is first delayed and then multiplied with weight. The sum of weighted input and along with bias function is sent to output activation function.

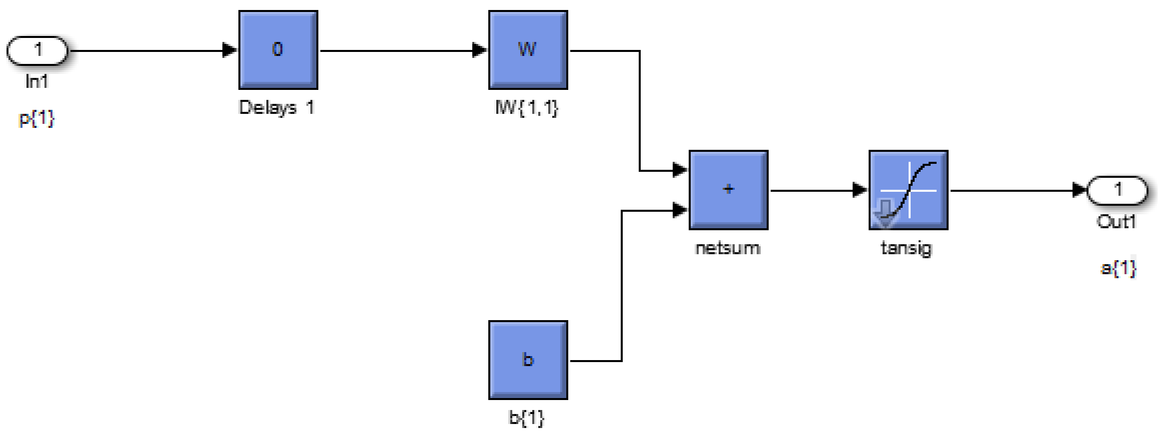


Fig. 36. Basic structure of neuron

The input and output layer contains ten hidden neurons as shown in the Fig.37. In order to multiply input with weight matrix dot product function is used. Dot product output is fed to mux, and the output obtained from here is fed to next layer hidden neurons. There are also 10 hidden neurons are embedded, processing is done in similar way; as a result of which a trained overall network is achieved.

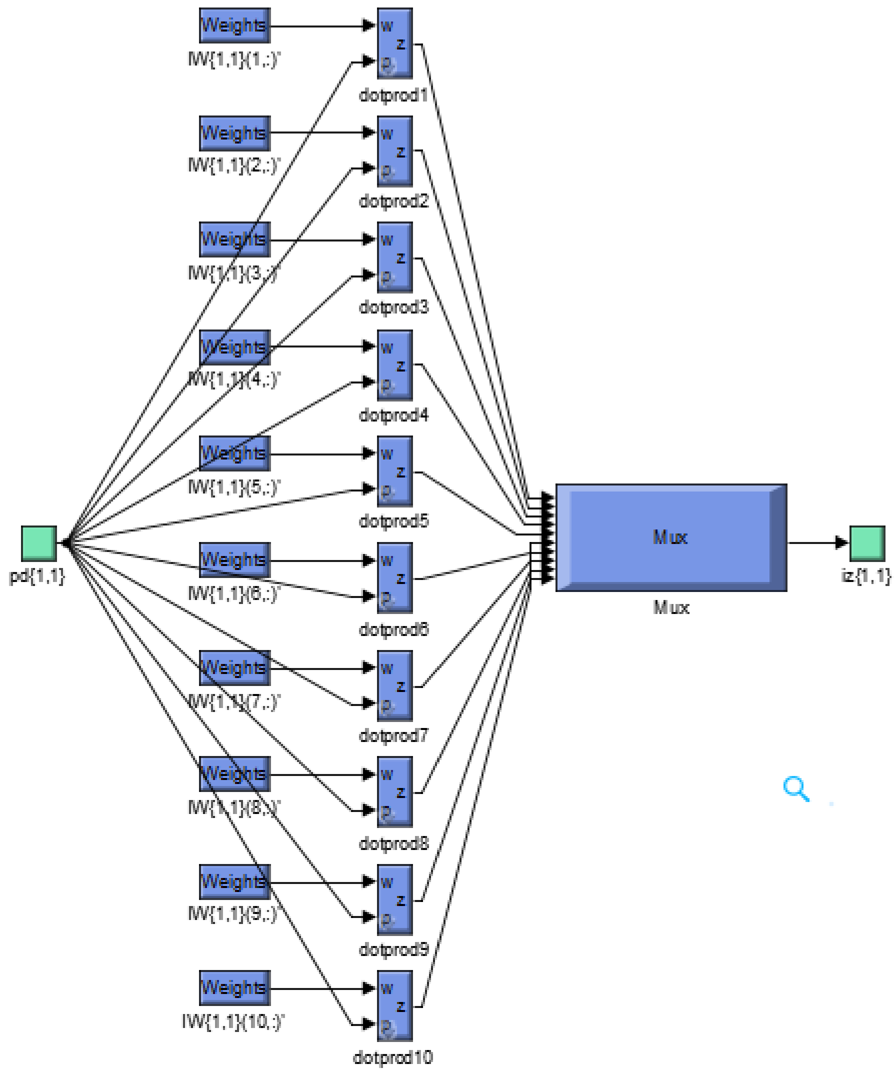


Fig. 37. Layer structure with 10 hidden neurons

The design of A-NN controllers is based on training data. The data for the design of NNC for SC control is obtained from PI regulator during simulation. In the same way, battery pack control data is achieved during the simulation PI controller. Table 9 shows the training parameters of A-NN controllers at which successful trainings were obtained after various repeated tests.

Parameter	**SC control**	**Battery control**
Input count	1	1
Output count	1	1
Hidden layer count	1	1
Hidden neurons count	10	10
Training samples	210442	420001
Validation samples	45095	90000

Testing samples	45095	90000
Epoches	754	1000

Table 9. Training parameters

Undertaking above performance parameters and by excecuting them in our system best performance is achieved at epoch 748 with mean sqaure errror = 5.0716e-09 . As shown in Fig 38.

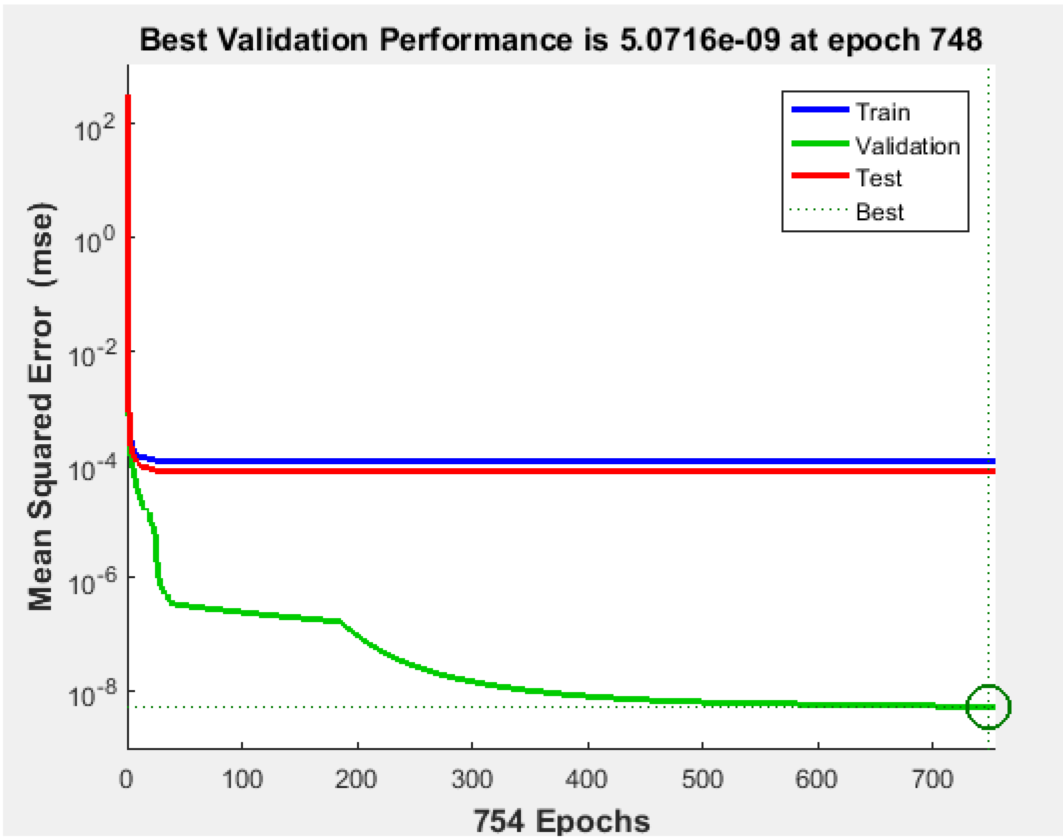


Fig. 38. Training, validation and test performance against mean squared error

The regression value measures the correlation between the output and targets achieved by trained network. The value of regression near 1 indicated close relationship is achieved between output values and input values. In Fig.39, for different input output equations, a close relation is established shown by regression values which are R=0.9973, 1, 0.99982 and 0.99979.

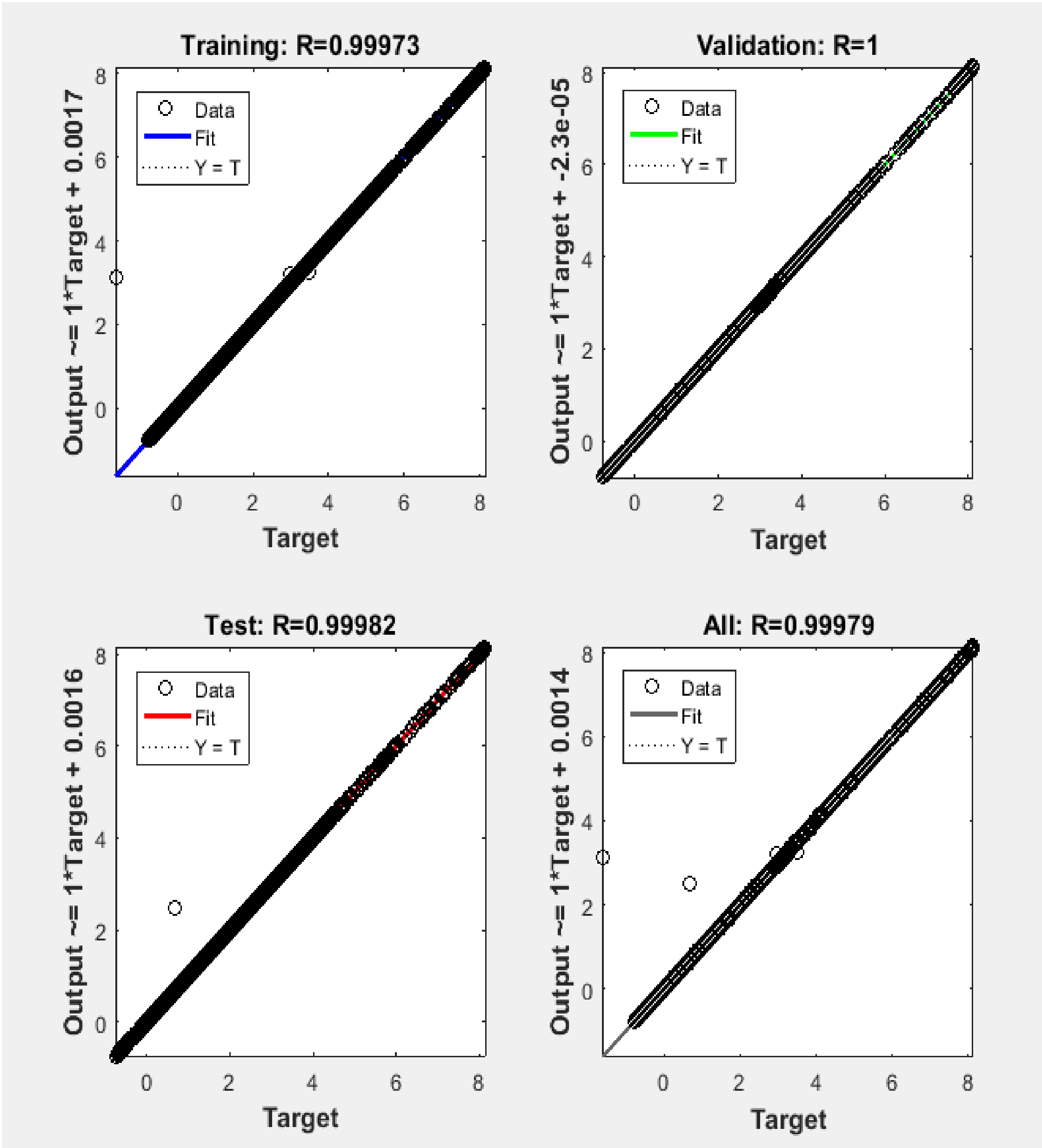


Fig. 39. Regression plot

In order to get a optimized output corresponding to the input training data, gradient value has to be minimized. By using aforementioned parameters the optimized output is achived at epoch= 754 with gradient value = 2.1137e-4 and mse = 1e-10 with total 6 validation checks being done at this epoch to validate the achieved parameters as shown in Fig. 40.

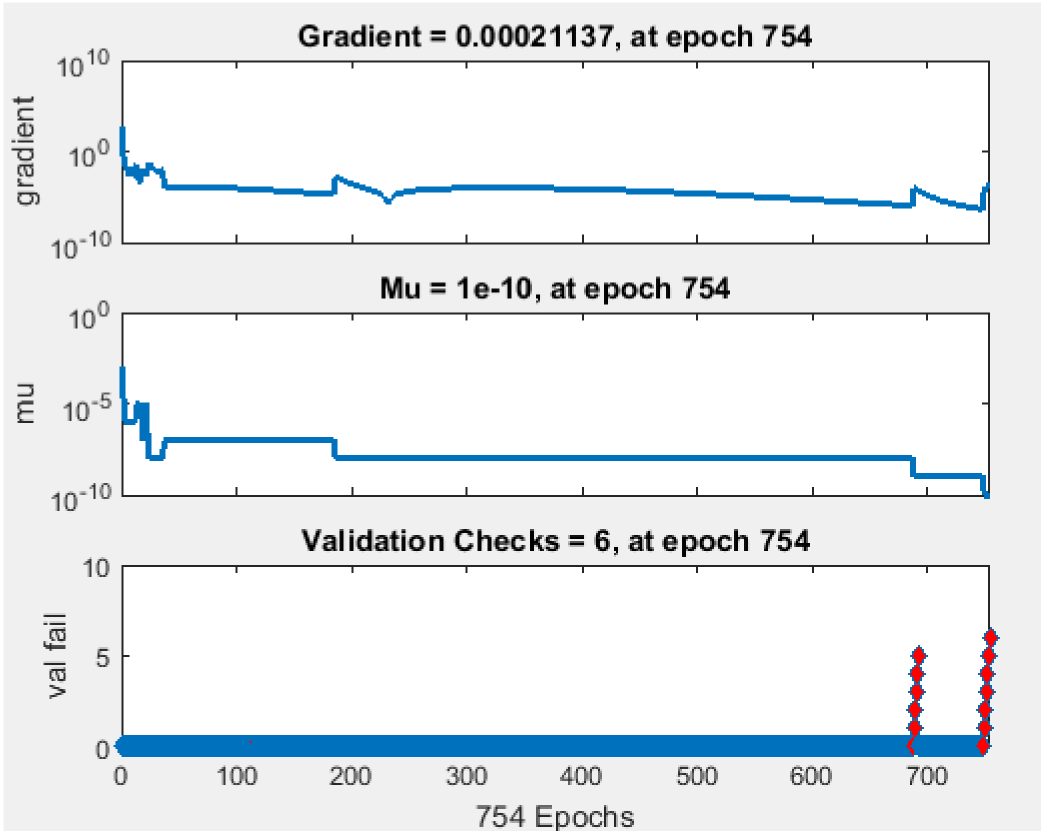


Fig. 40. Gradient, MSE and validation checks at epoch=754

5.2. RESULTS AND DISCUSSION

The simulation study of proposed hybrid energy storage system is done using proportional integral controller and an A-NN controller and results are compared for both the cases

SIMULATION RESULTS
Primarily, a typical driving cycle is simulated using staircase generator. The driving cycle comprises of parking mode, constant speed mode, acceleration mode, deacceleration mode and a regenerative mode. The voltage, current and power are analyzed in all the above-mentioned modes using both the controllers individually.

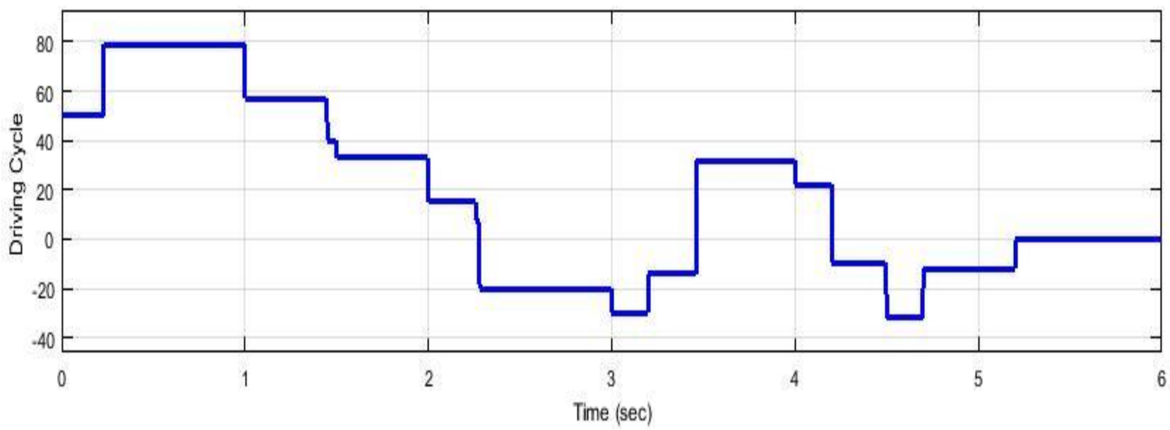


Fig. 41. Simulated driving cycle

5.2.1. System Response with PI Controller

The simulation result for PI controlled system discussed below. The PWM signals G1, G2, G3 and G4 generated corresponding to switches T1, T2, T3 and T4, by implementing overhead mentioned controller are demonstrated in Fig 42. By optimal switching on and switching off of T1 and T2 the flow is regulated across super-capacitor. And, by optimal switching of T3 and T4 the power flow is optimized across battery pack.

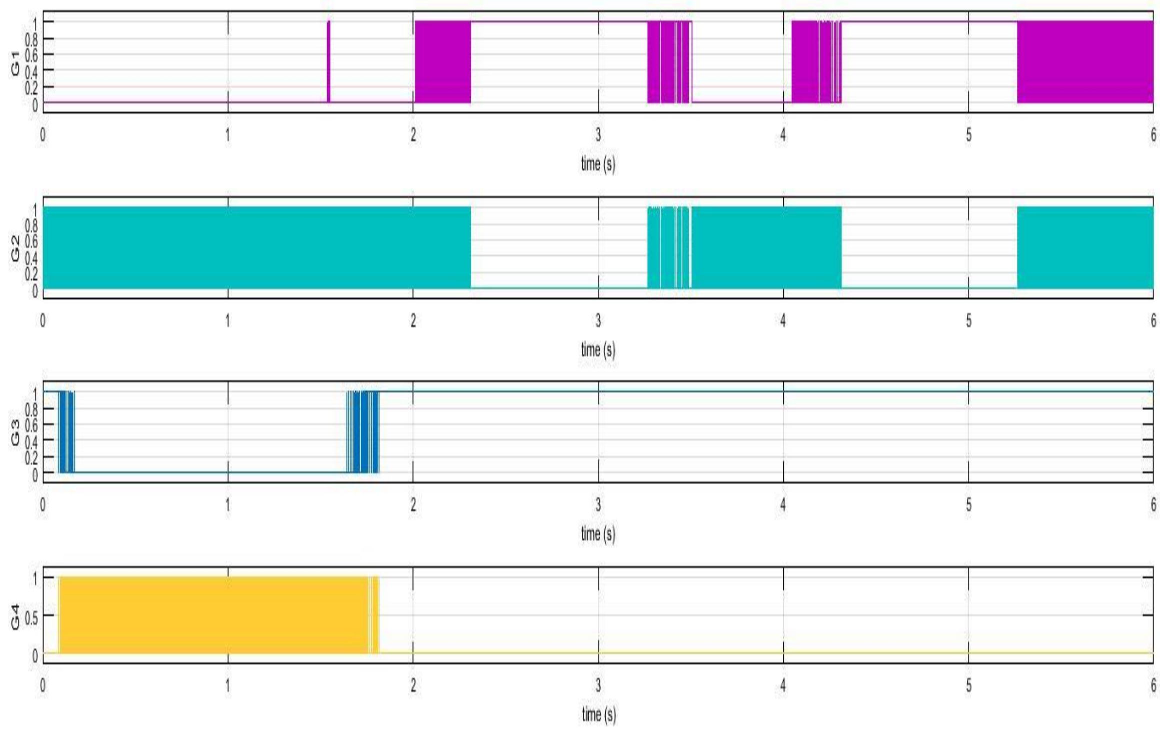


Fig. 42. PWM gate pulses generated by PI controller

When the battery switches T2 and T3 operate, following the constant load mode the battery supplies the load the required power demand maintaining the voltage across the battery constant.

Subsequently in acceleration mode, when vehicle power demand is greater than battery power, the voltage across the battery terminal could not be maintained constant and ultra-capacitor comes in play to support the battery pack in delivering the required power to the load. During this mode, the battery voltage experiences a droop and the ultra-capacitor will keep assisting the battery until Vuc ≥ Vth; otherwise if ultra-capacitor voltage falls below the threshold value than battery will unnecessarily charge the ultra-capacitor, which can further increase the stress on the battery. The Fig. 43, 44, 45 and 46, shows power profile, SOC profile, voltage and current waveform respectively for the battery pack.

Through peak load duration battery along with ultra-capacitor supplies power to load. During regenerative braking battery gets charged, as demonstrated in Fig. 43, with negative power flow in power profile of battery. The battery current is quite smoother as compared to UC current.

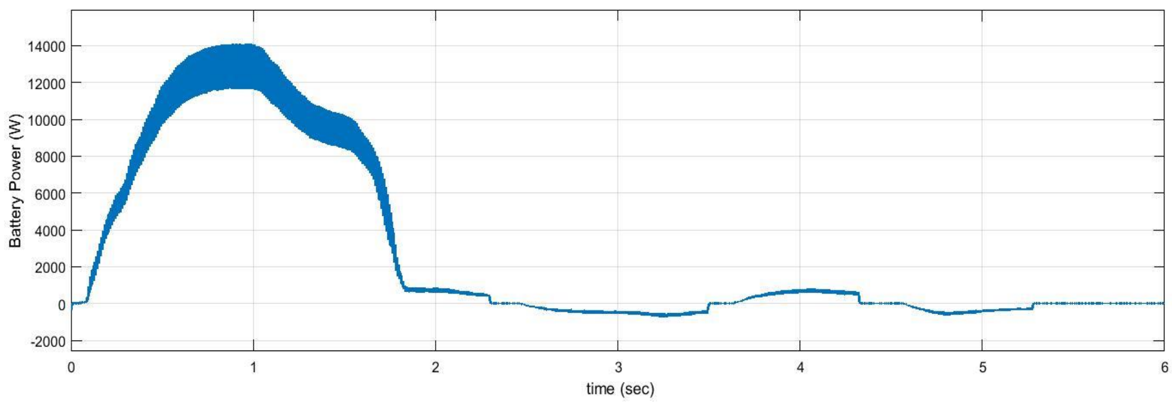


Fig. 43. Power profile of battery pack with PI controller

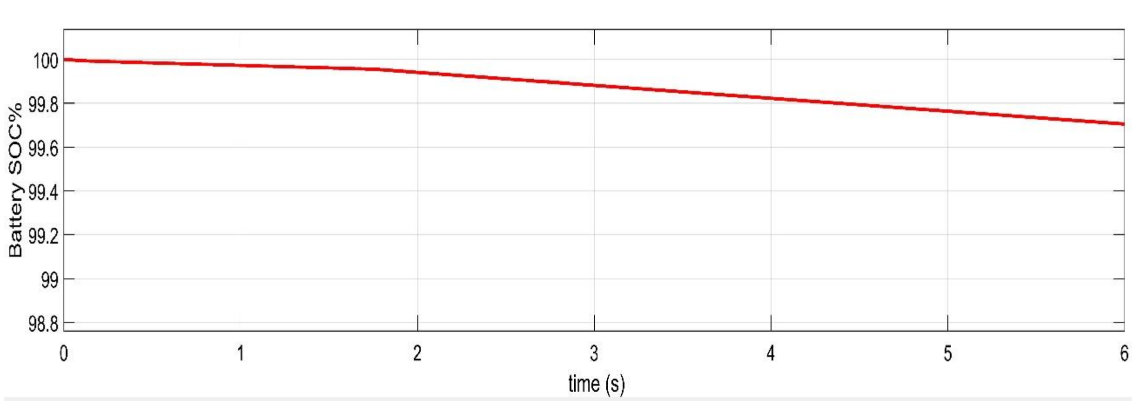


Fig.44. SOC profile of battery pack with PI controller

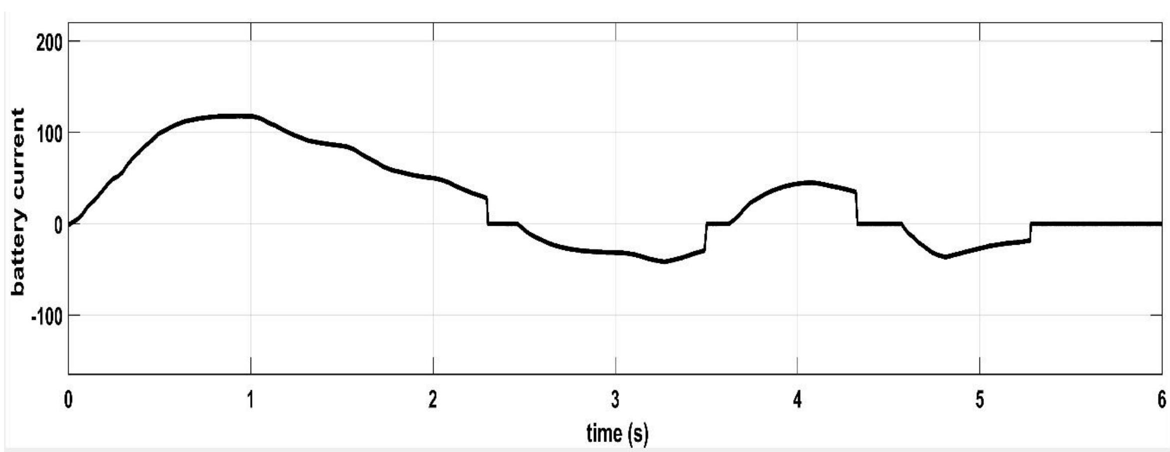


Fig. 45. Current profile of battery pack with PI controller

The ultra-capacitor’s response to simulated driving cycle is as shown below in Fig. 46, 47, 48 and 49, outlines UC power generation and absorption, UC SOC, UC voltage and UC current. The UC dispenses high transient current component to reduce down the stress on the battery and meets the load requirements.

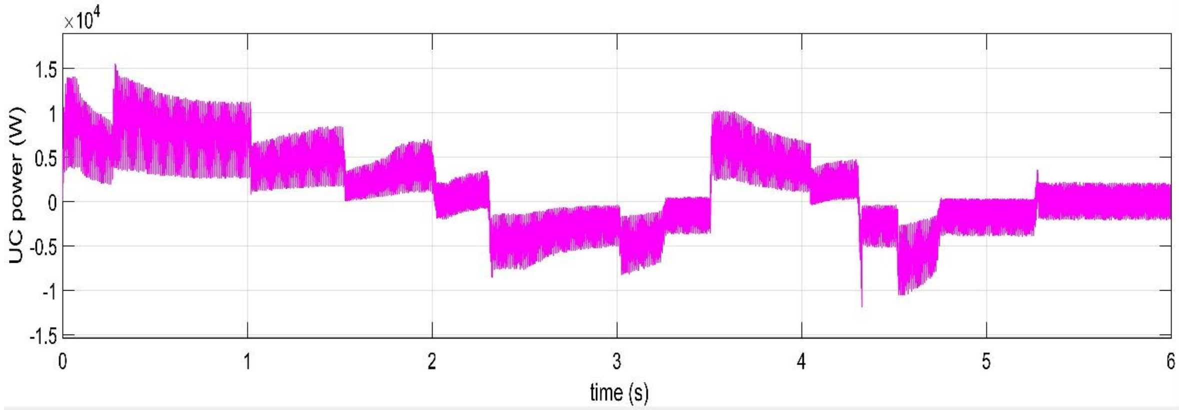


Fig. 46. Power profile of ultra-capacitor with PI controller

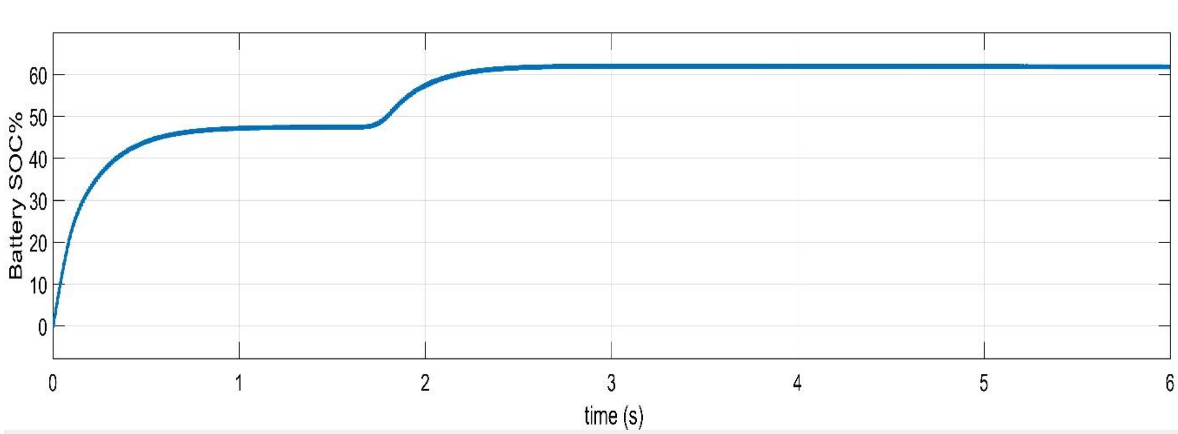


Fig.47. SOC profile of UC with PI controller

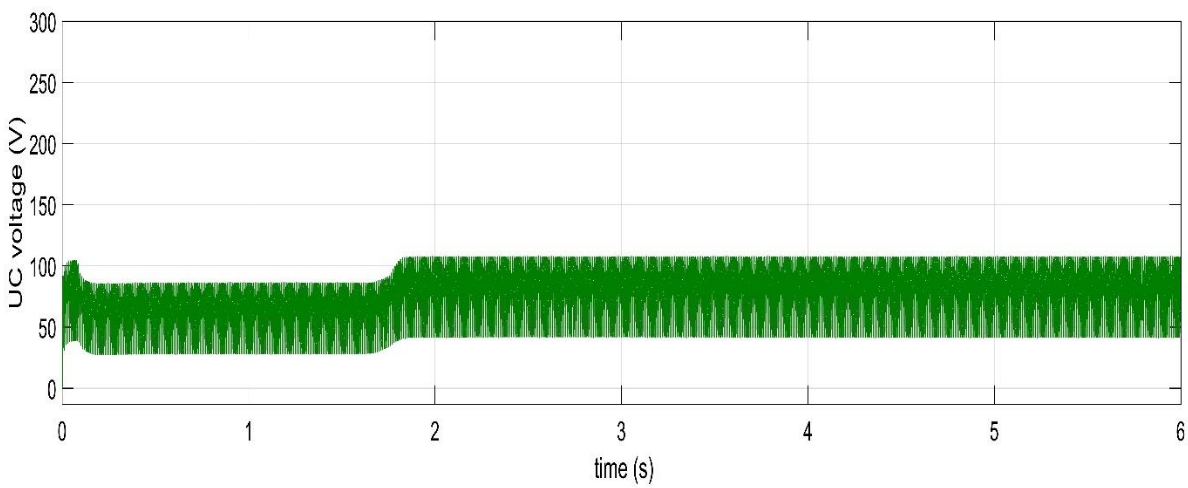


Fig. 48. Voltage profile of ultra-capacitor with PI controller

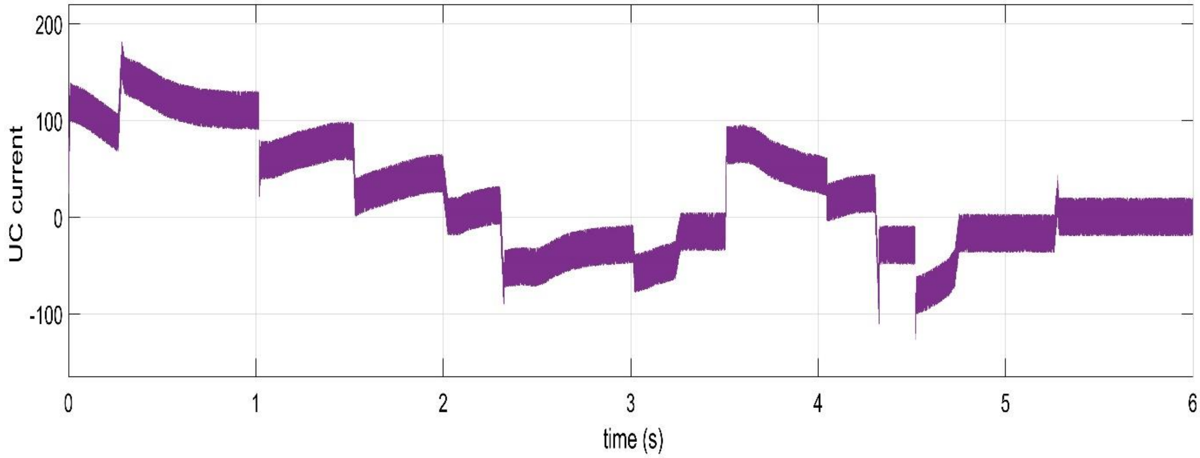


Fig. 49. Current profile of ultra-capacitor with PI controller

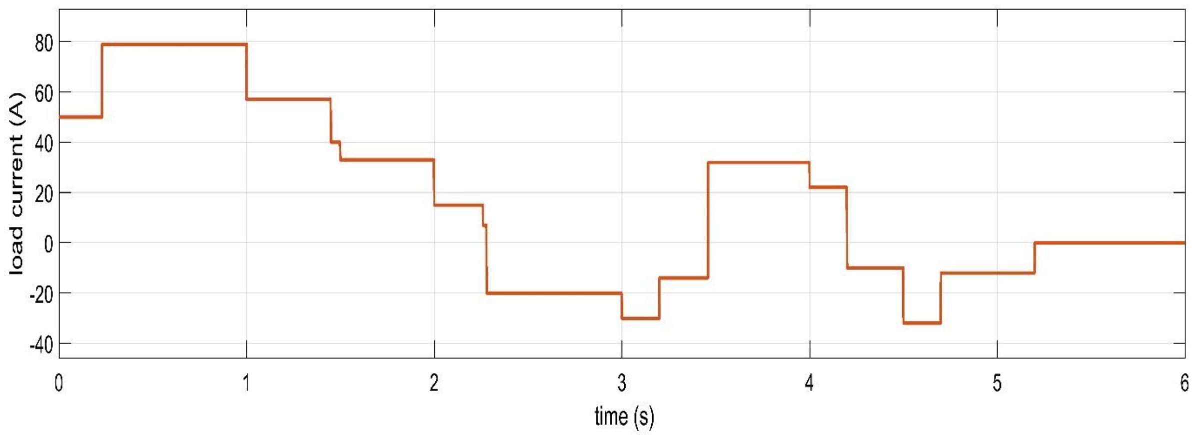


Fig. 50. Current cycle of load

The load voltage is maintained constant at 300V by operating the DC/DC converter with controlled PWM pulses and the load current varies in response to the driving cycle as shown in Fig.51. During regenerative braking the BLDC motor starts acting as generator, supplying the current back to ultra-capacitor and battery pack. The negative current shows barking mode occurring at t=3 sec and t=4.5 sec.

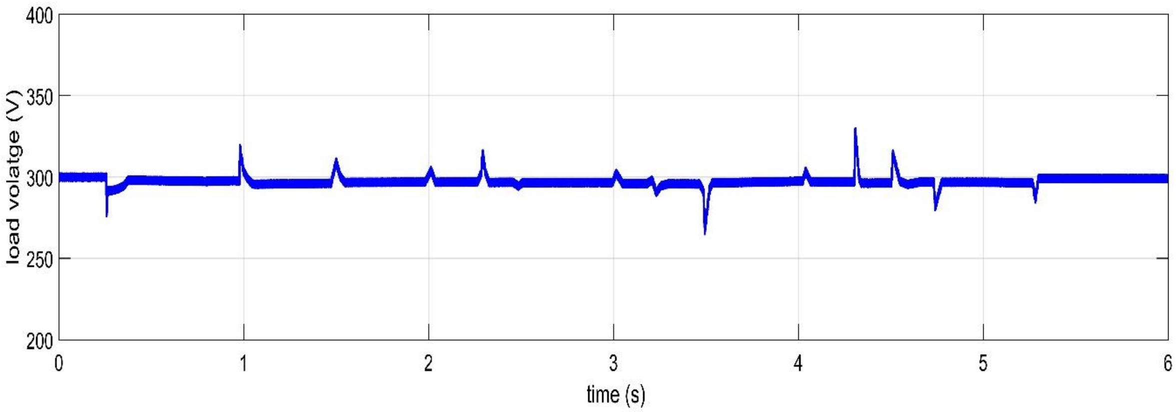


Fig. 51. Voltage profile of load using PI controller

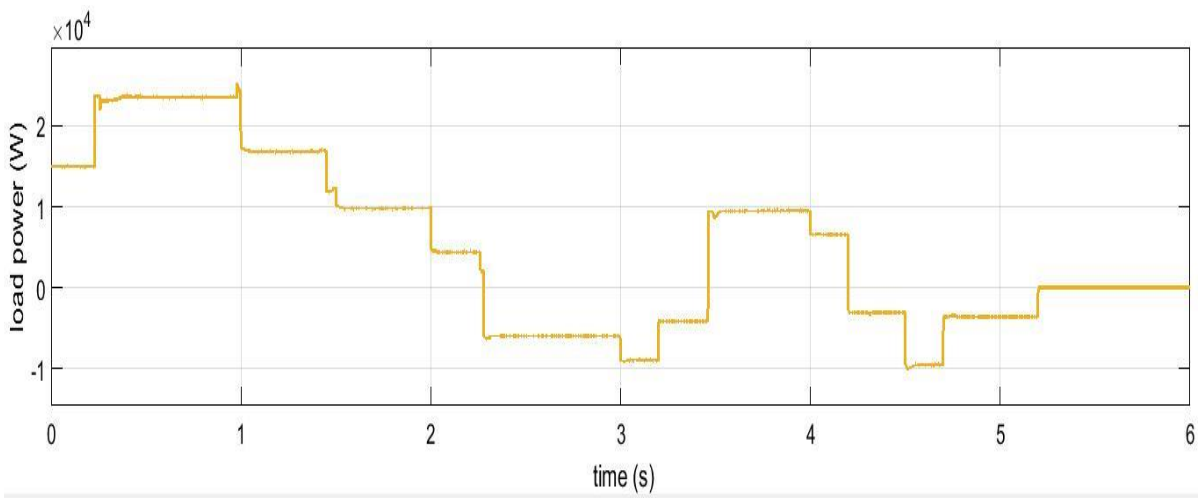


Fig. 52. Power profile of load obtained using PI controller

Ripple factor determines AC component available in the response waveform, when calculated for our system topology which comes out to be around 13%. This is verified by waveform in Fig.53.

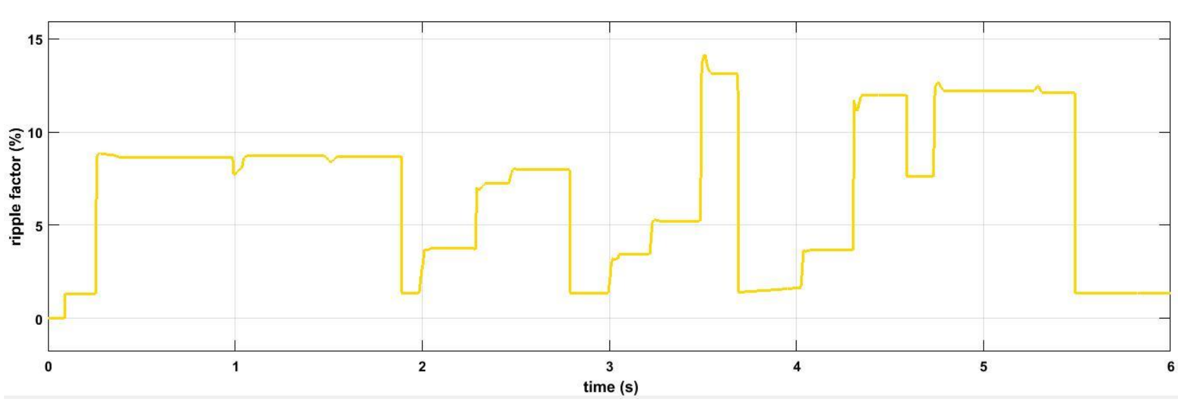


Fig. 53. Ripple factor using PI controller

5.2.2. System Response with A-NN Controller

Comparing load voltage with reference voltage produces error signal, which when processed by the A-NN controller generated reference UC current. UC current reference is being compared with system UC current to generate controlled PWM pulses G1 and G2 as shown in Fig.53, for DC_DC converter to operate and thereby optimize the power flow in UC pack. Similarly, UC voltage is equated with reference; its reference voltage is fed to the A-NN controller when processed generated reference battery current. This generated reference current is compared with system battery current to produce PWM pulses G3 and G4 as shown in Fig.54.

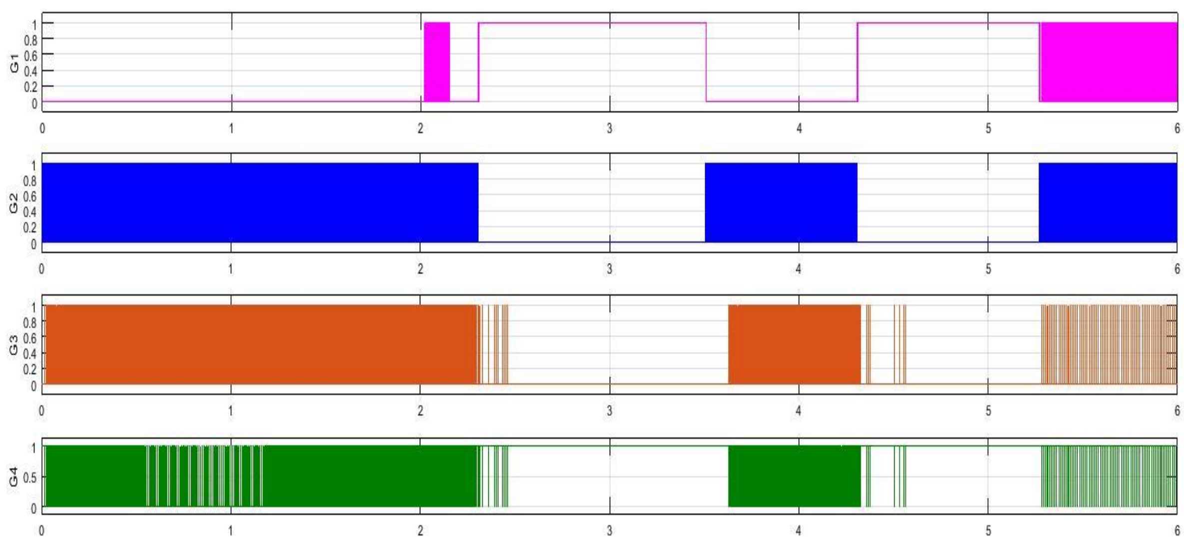


Fig. 54. PWM pulses with A-NN controller

Now on, results of proposed hybrid storage model employing A-NN controller are analyzed. PWM pulses are generated for supervised operation of DC/DC converter, which further helps in maintaining the load voltage constant at rated value = 300 V. Since, the UC is assisting the battery, battery current tends to be much smother. As shown in Fig.55, the maximum power being supplied by the battery is 12.820 kW at t = 0.895 sec, when the load demand = 23.636 kW, the rest power demand is being supplied by magnetic and capacitive energy storage elements. Thus, burden on battery reduces and battery life enhances. During regenerative mode, the battery absorbs power= 708.73W at t=3.67s.

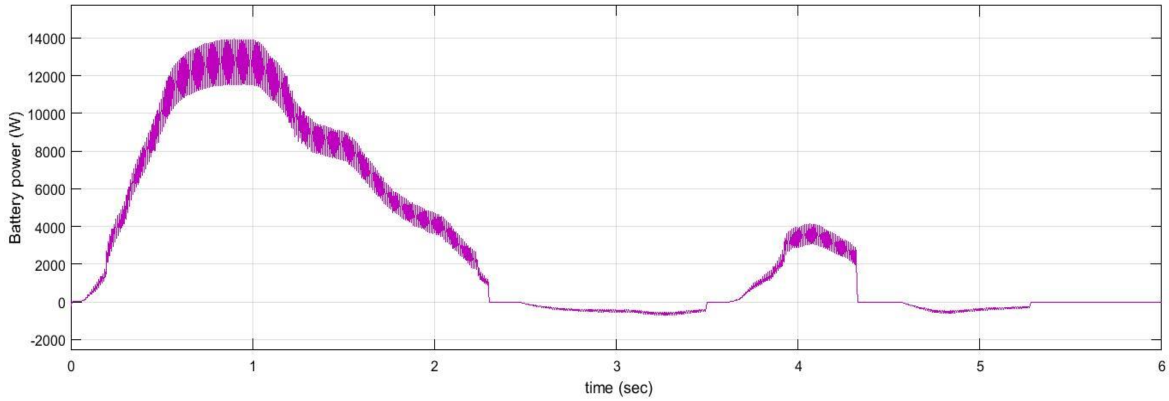


Fig. 55. Battery power profile with A-NN controller

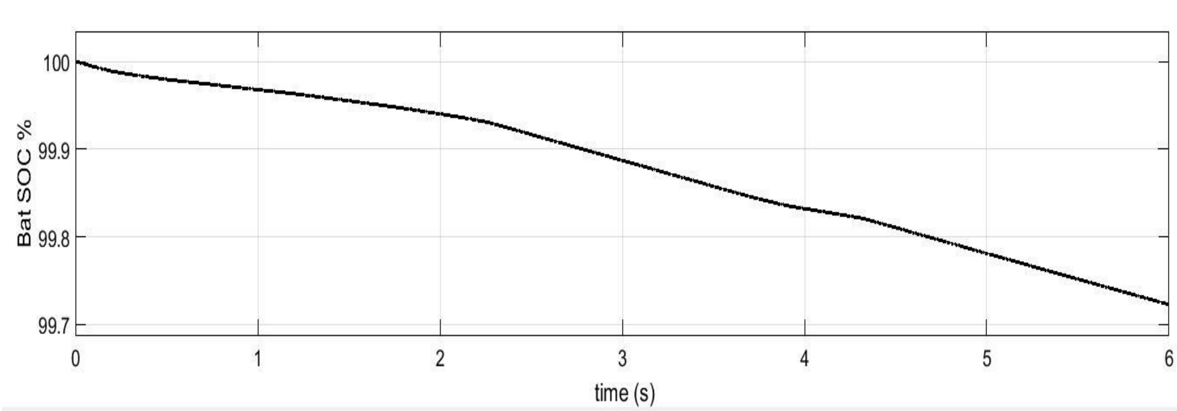


Fig.56.Battery SOC profile with A-NN controller

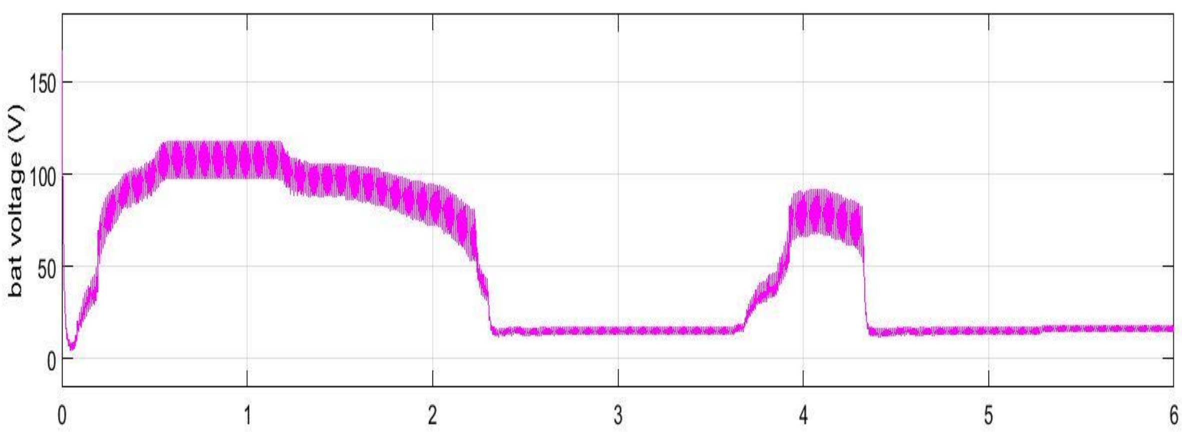


Fig. 57. Battery voltage profile with A-NN controller

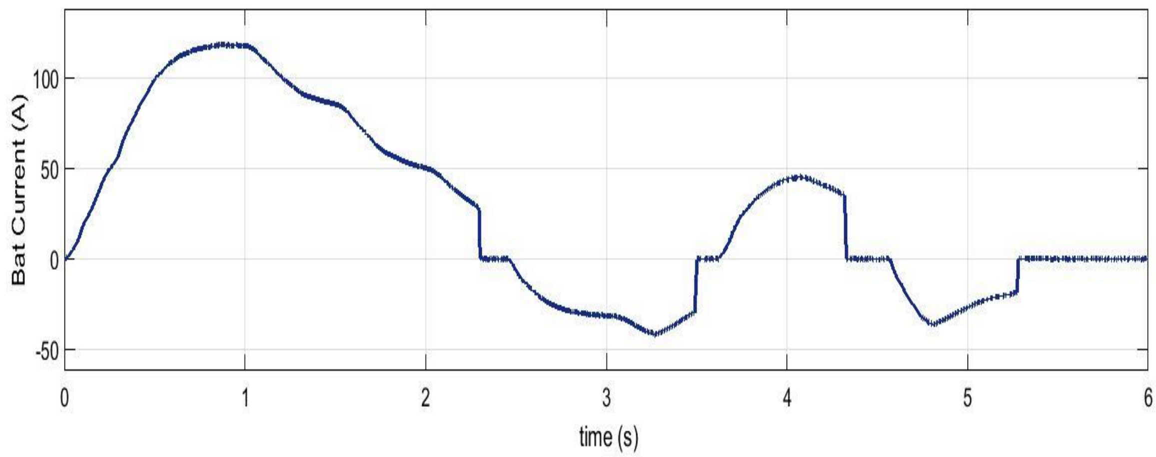


Fig. 58. Battery current profile with A-NN controller

With A-NN controller employed after proper weight training, results in smooth flow of current reduces down the current ripples to a very optimal value. With further results in smooth acceleration and deacceleration of the vehicle. UC characteristics are shown in Fig.59, 58, 60, 61 and 62. The maximum power supplied by UC =14.792 kW at t=0.285s and in regenerative mode, it absorbs the power= 8.529 kW.

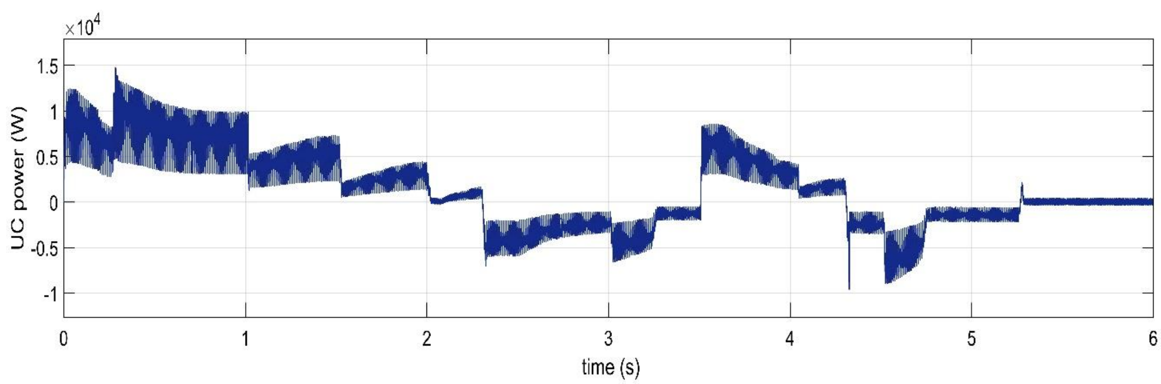


Fig.59. UC power profile with A-NN controller

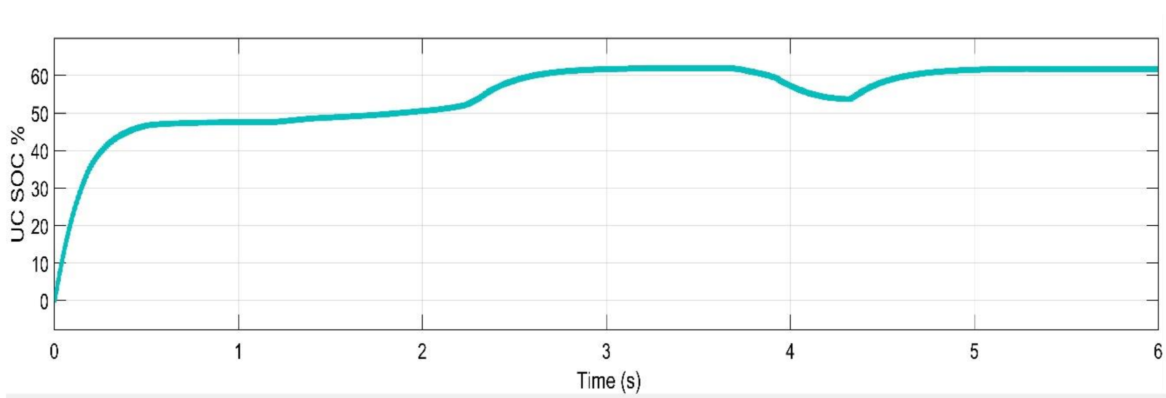


Fig.60. UC SOC profile using A-NN controller

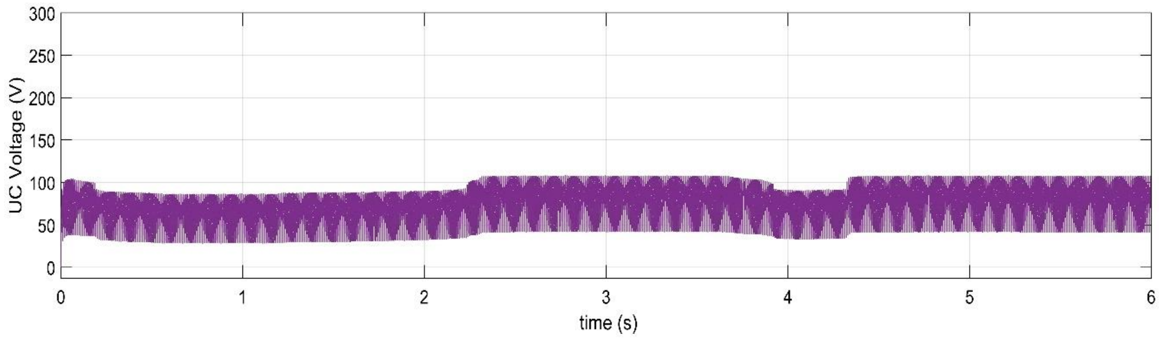


Fig. 61. UC voltage profile with A-NN controller

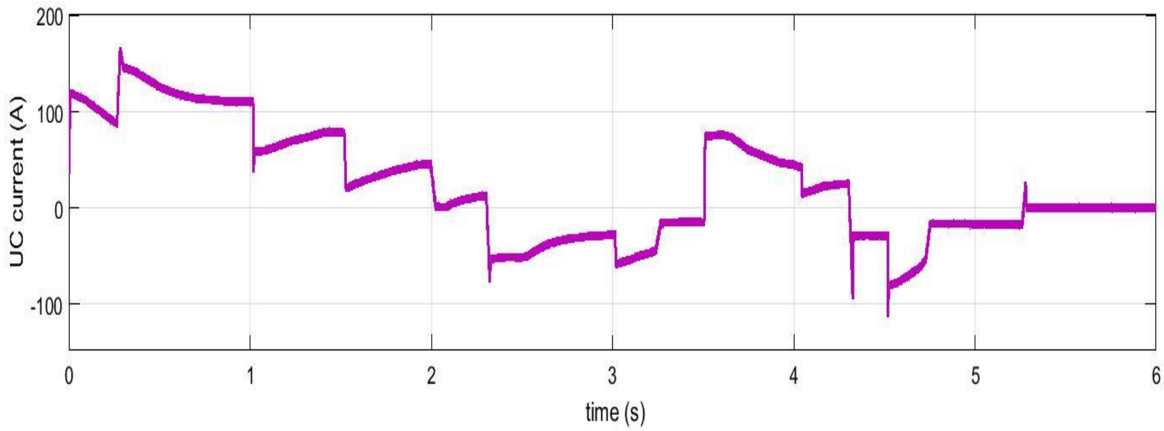


Fig. 62. UC current profile with A-NN controller

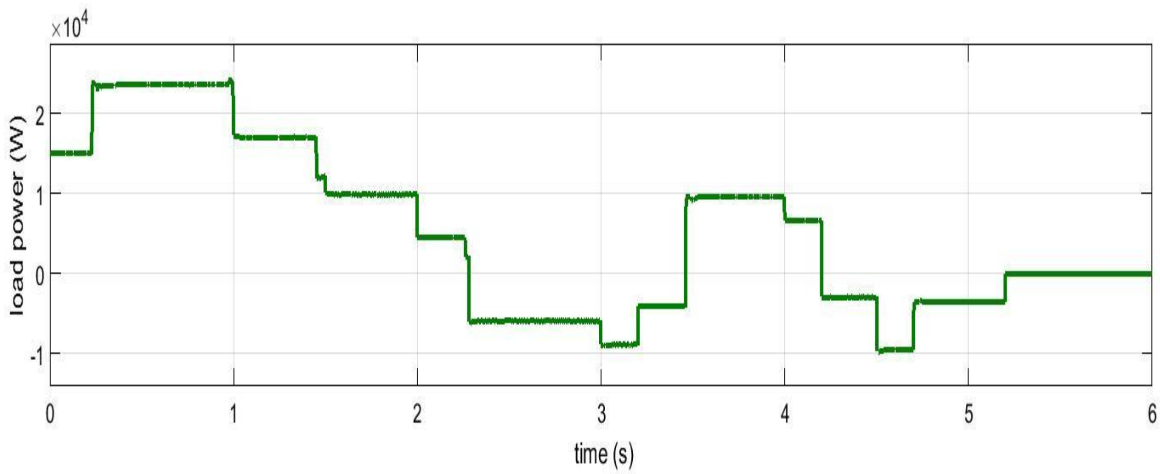


Fig. 63. Load power

Spikes in output voltage reduces as shown in Fig. 64, comparative to PI controller which can further be verified by calculating and observing ripple factor in output voltage shown in Fig. 65. The maximum ripple is encountered at t= 4.7 sec which is equal to 6%.

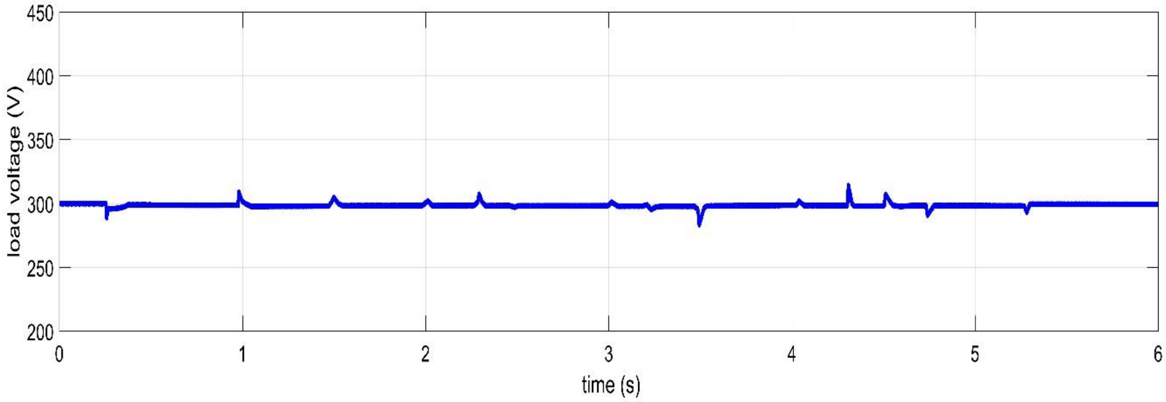


Fig. 64. load voltage with A-NN controller

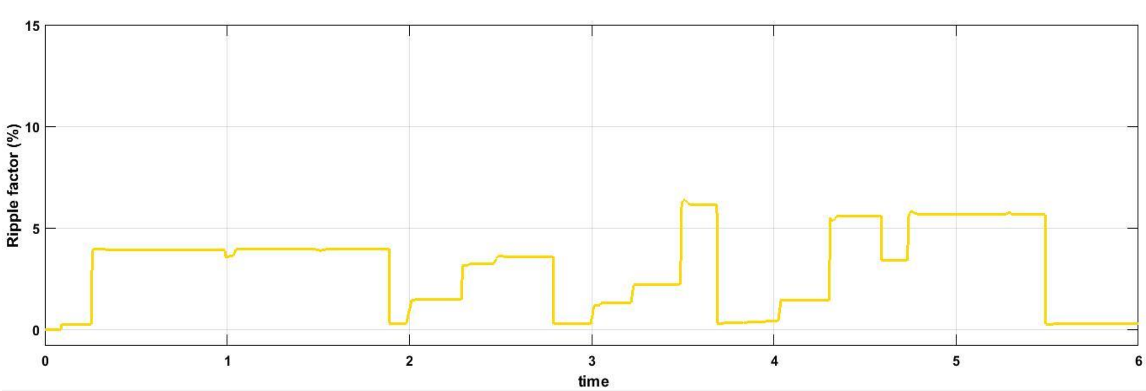


Fig. 65. Ripple factor with A-NN controller

From the above results, it can be concluded that ANN provides superior performance than PI controller in terms of stable and smooth operation, response time, power management for vehicle driving.

For another typical driving cycle simulated for the duration of 100 sec, the load power demand which is power command as that shown with black color waveform, the distribution of power between battery and ultra-capacitor is illustrated in Fig.66 to successfully meet the load requirements

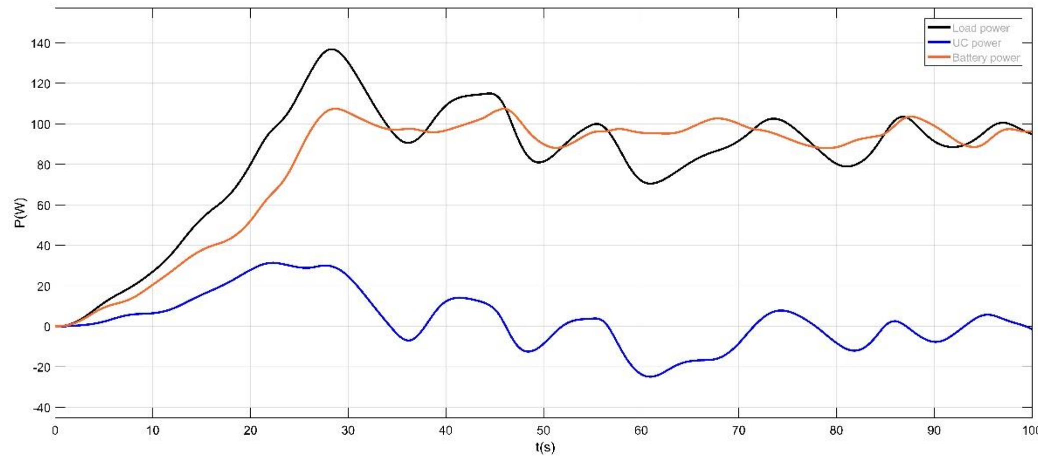


Fig. 66. Power command, battery power and UC power

CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE OF WORK

6.0. CONCLUSION

The offline simulation of proposed hybrid energy storage topology is implemented using MATLAB/Simulink. A magnetic integration is provided between battery pack and ultra-capacitor which helps in reducing down the component size of our system by capturing the additional energy. This magnetic integration further condenses current ripples and provides smother waveform which results in better current handling by the battery pack and battery life also enhances. The load voltage is maintained at its rated value using PI controller along with A-NN controller and ample study of responses obtained for simulated driving cycle is done. In A-NN controller, Levenberg-Marquardt algorithm is employed for rigorous weight training and when optimal controller parameters are achieved, the controller is then employed in our proposed hybrid energy storage topology. The responses for both the controllers are then compared and as per the obtained results it stated the A-NN controller further enhances the results obtained from PI controller by diminishing the ripple factor and thereby providing superiors performance of the hybrid energy storage system.

6.1. FUTURE SCOPE OF WORK

Above topology is executed in software, further the hardware implementation this hybrid energy storage topology can be carried out. Also, other advanced A-NN training algorithm can be employed in weight training and thereby ripple factor can be further minimized. Also, in the hybridization system a greater number of energy storing elements can be integrated and by arranging them in different topologies analysis can be done.

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