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# Dual-Converter Control Strategies for Electric-Vehicle Battery Charging: A Review

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**Abstract:** Electric vehicle charging systems are a major factor where modern transportation will happen, specifically as there is a growing demand for fast, efficient, and good quality charging stations to be built. The use of advanced power-electronic converters and control systems are critical for both enhancing charging efficiency, improving battery protection and extending battery service life. There is currently a lot of interest in the utilization of dual converter systems based on dual-active-bridge DC-DC systems because of their ability to support both direct current and alternating current power distribution plus their capability to isolate the battery from the electrical supply source.

The intent of this paper is to provide a detailed overview of the charging system control strategies that exist for modern EVs that utilize a dual-converter system. This review will focus on Lithium-Ion battery systems, which are most charged using the constant current/constant voltage charging profile. Traditional control techniques, which include Proportional-Integral-Derivative and Sliding-Mode Control will be discussed along with the more recently introduced intelligent control techniques, such as Fuzzy Logic, Artificial Neural Networks, and Reinforcement Learning. The various control methodologies and their comparative advantages/disadvantages will be evaluated according to several different categories, including their dynamic response capabilities, knowledge robustness, computational complexity, real-time application capability and their impact upon the overall battery performance.

According to this review classical controllers are still suitable for low-cost and real-time applications, intellectual and hybrid control strategies have greater adaptability, efficiency, loaded current stress reduction, and greater electrification and battery lifespan when considering real-world operational constraints. This review provides a structured synthesis of existing literature, including comparative summary tables, and identifies opportunities for research into data-driven and battery-aware control strategies for future EV charging systems.

**Keywords:** Electric-Vehicle, Battery Charging, Electric-Vehicle Battery, Reinforcement Learning, Battery Management System (BMS), Dual-Active-Bridge (DAB) Converter, Control Strategies

## 1. Introduction

Due to an increasing demand to reduce CO2 emissions and increase fuel efficiency efforts are underway worldwide to explore and develop electric vehicles (EVs). EVs are replacements for fuel-powered vehicles [1]. Electric vehicles can be a strong strategy for decreasing the environmental impact of transport, as well as promoting less dependence on energy given their low power requirement and a lack of local emissions [2], [3].

In addition to their environmental aspects, EVs bring in a new dimension of functionality when looking at these vehicles as distributed energy storage systems. However, despite the great availability of renewable energy, it is infrequently stored [4]. Effectively addressing the value of storage for clean energy and the speed of converting stored energy for use could bring about the needed change to a more emission-free society without incurring a great deal of expenses related to smart grid infrastructures [5], [6] From this viewpoint electric vehicles can present an incredibly interesting role due to their features with storing energy particularly because electric vehicles maintain a large capacity of electrical energy in the electrical

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battery which is eventually available to the electricity grid [7][8].The exchange of energy stored in a vehicle to and from the electricity grid, called Vehicle-to-Garid (V2G), may be one of the main tenets of future generations of electricity grids [7]. Figure 1 illustrates the bidirectional energy flow between the electric vehicle and the power grid, The Power Grid and is represented visually G2V and V2G. The term implicitly covers both energy directions: the grid-to-vehicle (G2V) is known as battery charging operation and the V2G is known as battery discharging operation [3]. Consequently, during the V2G operation, the EV will automatically interact with the smart grid to take advantage of the electrical energy stored in the battery in favor of the electricity system and during periods of peak consumption [9], [10].

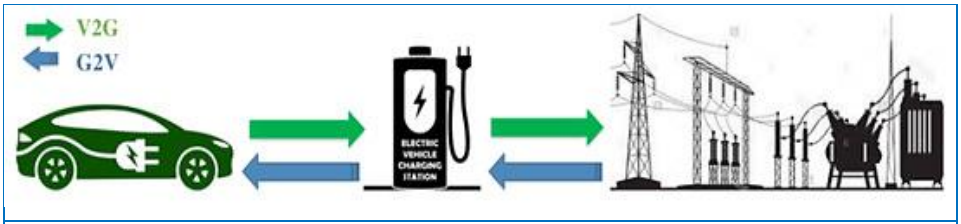



Fig. 1. G2V & V2G Energy flow

Additionally, in the case of a power outage, the EV battery can directly serve as an electricity emergency power source to supply a household electrical load. This EV bidirectional charging and usage scheme is referred to as vehicle-to-home (V2H) technology [11].In summary, these V2G and V2H use and other capabilities like vehicle-to-building (V2B – EV can supply services to a building's existing electrical installation) or quite possibly vehicle-to-load (V2L – i.e. to supply electric loads at a camping site), are referred to as vehicle-to-everything (V2X) [12], [13].The imaged in Figure 2 describes such functionality to be a leading indicant of electromobility technology for providing energy exchanges between EVs and its surroundings [14] The energy exchanges can take place using bidirectional EV chargers installed in EVs or at EV charging stations.

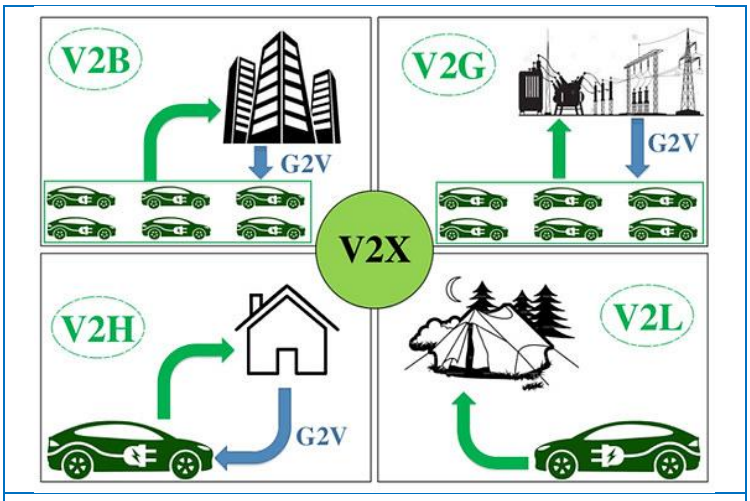



Fig. 2. The topology of V2X technology.

EV charging systems are typically classified as slow and fast as charging systems. Slow charging systems are usually defined as either level 1 or level 2 on-board charging systems. Level 1 on-board charging systems are characterized as slow charging systems where it takes approximately 8-10 hours to charge a power battery to full.

This is found in residential buildings generally with less than 10 kW power output. Level 2 charging systems, on the other hand, create complete charge capacity in a shorter amount of time compared to level 1 charging systems. Level 2 charging systems are typically found for use in shopping malls, public facilities, etc. where power can go up to 20 Kw [15].

Just as the topologies, there are two general types of slow-charging systems, also known as onboard charging systems. One is a single-stage topology consisting of an uncontrolled rectifier and a high frequency DC/DC converter. The types of single-stage topology include forward flyback, push-pull, half-bridge and full-bridge. Single-stage topology has the benefits of a simple structure, smaller number of components and small size however, due to the system being directly connected to the grid eases the ability for the system to pollute the grid.

The other type is a two-stage charging system, which has power factor correction in the front stage and a DC/DC converter in the second stage. The two-stage charging configuration can mitigate issues of low power factor and high harmonic pollution, but it comes with a high cost and low efficiency associated with all conversions. The conventional PID control strategy is common for slow-charging systems however, more advanced strategies have been researched for more effective control strategies such as neural network, PID control strategies, fuzzy adaptive PID control strategies, and machine learning, which may have a significant impact on charging output characteristics[16] .

The fast charging system is made up of two stages of conversion from AC/DC, the first stage is a rectification stage of three-phase AC power to high voltage DC power that is high voltage by design beyond the battery voltage level AC/DC it also included power factor correction (PFC) this component improves the power factor and utilization. The second stage converts the high dc voltage to the system dc voltage DC/DC. This includes charging strategy development where typical EV charging strategy consists of battery constant current (CC) charging and constant voltage (CV) charging using dc-dc converters [17].

The control algorithms for charging mode operation of the power control unit involve one of the following: proportional-integral (PI) control, proportional-integral-derivative (PID) control, sliding mode control, neural network control and reinforcement learning outcomes [9].

The interrelation of sensing units, control algorithms, and dual-converter topologies are shown in Figure 3. Feedback signals are a key component of The Battery Charging process and are critical to the achievement of Optimal Performance and Stability in this process. The grid's AC power is rectified by DC followed by a bidirectional dual-converter topology that governs the flow of energy from the charger to the battery pack itself. A control algorithm is developed to have the ability to generate the best switching commands for charging in a highly efficient way and always fulfil ZVS and low battery stress objectives. The system incorporates sensing feedback of voltages, currents, and SoC to adapt the control policy and demonstrate improvements in charging performance and improvements based on time.

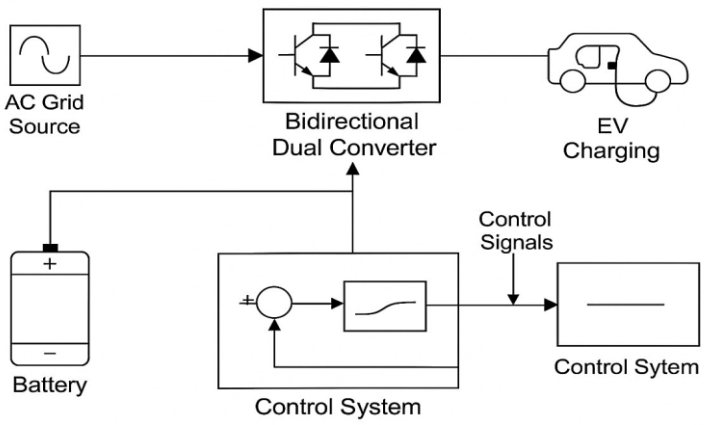



Fig. 3 Control-oriented block diagram of the bidirectional dual-converter EV charging system

The control target for the rear-stage DC/DC converter has an overall attempt to allow charging under ZVS at specified full load range to decrease current ripple and increase system efficiency, Furthermore the introduction of rapidly changing technologies for EVs is dependent upon efficiency, cost, safety, reliability and control methods of the converter topology [16].

The paper addresses the topic systematically by categorizing it into various components. Section 1 presents the introduction of electric vehicles (EV) and the rationale associated with the transition to electrified transportation. Section 2 presents the basic background of EV systems including its configuration, and respective powertrain characteristics. Section 3 presents battery technologies and their types of characteristics and energy storage challenges. Section 4 shows the BMS and the significance of providing safety, reliability and optimal energy utilization. Section 5 reviews the dual-converter and dual-active-bridge (DAB) topologies including principles of operation, modulation strategies, and performance. Section 6 showed multiple control techniques including classical techniques (i.e., PID control, sliding-mode control, model-predictive control), and advanced A.I.-based control algorithms (i.e., fuzzy logic, neural networks, genetic algorithms and reinforcement learning).In additional it presents a qualitative comparative table that compares each method based on the practical application, pros, cons, and effectiveness through actual test conditions also shows a prospective analysis of future research directions offered, emphasizing the trends developing towards intelligent, data driven, and battery-centric control methods for next-generation EV charging systems.

## 2. Background on Electric Vehicles (EVs)

The automotive sector has been increasingly recognized as a global engine for economic and research activities. Many of the technological aspects of automobiles are reformulating themselves around safety for both passengers and pedestrians. As the number of vehicles increases urban travel becomes more efficient and enjoyable. Nevertheless, these developments in vehicle technology are impacting air quality in urban spaces with emerging pollution emerging in the form of particulate matter (PM), nitrogen oxides (NOX), carbon monoxide (CO) and sulfur dioxide (SO2) [18].

Compared to those powered by fossil fuels, electric vehicles (EVs) offer several advantages:

- **zero emissions vehicles**: They do not emit any tailpipe toxic pollutants, CO2 or nitrogen dioxide (NO2) [18]. In addition, although not all battery manufacturing processes have an environmentally friendly manufacturing process, the manufacturing process of EVs is less harmful than fossil fuel vehicles without a battery.
- **Simplicity:** There are fewer parts associated with an electric vehicle (EV) engine that makes maintenance electric vehicles less complicated and cheaper. The electric engines themselves are simplified and more compact, without needing a cooling circuit or any sort of clutch, gearshift or engine noise suppression component.
- **Reliability**: Fewer components mean lower levels of breakdown in this same type of vehicle. Electric engines do not have parts that wear down due to explosions, vibrations, or fuel er actions.
- **Price:** The process of maintaining electric vehicles is far easier than maintaining a similar petrol, diesel, or fossil fuel vehicle, as is the process of getting electricity into the vehicle [19]. The cost at the pump is typically lower too. In fact, the cost/km of energy consumption in electric vehicles is significantly lower.
- **Comfort**: EVS are a generally more comfortable vehicle than fossil fuel vehicles, where neither vibrations nor engine noise from amplifying effects [20] generates higher levels of vibrations or noise levels. Registered net efficiencies upwards of 70%.
- **Efficiency**: Electric vehicle operating efficiency surpasses any other form of vehicle at least in operational fluency and efficiency. However, total well to wheel (WTW) efficiency is ultimately dependent on the power plant efficiency operating the vehicle. To illustrate, gasoline WTW efficiencies are often pooled between 11% - 27%, while diesel fuel WTW efficiency are often pooled around 25% - 37% [19]. In contrast, for electric vehicles, WTW efficiencies provided by natural gas power plant are pooled between 13% and 31% efficiency, and electric vehicles supplied by renewable energy can be pooled toward a total efficiency of 70%.

- **Accessibility**: This vehicle type can also access urban areas that are limited to no other type of combustion vehicle (i.e., low emissions zones). Moreover, it is not necessarily the case that electric vehicles will have the same traffic restrictions, particularly under high peaks of contamination. Interestingly, there was a recall back to an OECD study at the other end which indicated that electric vehicles would not improve air quality, at least in the Particulate Matter (PM) perspective [21].

On the other hand, electric vehicles do have notable challenges related to batteries:

- **Range:** typically, the range of the electric vehicle is limited to 200 – 350 km (or better). For example, a Nissan Leaf offers a range of 364 km [22], while the Tesla Model S has a range of more than 500 km.
- **Time**: The time to recharge recharging a battery can take 4 – 8 h to get a full charge. Even for a fast charge, it can take up to 30 minutes to get to 80%. For example, with the Tesla supercharger, it will charge a Model S 50% in 20 minutes, and 80% in 30 minutes [23].
- **Cost of the battery:** the battery pack is expensive, and the weight of the pack drives the cost.
- **Size and weight of the battery**: the batteries take up space in the vehicle, space that could be better utilized. It is estimated that batteries in this type of vehicle weigh 200 kg [20], although this can vary depending on battery capacity.

An electric car runs only on electricity. It has electric propulsion motors powered from its stored battery energy. There is no conventional fuel tank, fuel pump, fuel line or internal combustion engine. It requires a connection to a charger to replenish its battery. It only uses energy to operate; thus, no tailpipe emissions occur the major subsystems of an EV and the elements which comprise each Subsystem are illustrated in Figure 4 (Battery Pack, Power Electronics, Electric Motor, and Drivetrain).[24]. Since an electric vehicle is classified as a use of electrical energy only it must be recharged using a charging port. The onboard charger converts the incoming source of AC energy to DC energy to recharge the traction battery pack. The electric traction motor requires electrical energy to operate which is stored in the traction battery pack. The electric motor moves the vehicle wheels by transferring mechanical energy through a transmission [25].

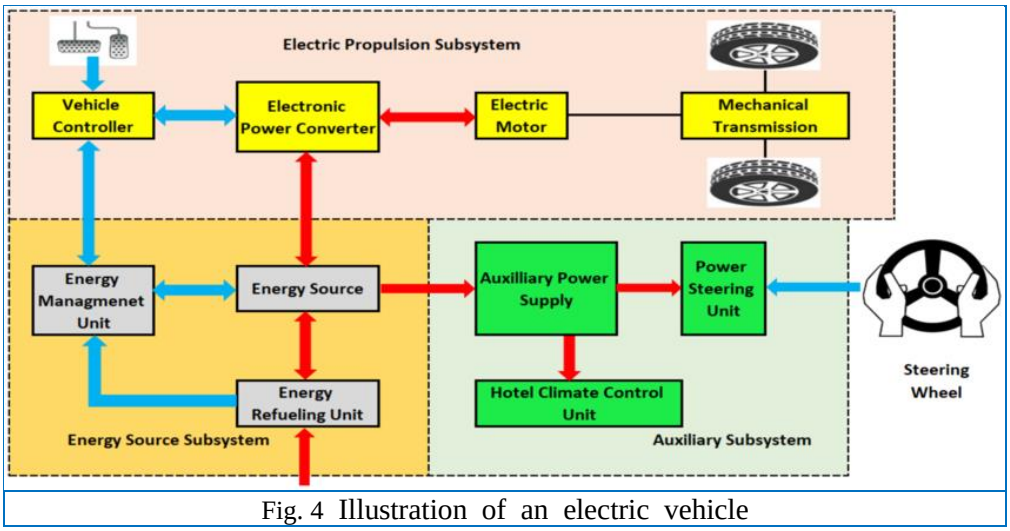



Fig. 4 Illustration of an electric vehicle

The high voltage direct current (DC) from the traction battery may be transformed to a lower voltage DC with a DC/DC converter. From that point, the system will provide power to operate the vehicle accessories and recharge the auxiliary battery that operates these accessories.
A power electronic controller will regulate the driving speed and torque of the traction motor by controlling the flow of electrical energy from the traction battery.

## 2.2. Potential of Electric Vehicles

There exists a commercial viability to the culture of electric cars. Internal combustion engines (ICE) typically have an efficiency of 50% compared to electric vehicles (EV) which have an efficiency range of 85-90%. Electric vehicles utilize 77% of the energy provided from the grid to the wheels compared to gasoline-powered vehicles which generally return 12-30% of the energy back to the wheels for the same capability. Regardless of the drive range the efficiency of the electric vehicle is estimated at 3.59 times the efficiency of a conventional vehicle within the range of 100 - 300 miles [26].

Plug-in electric cars (PEVs) and plug-in hybrid electric vehicles (PHEVs) can enhance efficiencies in fuel usage, costs, and emissions. Greenhouse gas emissions are 40% greater with internal combustion engine vehicles compared to electric vehicles. In 2018, internal combustion engine (ICE) vehicles emitted 78 Mt CO2-equivalent and electric vehicles (EVs) emitted only 38 Mt CO2-equivalent. At that time, it did not have any EVs in operation. The fleet of electric vehicles consumed around 58 TWh of electricity then, as reported by the International Energy Agency (IEA). China is the largest producer of electric vehicles globally, with 44% of total electric vehicle power use, while Europe, the USA, and the United States all have approximately equal shares of 24% and 22%, respectively [27].

Electric vehicles do not produce any greenhouse gas emissions or other air pollutants from their tailpipes. However, this is dependent on the energy sources used. While EVs do not produce direct exhaust emissions they are still considered zero-emission vehicles by the US Environmental Protection Agency (EPA) even though the production of electricity can cause pollution particularly related to air pollution [28].

In addition, some empirical research shows that EVs consume less energy when they are being driven in urban settings. Using the regenerative braking principle, EVs also can recapture energy when it breaks. The electric motor acts as a generator that moves power from the vehicle wheels to the battery-powered electric motor. As a result of Congress's regenerative braking system of capturing energy, the AEFC showed that EVs are much more energy efficient when using "intermittent" urban routes versus freeway routes [29].

Other benefits of EVs are less interior noise and vibration, better low-speed acceleration, easy home charging, better fuel economy, and no tailpipe emissions when powered by their battery. EVs also have a lower total cost of ownership (TCO) than internal combustion engines (ICEs). The TCO is comprised of direct expenses and indirect costs, such as taxes, fees, depreciation, finance charges, insurance, gasoline expenses, maintenance and repairs [30].

## 2.3. Taxonomy of Electric Vehicles

We can now distinguish several types of EVs, grouped according to the technologies used for their engines. These can be generally divided into five categories and the methods utilized to Classify EVs Based on Propulsion Technology are shown in Figure 5.

- **Battery Electric Vehicles (BEVs):** These vehicles draw energy exclusively from electricity and do not use any internal combustion or liquid fuel in their propulsion. They typically rely on one or more battery packs to achieve an acceptable level of range [31].
- **Plug-In Hybrid Electric Vehicles (PHEVs):** these vehicles feature both an electric engine charged through a plug-in cord from the electricity grid and a conventional combustible engine which, under most operational scenarios, can store sufficient electricity at home through grid usage to drastically reduce gasoline use altogether [32].
- **Hybrid Electric Vehicles (HEVs):** This type of vehicle uses an electric motor in conjunction with an internal combustion engine. Unlike PHEVs, HEVs cannot be plugged into the grid. In actuality, the electric motor derives its energy from batteries that are charged through the combustion engine of the vehicle. Some newer vehicles have also been able to harvest the work generated by brake applications to charge the batteries, by converting kinetic energy into electrical energy [33].

- **Fuel Cell Electric Vehicles (FCEVs):** this type of vehicle uses an electric motor powered by a mixture of compressed hydrogen and oxygen from the atmosphere that only emits water as it exhausts. These vehicles can easily come to mind as having "zero emissions," but that can bring in significant complications [34].
- **Extended Range Electric Vehicles (ER-EVs):** as previously discussed the ER-EV is extremely like the BEV. The ER-EV includes a combustion engine that will charge the batteries if they deplete. This combustion engine is also only designed to charge and is unconnected to the drive wheels as is the case with PHEV/HEV [35].

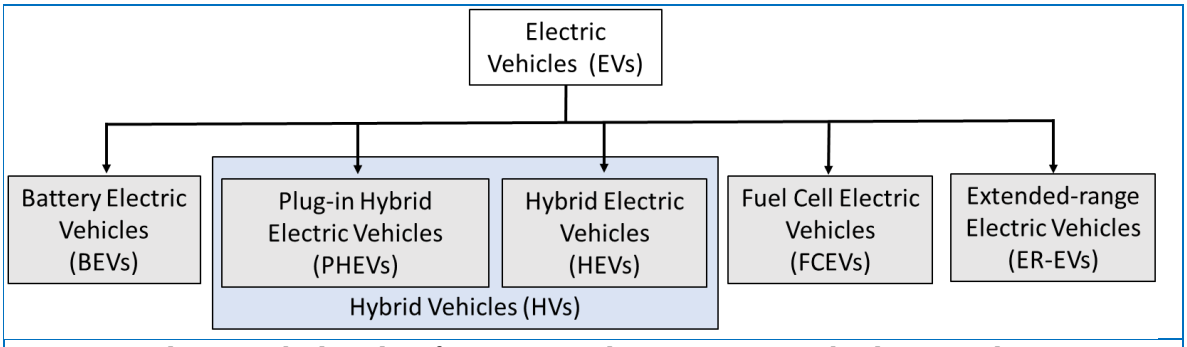



Fig.5. Electric vehicles classification according to engine technologies and settings.

## 3. Electric Vehicles Batteries

There are a few compelling statistics about batteries in this category: increasing global production, cost reductions, emerging features and the battery technology supply chain in the production process. Battery technology has changed dramatically in only a few decades. Additionally, while global production of EV batteries is estimated to have increased 66% in total production, EV sales increased showing the connection between increase in EV battery production and forecasts for demand. Again, the forecast is for not only increased battery supply driving EVs but also increased EV demand[36].

### 3.1 Characteristics of the Batteries

In terms of battery's primary characteristics, we might highlight the following [37].

- **Capacity:** Electric power has issues especially the cost and complexity of storage. Currently, considerable amounts of funds are being spent to develop new batteries that can store more energy and are more reliable. Battery capacity is the amount of energy that can be withdrawn from a battery under standard conditions. Capacity can be expressed in watt hours (Wh) or ampere hours (Ah).
- **State of charge**: indicates what level the battery is at or how full the battery is compared to its defined capacity.
- **Energy density**: An additional key factor for battery development is achieving the highest density of energy possible which for all intents and purposes relates directly to having a greater energy storage capacity when compared to size and weight. Energy density relates to how much energy a battery can provide for each unit of volume to be delivered to the load thus, energy density rated units of energy density can be represented in Wh/L.

- **Specific energy**: Wh/kg is the respective energy that a battery can deliver to a load for every unit of mass. This characteristic is also referred to by some authors as energy density and can be expressed in Wh/L or Wh/kg.
- **Specific power**: W/kg is the amount of power that a battery can provide for each unit of mass.
- **Cycles of charge:** is When the battery is entirely charged or discharged, a load cycle is complete.

- **Lifespan**: The number of charging/discharging cycles that a battery can withstand is known as its lifespan. Finding batteries that can withstand more charged cycles while charging and discharging is the goal.
- **Internal resistance**: Since no part of the battery is a perfect electrical conductor, internal resistance exists. As a result, during charging some energy will be lost as heat; this process is known as thermal loss.
- **Effectiveness**: This refers to how much power the battery produces in relation to the energy used to charge it.

When it comes to high power draws, the internal resistance factor becomes more pronounced as the heat developed per time can be equivalent to power lost in the resistance [38]. Therefore, charging at higher speeds will lose more energy compared to charging at slower speeds. Consequently, batteries must be able to operate at high charge rates while coping with heat caused by internal resistance. Furthermore, decreasing this factor should make charging faster, which is one of the principal disadvantages of these automobiles today.

## 3.2. Battery Types

increasing numbers of EVs and the numerous battery types and the lack of standardized batteries make the operation of BESs an inefficient process for charging vehicles [36]. EVs are also beginning to use lithium-ion (Li-ion) batteries as well, but there are many types of batteries, the following batteries are the most notable:

- **Lead-acid (Pb-PbO2) batteries:** In 1859, the first rechargeable batteries were created. They are mainly useful in conventional automobiles. Electric vehicles also use this kind of battery. Both specific energy ratios and energy density are low. Sulfuric acid surrounds or submerges a group of lead plates that make up the battery's construction. Lead sulfate is converted to metal on the negative plates during the load phase of initial charging, whereas lead oxide (PbO2) is developed on the positive plates [23].
- **Nickel and cadmium (Ni-Cd) batteries**: These batteries were the preferred technology in the 1990s because they could be produced with a higher energy density. But they are short-lived, have a strong memory effect and cadmium is a costly and hazardous metal. Nickel-metal-hydride (NiMH) batteries have supplanted nickel-cadmium batteries because of these characteristics[39].
- **Ni-MH batteries**: also known as nickel-metal-hydride batteries, use an alloy to store hydrogen in place of cadmium (Cd) in their negative electrodes. They are currently found in many hybrid cars due to their higher self-discharge than nickel-cadmium batteries[39].
- **Zinc and bromine (Zn-Br2) batteries**: The zinc-bromine solution used in these batteries is stored in two tanks, and the positive electrode transforms bromide into bromine. When the 'T-Star' prototype was tested in Santa Barbara, California, in 1993, it was able to sustain energy storage for up to five days, which prompted designers to investigate its potential for usage in electric vehicle applications[40]
- **Zebra batteries:** which are built of nickel and sodium chloride, or Ru-NiCl are comparable to sodium sulfur batteries. Even though they operate best at temperatures between 260 and 300 degrees Celsius, sodium-sulfur (Na-S) batteries are a great option for electric vehicle applications since they can provide up to 30% more energy at lower temperatures [41].
- **Sodium-sulfur batteries:** use inexpensive materials, have extended life cycles, high energy densities, and good loading and unloading efficiency (89%–92%). On the other hand, sodium-sulfur batteries are made to function at high temperatures, usually above 300 degrees [42].

- **Lithium-ion (Li-Ion) batteries**: They utilize lithium salt as an electrolyte, which provides the ions needed for the reversible electrochemical process that occurs between the anode and cathode. Lithium-ion batteries' benefits include a high loading capacity, internal resistance, high loading and unloading cycles, low weights of components, and a lower memory effect[4].

Lithium-ion batteries use lithium salt as their electrolyte, which facilitates the movement of ions during the reversible electrochemical process between the battery anode and cathode. [43]

## 3.3 Lithium-Ion Batteries:

Lithium-ion batteries are the battery technology of choice for most nickel-based systems because they provide higher voltages and densities. The cell configuration of Li-ion batteries can be either prismatic, punch, or cylindrical.
Battery Management Systems (BMS) and all Li-ion battery banks are divided into two types: high voltage (defined as 30-1000VAC or 6-1500VDC) and low voltage (defined as 30VAC or 60VDC). Li-ion battery cells can be arranged into four different configurations depending on user requirements:
(i) single cell, (ii) series, (iii) parallel and (Iv) series-parallel [44].
Monitoring of lithium-ion battery performance is accomplished through Battery Management System (BMS) systems. This type of system collects sensor data to determine the current State Of Charge (SOC), State of Health (SOH), and temperature rating of the battery and to help optimize its performance. Monitoring these variables allows BMS to facilitate the most efficient use of energy stored in the lithium-ion battery, especially in electric vehicles. BMS control processes of the energy amount used in charging and discharging lithium-ion batteries allow BMS to control and improve energy use in all batteries, as well [45].
In addition to enhancements to BMS for the proper monitoring of lithium-ion batteries, many researchers have also been investigating improvements in algorithm coding methodologies as well. The advantages of lithium-ion batteries can be categorized into four main categories[45]:

1. The lithium-ion battery has the highest energy density.
2. Lower self-discharge time compared with other rechargeable batteries.
3. The lithium-ion battery does not need to be serviced during its life.
4. The nominal voltage rating is equal to 3.7 volts, which is higher than other types of rechargeable batteries.
5. Different types of Li-ion batteries are available, and we choose the best one with respect to requirements.

The following comparison in table 1 shows how the advantages of Li-ion batteries can be compared with those of other types of batteries, both in terms of capacity reduction from 70% to 90% within 5 cycles and their shorter life span. The demand for lithium-ion batteries, therefore, will increase dramatically to eliminate as many of the lithium-ion batteries are currently in use, particularly in automotive and personal electronic devices [45].

Table 1. Comparison of Li-ion battery.

| Battery Type | Life Cycle | Temperature Tolerance | Heavy Weight | Easy Access | Energy Efficient |
|---|---|---|---|---|---|
| Lithium-ion | High | Yes | Yes | Yes | Good |
| Nickel-metal hydride | Low | No | Yes | No | Good |
| Ultracapacitor | Low | Yes | Yes | No | Good |
| Lead-acid | High | No | Yes | Yes | Good |

## 3.4 Charging Strategies for EV Batteries

The cycle life, performance, and safety of a battery are greatly affected by the way in which one charges or discharges the battery. The most used battery charge/discharge strategies include [46], [47], [48]:

- Constant Voltage (CV) - charging a battery by maintaining a constant voltage between the battery's terminals, while allowing the battery current to slowly decrease to 0. While this method of battery charging is easy to implement across all battery types, it has the disadvantage of having high initial charge current.

- Constant Current (CC) - a method of charging/discharging electric vehicle batteries by maintaining a fixed C-rate of current Ib with increasing voltage Vb until reaching the maximum charge voltage. The charging ends at that point.
- The Constant Current-Constant Voltage (CC-CV) charging method for battery charging is a dual phase method consisting of a constant current charging stage followed by a constant voltage charging stage as depicted in Figure 6. The constant current stage is where the battery is charged with a constant current at a given reference current until the voltage of the battery reaches the maximum voltage for the battery type, called the full charge voltage (Vre f). The constant voltage phase of the charging process continues to maintain a constant voltage across the terminals of the battery until the current being supplied to the battery drops to the cutoff current (I). The cutoff current is typically around 0.1C and 0.05C for most lithium-ion batteries[49].
- The Multi-stage Constant Current (MCC) method for fast charging lithium-ion batteries is a multiple-level constant current charging strategy that has multiple levels of constant current charging, with the rate of constant current charging reducing indirection during each charging cycle tin order to maintain optimal battery temperatures and minimize the time required for charging [50] .

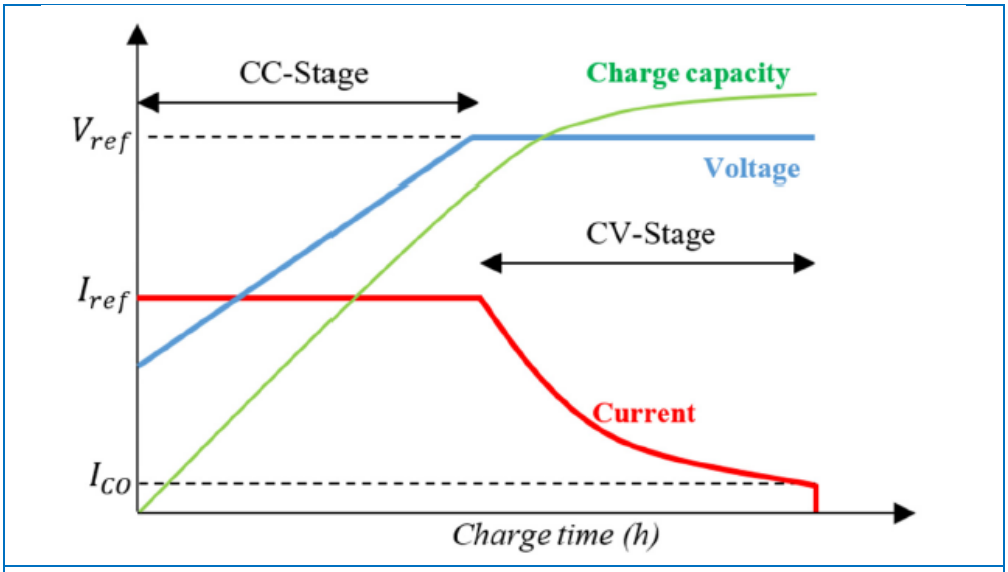



Fig. .6 . CC-CV battery charging strategy.

This review focuses on the Control Strategies and Comparison presented with an emphasis on applications related to lithium-ion battery charging, using CC-CV charging profiles.

## 4. Battery Management System (BMS)

Energy management represents a crucial factor for electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs). The battery management system (BMS) is a key tool for controlling the battery unit in this class of vehicles. More specifically, the BMS is the tool that controls how the energy is supplied to the vehicles batteries while meeting reliability, safety, and validation objectives. Today's BMS includes several connected blocks which utilize wire communication, sensors, and power delivery unit [51].

The BMS is primarily responsible for power delivery to reduce battery strain and eliminate a buildup of energy during charges and discharges. The BMS serves as the primary form of regulation reducing sudden changes in current and, thus, increasing the speed of discharges. For the powerful battery packs for EVs, the concept of cell balancing is important because a long arrangement of series connected cells is only as reliable as its weakest cell.

This implies the BMS does balance cell balancing by compensating for the load of the weaker cell.

It directly balances the voltage on each cell in the series of cells to extend total life of the battery pack. In this way the BMS prevents individual cells from suffering excessive strain [43]. Additional important BMS tasks include calculating the driving range and monitoring state of charge. The battery pack also powers auxiliary loads such as the cooling/heating unit, dash console, and headlamps. While the auxiliary loads are not intelligent and do not communicate with BMS, more intelligent load management could provide better energy management without causing a decline in energy efficiency for the power train [51].Several authors have proposed several potential BMS architectures to mitigate the challenges. For example, Hauser and Kuhn [52] state BMS functional requirements that address data collection, data processing and storage, electrical management, thermal management, safety management, and communication.
They illustrate a schematic diagram of a BMS, and the major components (Functional Elements) of The Battery Management System (BMS) are shown in Figure 7 that considers all aspects of BMS requirements. Other researchers, such as Xing et al. [53], assess BMS in Hybrid Vehicles (HVs) and Battery Electric Vehicles (BEVs), but emphasize state of life, health, and charge as the key characteristics for what BMS should assess.
In a study by Zhang et al. the authors push BMS functionality further [54]. The authors model that as the vehicle is operating the driving range can be expanded by modeling the behavior of the terrain and the leading vehicle. The authors' simulation, they establish a nonlinear predictive controller model to optimize motor torque and EV velocity, to minimize energy consumption of the EV.
Future BMSs will be faster and smarter by implementing on-chip analytic functions to improve power supply, and more accurately foresee driving ranges. Furthermore, BMSs will operate several:

1. charging protocols, flexible and adaptable
2. number, size, and arrangement of battery cell.
3. vehicle-to-grid, i.e., allowing charging transactions or scheduling charging times.

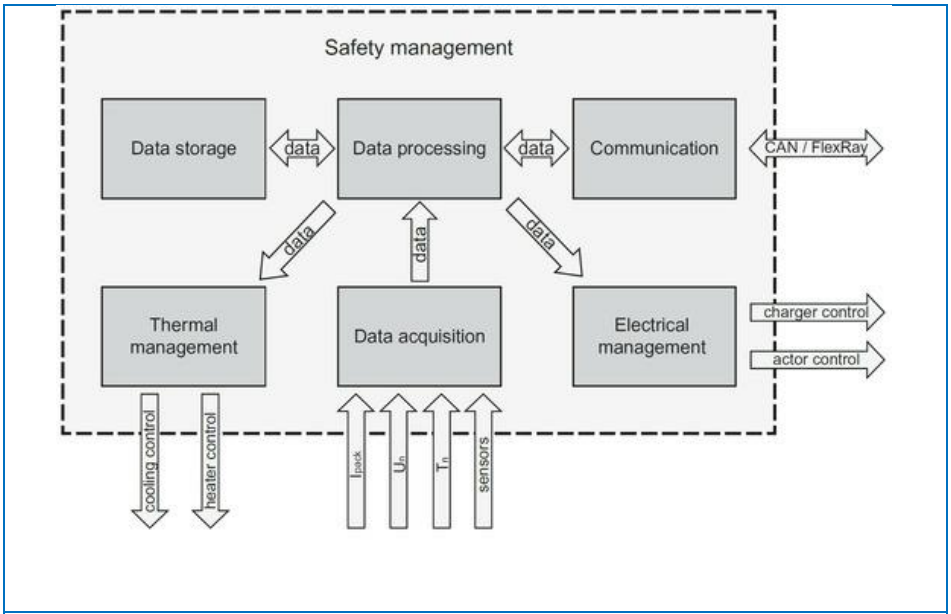



Fig. 7 . Main components of the Battery Management System (BMS)

### 4.1. Battery state Estimation parameters: SOC, SOH, SOE and SOP

BMS typical features would consist of SOC estimate, SOH estimate, temperature measurements, estimates cell balance, fault detection with diagnosis and thermal management [55]. The purpose of the controller circuit would be to leverage analog signals and innovative algorithms to estimate the SOC, SOH, SOE, and SOP of batteries [56].

- **State of Charge**: The fuel indicator in a car powered by regular fuel is analogous to the battery's state of charge in BMS. The primary function of SOC is to inform the driver about the condition

of the battery and to protect the battery from overcharging and over-discharging the battery [57]. The challenge of estimating SOC an issue for every energy-storing technology provides information and accurate estimations of battery reliability [58].

- **The battery state of charge (SOC)**: is a useful gauge of how much energy is left in a battery and provides estimates of how long a battery can function in a real-world sense before a recharge needs to occur. The state of charge (SOC) is a critical estimate to ensure reliability and safe operating of an electric vehicle. The SOC is defined as the ratio of the remaining capacity of the battery and the total nominal capacity of the battery. SOC at a time, $t$ ($SOC(t)$), can be defined in equation (1) as the nominal capacity of a battery ($Qn$) relative to the available capacity of the battery ($Q(t)$) The nominal capacity provided by the manufacturer is the maximum amount of charge that the battery can contain [59].

$$\mathrm{SOC(t)}=(\mathrm{Q(t)})/\mathrm{Qn} \tag{1}$$

- **State of Health:(SOH**): assessment can be classified into three categories: data-driven, model-based, and direct calibration-based methods. The data-driven technique can provide a successful understanding of the complex nonlinear interactions between SOH and measurements without a detailed understanding of internal chemistry.

The accuracy of the estimation relies on the quality of data and the capability to extract features from data. Big data and SOH allow tracking of reused power batteries and aid with disposal of EV batteries after they are discarded. A complete data collection system will retain large amounts of data. Data filtering methods will play an important role in SOH assessment. In addition, the data generated from a big data platform is not the same as the data generated through lab studies. Power battery operating conditions will be significantly different during regular vehicle operation due to changes in driving conditions and driver behavior [60].

SOH is consequently defined in relation to capacity and internal resistance [44].SOH is an indication of decreased performance in maturing lithium-ion batteries due to degradation. SOH can be simply expressed by equation (2) where C actual is the actual battery capacity and C fresh is the rated capacity of the battery.

$$\mathrm{SOH(t)}=\mathrm{Cactual}/\mathrm{Cfresh}\times 100\% \tag{2}$$

The authors in [53] considers 100 to 90% of the rated capacity normal, 90 to 80 % as a warning and below 80 % as a defect.

- **State of Energy (SOE)**: relates to the ratio of residual energy to total accessible energy in relation to specific operating conditions (i.e., varying load and temperature). The following function can be used to reflect the definition of SOE [61].

$$SOEt = SOEo - \frac{\int_0^t P(\xi)d\xi}{En} = SOEo - \frac{\int_0^t i(\xi)u(\xi)d\xi}{En} \tag{3}$$

In this case, $SOEt$ represents the value of the State of Energy (SOE) at time t, while $SOE0$ denotes the initial SOE value. In addition, $En$ is the total energy that the battery has available, while p($\xi$), i($\xi$), and u($\xi$) are the power, current, and voltage at time ($\xi$), respectively.

Various methods have been suggested to estimate SOE. The power integrated method was the most frequently used, as it readily allowed utilization energy from the battery to be assessed directly [62].

- **The state of power (SOP):** defines the maximal power that a battery can reliably discharge from the battery or intake to the battery in a specified period. Assessing the SOP is a key component of the evaluation in a battery management system (BMS), as it enables electric vehicles to operate reliably and consistently without exceeding the specified limits. Therefore, the SOP enables the rapid charging or discharging of a battery based on the design specifications of the battery capabilities [61]. In addition, there are two forms of SOP estimation methodologies: equivalent circuit model (ECM) based and characteristic mapping (CM) based methodologies. The CM based

methods use known static interdependencies between battery power capacity, State of Charge (SOC), temperature, power pulse duration, needed power and battery voltage. In the last decade, techniques of estimating state of power (SOP) using equivalent circuit model (ECM) have gained more favorable acceptance because of their capacity to correctly characterize the internal behavior of the battery, robustness, flexibility, and relatively low processing burden [63].

## 5. Dual Converter (Dual Active Bridge)

Research on renewable-energy-based power router systems has considerably expanded in recent years it is viewed as the future key equipment changing electricity, "power hour" [64], [65] For such systems, there are many types of renewable-energy-based generation units, DC buses, and load (i.e. consumption) units form a power network [66], [67]. These systems are not without risk, though, since scattered (random) renewable energy generation is not continuous or at least has a level of uncertainty and variability. Therefore, it will be necessary to introduce energy storage units (i.e., batteries) in these systems, and/or incorporate bidirectional power transfer, to have stability in the electrical energy output [68], [69], [70]. The dual active bridge (DAB) type DC-DC converter has received a lot of attention because of its symmetrical topology, high power density, modular characteristics, electrical isolation and ability for soft switching [71], [72].

The DAB circuit diagram presented in Figure 8 features a high-frequency transformer with an additional inductance Lr, along with H1 and H2 bridges. In turn, the switches M1-M4 constitute bridge H1 and the switches M5-M8 compose bridge H2. The high-frequency transformer's turn ratios are n:1; the primary current passing through Lr is indicated as iLr; the AC side output voltages for the H1 and H2 banks are respectively uab and ucd, while the currents on the H1 and H2 DC sides are signified as I1 and I2 respectively. The outer phase shift ratio between voltages uab and ucd is denoted as D2 while the inner phase shift ratios of H1 and H2 are respectively denoted as D1 and D3. A depiction of the driving signal and voltage waveforms for DAB with TPS modulation can be found in Figure 7a, where Ths represents the half switching cycle. If D1 and D3 are established to be 0 [73].

The operating characteristics of The DAB Converter as Related to The Various Modulation Strategies used in its operation are illustrated by Forms of Waveforms shown in Figure 9. As established in [74], [75], the TPS control's operating mode can be categorized into 12 modes. For simplification purposes, we will define unified transmitted power as PN=NU1U2/8fsLp where fs is the DAB switching frequency. If Po is the output power of DAB, then the normalized output power is PU=P0/PN, the definition of the voltage conversion ratio factor where k >1 boosting q and is bucking if K<1.

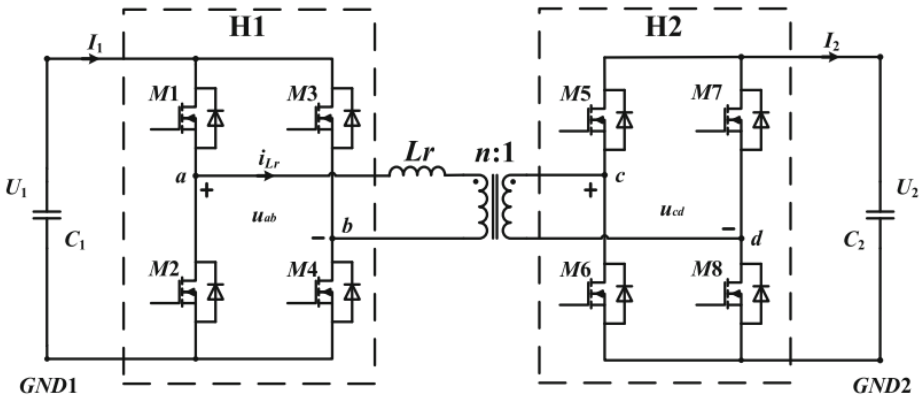



Fig. 8 . Typical topology of DAB converter

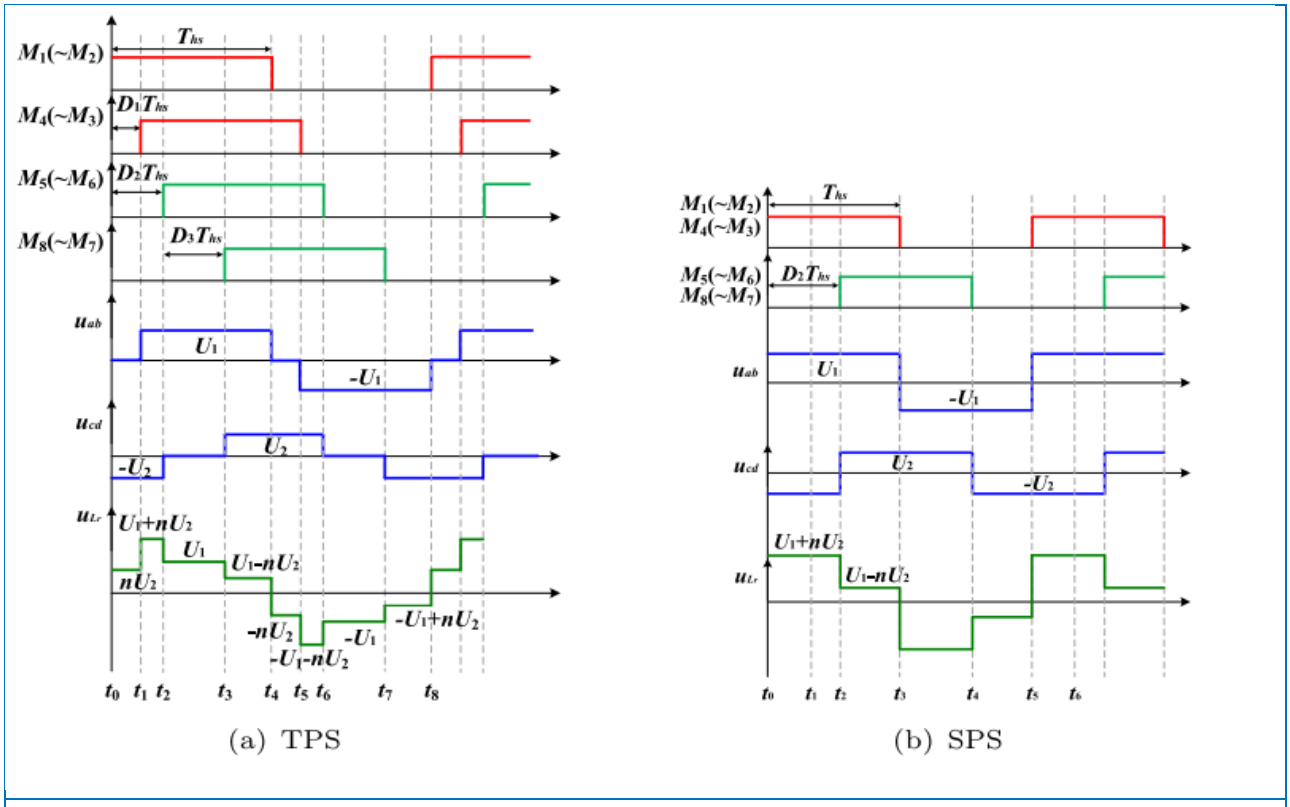



Fig. 9 . General operating waveforms of DAB with different modulations

The Main Voltage and Current Waveforms produced when operating a DAB Converter under Triple Phase Shift Modulation is illustrated in Figure 10. The voltage conversion ratio is defined by: K=V_1/⇳(V_1 nV_2 ) nV_2 To simplify the analysis, this paper mostly deals with the case of input and output voltage modulation ratio K>1 , meaning that T is half of the switching period whereT=1/⇳(12f_s ) 2f_s and fs is the equivalent switching frequency[76].

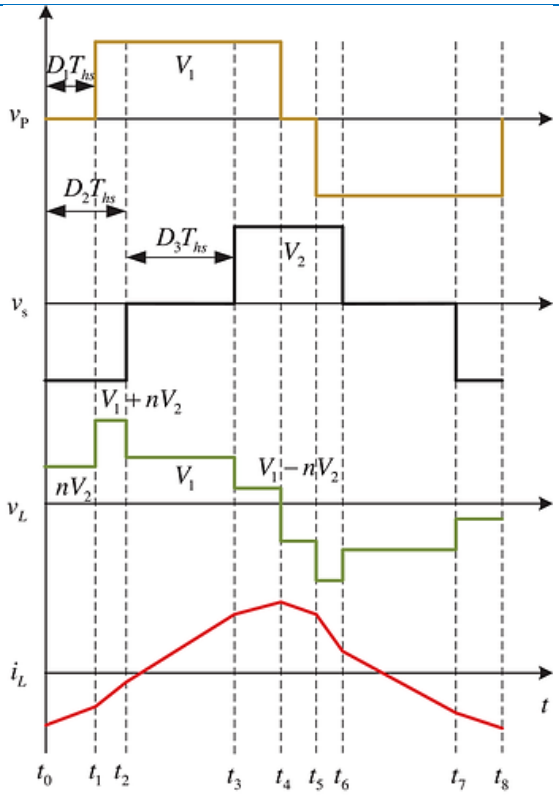



Fig.10 . Main working waveform under TPS modulation.

Based on the symmetry of inductor current and the analysis of the operating mode of the converter, the inductor current il in half of the switching cycle can be given as follows.

$$\begin{aligned} & i_L(t_0) + \frac{NV_2}{L}(t - t_0) && (t_0 \le t \le t_1) \\ & i_L(t_1) + \frac{V_1 + NV_2}{L}(t - t_1) && (t_1 \le t \le t_2) \\ & i_L(t_2) + \frac{V_1}{L}(t - t_2) && (t_2 \le t \le t_3) \\ & i_L(t_3) + \frac{V_1 - NV_2}{L}(t - t_3) && (t_3 \le t \le t_4) \end{aligned} \tag{4}$$

From Equations (4) the transmission power under TPS modulation is as follows.

$$P = \frac{1}{T_{hs}} \int_0^{T_{hs}} V_1 \, i_L(t) \, dt. \tag{5}$$

The rated power of the converter is defined as the reference power, and the per unit value of the transmission power is further obtained.

$$\begin{aligned} P_0 \quad = \frac{P}{P_N} = 2(-D_1 + 2D_2 + D_3 - D_1^2 - 2D_2^2 \\ -D_3^2 + 2D_1D_2 + D_1D_3 - 2D_2D_3). \end{aligned} \tag{6}$$

The current stress under TPS modulation which is the peak value of inductance current is obtained.

$$i_0 = \frac{i_L(t_4)}{i_N} = 2(-KD_1 + 2D_2 + D_3 + K - 1) \tag{7}$$

In the equation, $i_N = \frac{NV_2}{8f_sL}$ (8)

In practical use, the transformer turns ratio for a DAB converter would typically remain constant. Should the input or output voltage be changed, and two voltage conversion ratios do not match, it cannot be assured that each switch can ensure ZVS. Therefore, the ZVS range of the DAB converter can be obtained from the inductor current polarity during different time instances, or more mathematically from the inductor current equation shown in Figure 3, if Switch $S_1$ at time $t_0$, if $i_L(t_0) \leq 0$, then both switches $S_1$ and $S_2$ on the same bridge arm can ensure ZVS; if Switch $S_4$ at time $t_1$ , if $i_L(t_1) \leq 0$, then both switches $S_3$ and $S_4$ on the same bridge arm can ensure ZVS; if Switch $S_5$at time $t_2$ , if $i_L(t_2) \geq 0$, then both switches $S_5$ and $S_6$ can still ensure ZVS bridges. Therefore, using the stated conditions and time, all switches have been guaranteed ZVS[1].

The inequality conditions for all switches to achieve ZVS are:

$$\begin{gathered} -(K+2)D_1 + 2D_2 + D_3 + K - 1 > 0 \\ KD_1 - 2KD_2 + D_3 + K - 1 > 0 \end{gathered} \tag{9}$$

Recent studies show that dual converters, mainly dual-active-bridge (DAB) converters, can be more powerful and have longer zero voltage switches. Dual-active-bridge (DAB) converters are frequently applied in microgrids, battery energy storage systems (BESS), and electric vehicle battery chargers. One of its applications in DAB converters are SPS (single-phase-shift) [77], [78], [79] modulation utilizing its advantages including dynamic performance and controllability. SPS modulation has a trade-off that can lead to a significant reduction in efficiency from large circulating current, and that does not guarantee zero voltage switching in full load at wide voltage range. Many advanced repetitive modulation methods such as DPS (dual-phase-shift) [80], EPS (extended-phase-shift) [79], and TPS (triple-phase-shift)[81] have been proposed to address the inefficiency of SPS. Generally, TPS indicates a form of SPS, DPS, and EPS modulation in practice when it has three degrees of freedom. TPS is better than DPS or EPS in efficiency when it has three degrees of freedom.

## 5.1. Motivation and Challenges

DAB is a prominent topology in V2X applications, with the bidirectional OBC being a growing topic of research due to its smart capability to provide power to the grid. Despite this feature, this topology is nonetheless hindered by several issues surrounding control, efficiency and performance [82], [83].
DAB converter control is extremely challenging as the primary and secondary bridges must control optimally, as well as deal with many factors and variables of dynamic interaction (e.g., loading and line variations). Dual Active Bridge converter performance can be sensitive to varying parameters such as load, input voltage and component specifications. Robust control strategies and design techniques are required to ensure stability and performance in a range of conditions, so several control methods have been implemented to minimize the challenges[84].

## 6. Control Techniques

Researchers have proposed several control approaches strategies have been used to help with these challenges in their design, this can be classified into three main categories. Classical control methods like Proportional-Integral-Derivative (PID) control and Model Predictive Control (MPC) have the advantages of simple and robust control methods, but in general have issues controlling non-linearities or time-varying uncertainties in the system. Intelligent control methods such as Fuzzy Logic Control, Genetic Algorithm, Artificial Neural Networks, and Reinforcement Learning (RL) offer additional flexibility as they have a level of learning or reasoning based on the behavior of the charging system to improve the charging efficiency or improve the health of the battery. Lastly, hybrid control methods combine classical control with intelligent control methods; for instance, PI control is implemented in conjunction with fuzzy or intelligent control methods, like RL o achieve a greater level of optimization for bi-directional charging tasks, such as G2V and V2G charging. [85]. Figure 11 shows a user-friendly overview of control techniques used When Operating a DAB Converter [86].

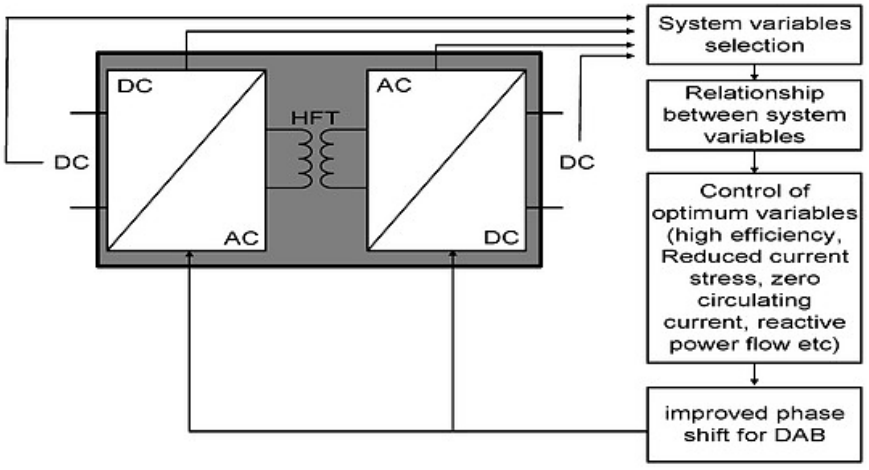



Fig.11 Detailed representation of DAB converter control techniques.

## 6.1Conventional Control

Classic controls, known as PI, PID, and MPC, tend to control voltage and current in DAB converters via feedback error reduction. Classic controls are simple, easy to implement, and provide steady-state performance under steady-state conditions, but they do not provide dependable performance under load changes or non-linear conditions. Therefore, classic control methods are frequently used for benchmarks when experimenting with intelligent or hybrid control[85].

### 6.1.1 Phase-Shift Control

Phase-shift control modulation has been around from the very start of DAB converter development up to today [87] and is part of the continuous development to improve efficiency in methods and of obtaining function DAB converters. The previous section has also encompassed the pros and cons of the methods we have presented and is outlined in Table 2. The new and assimilated style of phase-shift control modulation is flexible and incorporates all the previous styles of all the methods already comprehensively covered.

Figure 12 shows Basic design of the Dual-Active-Bridge (DAB) converter based on Phase-Shift Control modulation illustrating the power transfer occurring between the two bridges through a high-frequency transformer[88].

Table 2. Phase-shift modulation strategies [89].

| Ref. Technique | No Modulation | Pros | Con |
|---|---|---|---|
| **[2]** | SPS | 1. Soft switching control is easy.<br>2. System is more dynamic. | 1. Large circulating current.<br>2. Zero-voltage switching. |
| [3] | EPS | 1. Improved efficiency.<br>2. Improvement in zero-voltage switching. | 1. Circulating currents do exist. |
| [4] | DPS | 1. Easier to implement.<br>2. Excellent dynamic performance. | 1. Dynamics and stability increase make<br>2. the system is more complex. |
| [5] | TPS | 1. Broad range of inputs results in great dynamic performance for load changes. | 1. Control complexity.<br>2. Operating states vary for buck/boost approach. |

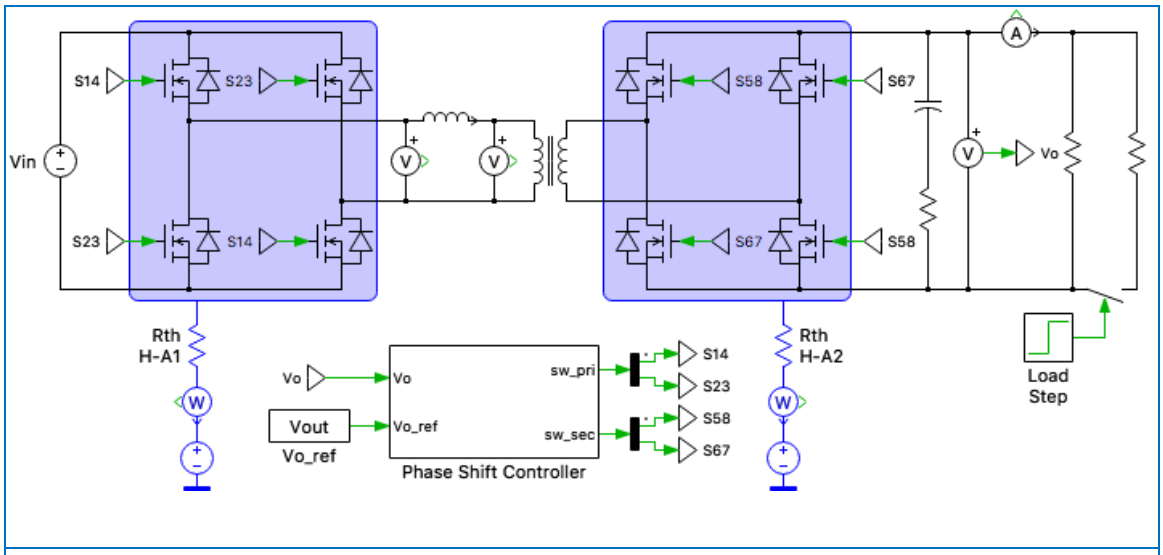



Fig.12 Detailed representation of DAB converter control techniques.

### 6.2.2 System Variables Control

Phase shift modulation typically involves several varieties of control and modulation techniques that are all part of the control stage for the DAB converters. Typically, in all scenarios, the control action factors of the DC voltage and output load current could be considered. The factors are to achieve ideal values, namely the power to carry through the system in different modes of operation. The factors may consider such characteristics as whether the value is either DC or part of the variable factors of the switching frequency. In some instances, authors of articles will use variable factors such those high frequency link factors say inverter voltage and inductor current both sides of the high frequency transformer. But, in this case control overall is hard to implement, as it needs an additional factor. The following control techniques are based on a slowly varied parameter in the concerned literature[86].

- Direct control of power in the DAB [94].
- Control for lowest current stress [95].
- Modulation of zero circulating current [96].
- Control for virtual direct power [97].
- Control for reactive power minimization [98]

The most basic and straightforward control solution for implementation is basic PID control. It has useful control dynamics, stability errors equal to zero, faster time responses and better stability in terms of the overall solution to the control algorithm design. In [99], a hybrid PI controller is based on a second-order Taylor series estimator for the offset, between the pulse-width modulation of both bridges and an extra PI controller was used. The switches were controlled via the single phase-shift (SPS) strategy, and the solution was constructed with an average model. Finally, it is important to note that the results were based on simulations and did not discuss efficiency.

The strategy given in [100]from 2012 was a study that proposed two control strategies using a Fourier series' model to try to improve the common PI control. An original system referenced in the study used a PI controller, which was used for the output voltage regulation along with a feedforward type strategy to control the ripple of the inverter power. The two control strategies used to involve the output voltage to control the leakage current were described as decoupled with the output as the basic Fourier series.

The second alternative is to possess a proportional-integral-resonant (PI-R) control algorithm, where the "PI" part regulates the output voltage, and the resonant part mitigates the voltage inversion ripple. The new and nominal PI solutions were both simulated to investigate the controllables outputs, with Bode diagrams displaying the responses to each controller.

In [101], a boost and DAB converter with a PV and battery is used within the share going into the DAB with a corresponding PI controller and simulated in MATLAB/Simulink to model the system, domain model and running the control implementation, without a validation experiment. The authors in [102] recommend and advocate for DAB converters for application with vehicle applications, while minimizing both electrical and control constraint via an appropriate control scheme, which in this case is a beneficial PI control system for output voltage regulation, where an experimental hardware prototype-based FPGA and battery emulator, achieving an efficiency of 95.6%.
The other authors [103] propose a new concept PV and battery-based DAB converter with proportional-resonant control, while a second PIRD controller will output to a microgrid inverter. Each subsystem, which is the PV and battery, and entire microgrid system will be modeled in MATLAB/SIMULINK – with the subsystem block following their related detainment.
A PID controller's typical block diagram is illustrated in Figure 13. In a basic bi-directional DC–DC converter, a PWM is used to generate the pulses that trigger the switch. The fire angle is adjusted, which can produce an extremely high regeneration of output voltage, given a very minimal change in input voltage. To mitigate this problem, the PID controller is employed[104]. The PID workflow principles are addressed in [105], [106] . Eventually, there was a change in input voltage, but no impact on output voltage, as the output voltage of the converter was observed about its corresponding pair of output values, and a fired signal was sent to trigger the switch for the desired output voltage. Similarly shown in [107], the output voltages' stability was of PID and PI controllers for bi-directional DC–DC converters of electric vehicles were presented for comparison. Using the PI control method, there was a lesser fluctuation of the output voltage on different input supply voltage levels. There is always compromised between output voltage overshoot and stability, when selecting PID to PI controllers. PID controllers are trustworthy, dynamic, and always applicable to a vast range of control problems.

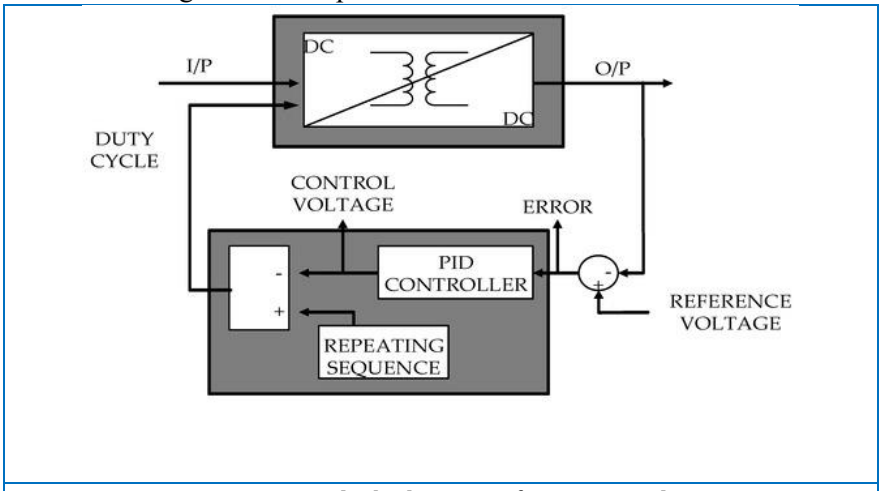



Fig.13 Block diagram of PID control.

### 6.3.3 Sliding Mode Control

Due to multiple nonlinearities in each type of two-way DC converter, whether overlap or buck-boost, the dynamic equation of the converter can be nonlinear. One of the ways to synthesize the control algorithm is to linearize the systems through various linearization methods, but this is not truly representative of the model, because of the assumptions and hypotheses. Therefore, to determine the closed loop estimation about reliable and stable response from bidirectional DC–DC converters to control a reliable and dynamic control scheme to reject disturbances from the outside, a nonlinear control design method is more suitable. Sliding model control is a common nonlinear control design method for its high-speed dynamic response, robustness to changed parameter specifications, and the ability to reject load and disturbances from outside [108]. The integrated block diagram for sliding mode control is shown in Figure 14. Sliding mode control is proposed for DC–DC bi-directional coupling inductor converter from [109].

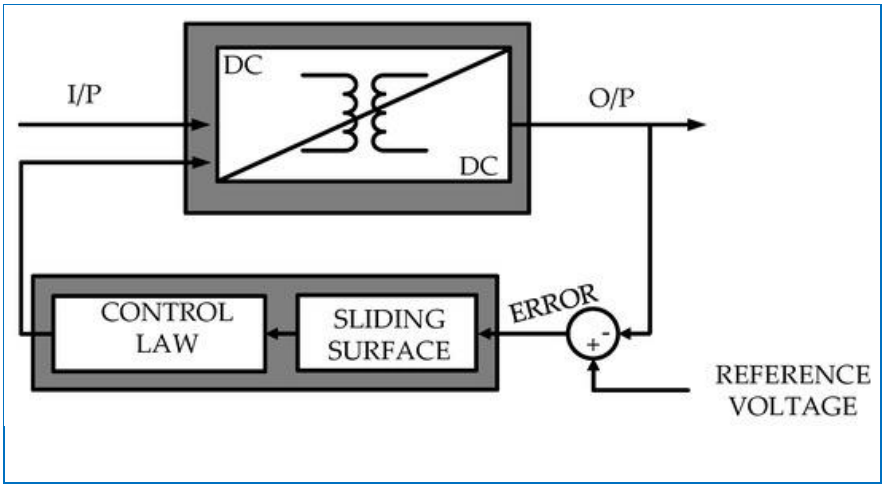



Fig.14 Representation of sliding mode control.

The sliding-control method was proposed with high performance tracking DC voltage on high side to verify robustness against disturbances. Furthermore, [110] presents a DC bi-directional converter to implement the sliding mode control technique. Comparations is done with load disturbances and parameter changes between sliding mode control and PI control. This study [111] outlines a DAB converter using a sliding mode controller (SMC) and fuzzy logic control.

The key aim was to regulate the output voltage Vout and the leakage inductor current iLK. The results show the advantage of using fuzzy logic controller rather than SMC based on gradual charging of battery and discharging. The simulation or meta-model platform use were MATLAB/SIMULINK and Proteus. In [112]describes an SMC in DAB converter with a DC load. Modelling of the converter is determined by dynamic modelling and Fourier series describe the AC operation of a converter. The model validation was using SMC and PI with perturbations.

### 6.4.4 Model Predictive Control

The practical and emerging algorithm for energy conversion systems, and power electronics model predictive control, the block model of the predictive can be seen in Figure 15 and this is more alluring as seeing the control method over other contemporary methods because it has extremely fast dynamic response a fast-tracking over contemporary methods.

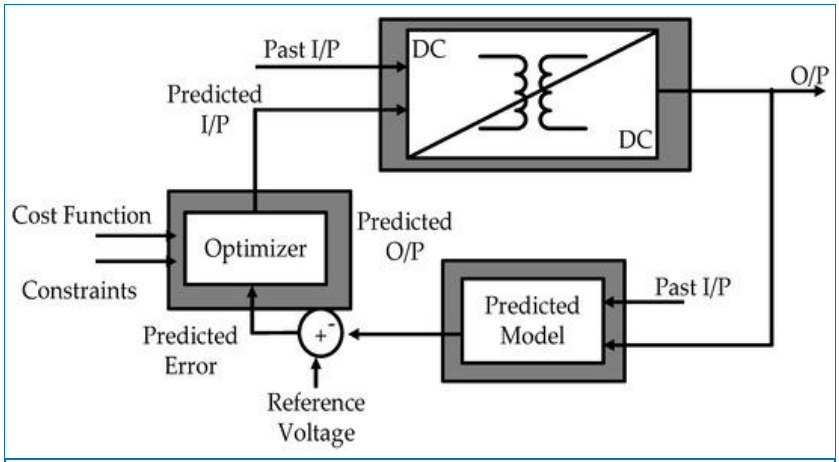



Fig.15 Block diagram of model predictive control.

[113], [114] explored a medium-voltage direct-current (MVDC) regulatory approach for ship power systems. A linear quadratic internal (LQI) control was used to form a linear model predictive controller (MPC). The results show satisfactory responses to disturbances. The authors in [115] proposed a model predictive controller for a dual DAB connected in parallel to the output ports, with the current stress optimization (CSO) introduced. The method uses a conventional voltage-mode control (VMC) approach followed by consideration of CSO to propose a combination mechanism of CSO and MPC. The article claims the CSO-MPC will operate the power in both converters, at all operating conditions, while not introducing any overshoot of output voltage and improving load robustness.

## 6.2 Intelligent Control

These past years, artificial intelligence approaches have emerged as another legitimate approach for Dc–Dc converters, such as deep learning [116], [117],neural networks (NNs) [118], [119], [120],and reinforcement learning (RL)[121], [122], [123]. Due to the model's uncertainty or nonlinearity, these features cannot be corrected by mechanism-based control approaches. Meanwhile, AI-based control approaches are more capable of resolving these features.

### 6.2.1. Reinforcement Learning (RL)

In reinforcement learning techniques, the learning agent observes state parameters from the environment and takes action to maximize the reward. In this case, the learning agent for the EV charging problem is the charge management controller, which takes a trial-and-error approach to determine which action provides the highest cumulative reward. Because actions influence both the immediate reward and the future rewards, RL techniques use cumulative reward when taking an action. This leads the learning agent to maximize reward and take the action that, based on the observed states, provides the highest cumulative reward, and seeks to accomplish this via the RL algorithm. [124]The use of RL algorithms for energy management can ultimately be placed into two broad categories, simplex and hybrid. Simplex algorithms are RL algorithms such as Q-learning, Sarsa, and Dyna algorithms tat solely focus on the RL algorithm to determine the energy management policy [125]. Hybrid algorithms apply RL in combination with alternative forms of algorithms to determine the policy. Examples of hybrid algorithms include model predictive control (MPC), deep learning, and predictive algorithms [126]. Using extra algorithms leads to a more practical and efficient method of conducting real-time EV regulation.
Reinforcement learning aims to determine the best policy via trial-and-error learning, and it works well on dynamic, non-stationary contexts. To put more weight on the most recent reward observation as opposed to earlier ones, this is implemented through a learning rate α, which is constant throughout the RL algorithm. Reinforcement learning (RL) offers possible solutions to a sequential choice task, like the discounted episodic Markov choice Process (MDP). Figure 16 shows the key elements of an RL system and the process of learning from reinforcement[125] .

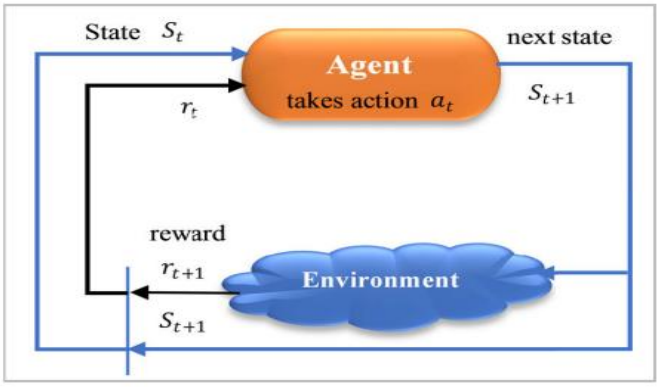



Fig. 16 Illustration of the reinforcement learning cycle

Several methods were applied to tackle the problem of EV charging systems with uncertainties Techniques that are model-free RL can be defined as either Deep RL, which combines RL with deep machine learning, or RL. In most of the studies, the authors have solved the RL problem with Q-learning techniques or deep extension of Q-learning called Deep Q-Network (DQN). In other studies, the authors tried out alternative methods to resolve some of the issues Q-Learning encountered, such as W-learning. In some studies, the learning problem was generated with State-Action-Reward-State-Action (SARSA) that did not rely on Q-learning[127]

The authors of [128] considered proposing the EV charging problem as a Markov Decision Process (MDP) to build an RL model that may find a way to accomplish an EV charging system goal. The MDP model is a mathematical model usually related to a problem of achieving the best possible decisions. The authors of [128] faced this issue since they could only utilize three inputs and quantized to relatively low levels of discretization, which affected their way to represent the charging system environment.

The Q-leaning algorithm is an advanced version of the SARSA algorithm. It defines a set of actions (A), a set of state-action values (Q), and a set of state values (V). It also uses the epsilon greedy algorithm to choose actions while appropriately updating the values of the state and state-action pair. Both Q-learning algorithms, unlike the SARSA algorithms, guarantee a solution to reach the absolute optimal policy considering the entire future "trail."[127] .

The DQN and DDPG approaches were modified in [129] to introduce a control deep deterministic policy gradient (CDDPG). They utilized DQN to select and implement the actions. They used a type of RNN, named LSTM, or long short-term memory, to obtain state information from the environment. The authors stated that there were three phases within the algorithms' behaviors: interaction, training, and testing. This system exploited deep reinforcement learning's ability to store and learn from experiences based on a target network and the ability to implement experience replay. [130] is another article that improves the DQN and DDPG processes. The authors' prioritized experience replies (PER), by prioritizing experience that had higher absolute TD error, allowed for quicker learning and better extraction of policies.

### 6.2.2. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) have the possibility to be a new model type for machine learning because they are very competitive with statistical models and classical regression regarding flexibility [131]. The true capabilities of ANNs could be explored based on their data analytic functions of processing speed/latency/fault tolerance/performance/volume/convergence accuracy, and scalability [132], [133]. ANNs were systems to process data from inspiration of biological neural systems and could predict a specific function when they were well-trained. While the ANN is well-trained from some experimental data, the ANN has the predictive capabilities to validate with independent data. When new data can be observed through a novel data set, the ANN can relearn and develop further predictive capabilities [116], [134]Typically, an ANN model can predict multiple output variables from multiple input variables [135] They had the ability to learn the system.

Some of the more recent publication[85], [136] describe an approach that would take an ANN and train it with the large dataset from hardware measurements or simulation tools. The trained ANN has now predicted the optimized phase shifts that have approximated optimized control variables for a given set of DAB converter operating conditions or measured variables. The optimized control variables are a function of the accuracy of the underlying DAB converter model unless the data is from hardware. Other approaches also utilize ANN for optimizations, such as [116], which estimates all circuit parameters of a buck converter with time-domain mapping ANN, while the work in[118] trained an ANN with a mathematical model that ignores switching losses and only allows linear modulation (SPS). In general, where ANN models are data-driven, they typically require training on a large dataset to accurately estimate input-output relationships, so practical use can be very difficult to utilize the data without sufficient data. Also, unlike data-driven ANN modeling, PINNs offer the ability to embed physical principles into, or embed a physics loss into the training of the neural network [85], [134], [135]. The overall block diagram of the RBF-SMC controller built in this research [137]is represented in Figure17.

The research proposes a control methodology for a DAB DCDC converter via the Reduced Order

Modeling-based neural network Sliding mode control approach to regulate the output voltage and improve the importance of robustness in the system. Sliding mode control (SMC) is recognized for its relative robustness and effectiveness in enhancing performance of nonlinear systems. The first step in the control module is to train data to create control action u, shift signal D, and send it to the switch transistor in the DAB circuit to produce a switch pulse for assured controls.

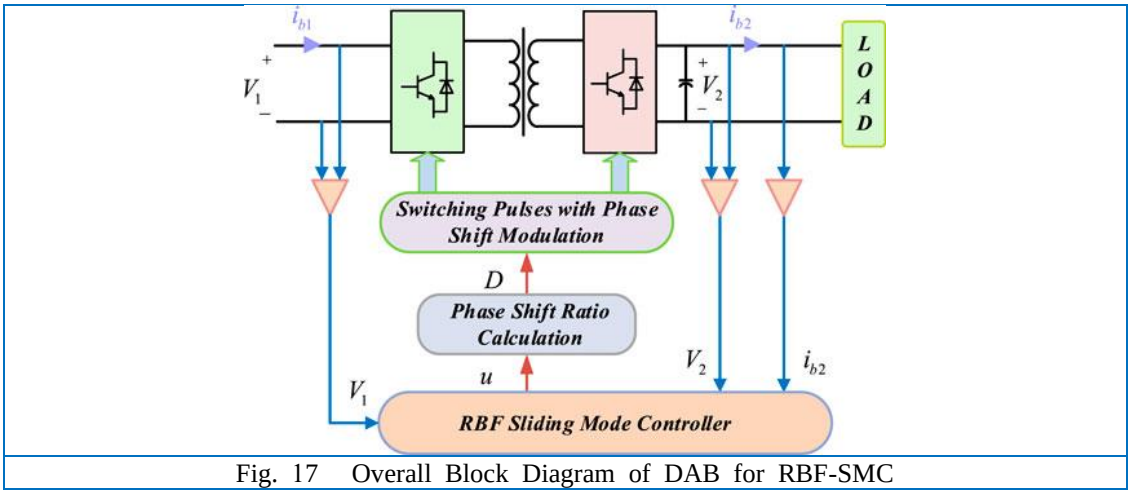



Fig. 17 Overall Block Diagram of DAB for RBF-SMC

### 6.2.3. Fuzzy Logic Controller

The fuzzy controller contains two inputs and one output. The input membership functions of the controller are typing Gaussian while the output membership is triangular. The error signal that will be sent to the fuzzy logic block is calculated by finding the difference between the actual value and reference value of the DC link voltage. The change in error is calculated from the input error signal with memory that stores the memory or past data of the input (error signal). The inputs of error and change in error will go the fuzzy controller. The output from the fuzzy controller is of one output that ranges in values from +2 to -2. The output of the fuzzy controller is combined with parks transformed signals of the current of the dual active bridge IGBTs, and the pulses are generated [138]. The control logic of the fuzzy logic controller is shown in figure 18.

The research by Jadhav and Linu[138] presented an optimized control strategy for an application involving a dual-active-bridge (DAB) converter in an electric-vehicle (EV) charging scenario which utilized a fuzzy-logic controller (FLC). The authors designed and implemented a fuzzy controller which modified the phase-shift angle of the DAB converter in response to load and input voltage variations to reduce current stress and improved the overall transient-load efficiency. Compared to classical PI control, simulation analysis in MATLAB/Simulink indicated the fuzzy controller exhibited a more stable voltage regulation, lower total harmonic distortion (THD), and a greater ZVS range. The authors also pointed out that rule-based adaptability of fuzzy logic resulted in a superior control performance under nonlinear and uncertain dynamics for converters where analytical models to govern the control response could not be developed. In other studies, by Farooq et al.[118], an ANN-based adaptive fuzzy control was similarly implemented to improve the robustness of a single-phase DAB converter. And in another study by Harrye et al. [119] a fuzzy neural control scheme was used to minimize reactive-power in a TPPM-DAB converter. These studies support the conclusion that fuzzy based control and hybrid AI influence the performance of fuzzy control schemes.

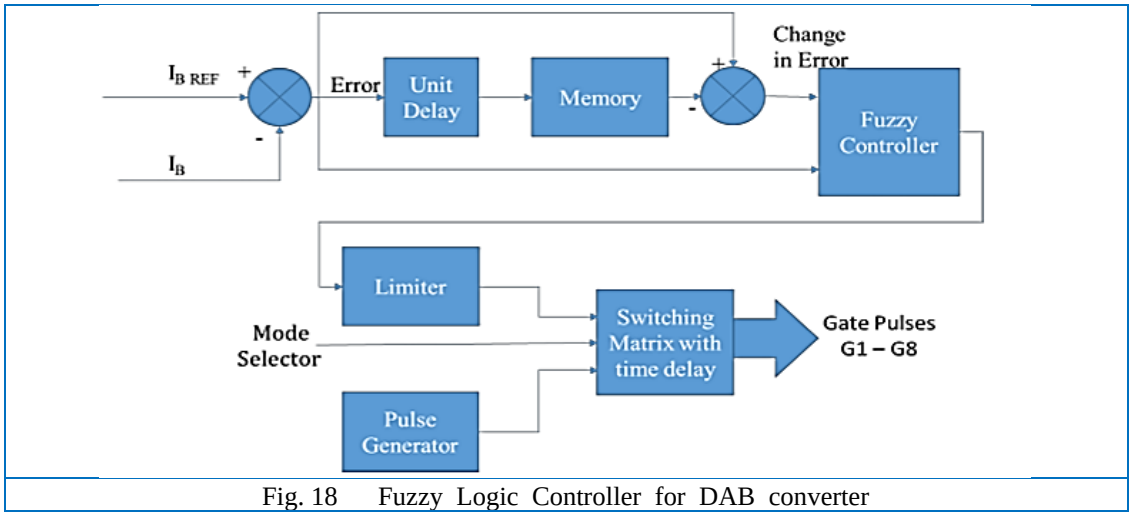



Fig. 18 Fuzzy Logic Controller for DAB converter

## 6.3 Hybrid Control

Dual Active Bridge (DAB) converters are receiving increased attention with Hybrid control models due to their ability to bring together classical and intelligent control in one schema. The Hybrid control model can optimize its overall control parameters in real time, thereby improving efficiency, transient response and ZVS performance over a wide range of loads and voltages[139].

### 6.3.1 Rule-Based Hybrid Control (Logic Integrated Hybrid Systems)

The connection between power electronics and their efficient control systems is critical for the implementation of energy sources for electric vehicle use. To address this, the authors present a hybrid fuzzy proportional integral (PI) based, control system for multiple input converter (MIC) topology. The hybrid fuzzy PI controller, as described in this paper, consists of PI at steady state and fuzzy PI at transient state. The paper [140] has shown that the control strategy is robust, provides bidirectional power management (source and sink), faster tracking with less steady state error, satisfactory dynamic response, enhanced flexibility and use of energy sources. The structure of hybrid fuzzy PI controller is shown in figure 19.

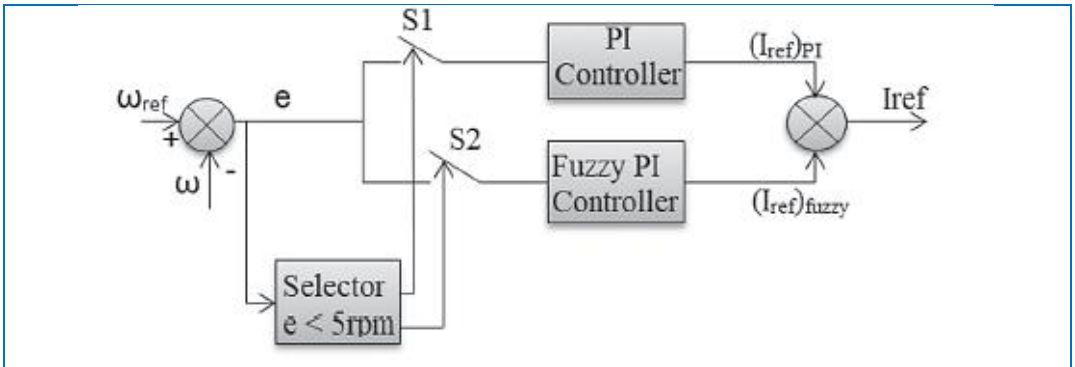



Fig. 19 structure of hybrid fuzzy PI controller

The study in[141] proposes a proportional-integral (FLC-PI) control method that is based on hybrid fuzzy logic control (FLC) to enhance voltage stability, power quality and value efficiency of central inverters operating in photovoltaic power plants (PVPPs).
The FLC-PI control is implemented based on several artificial intelligence (AI) based metaheuristic optimization techniques (MOTs) which are Grey Wolf Optimization (GWO), Harris Hawks Optimization

(HHO), and Arithmetic Optimization Algorithm (AOA) for tuning the gain parameters of the FLC-PI control and for using four specific error-based objective functions of which they are: Integral Absolute Error (IAE), Integral Square Error (ISE), Integral Time Absolute Error (ITAE) and Integral Time Square Error (ITSE). In this way, the FLC-PI type control model optimized voltage stability, enhanced power quality, and optimized performance of grid-connected photovoltaic (PV) systems in general.

### 6.3.2. Optimization-Based Hybrid Control (Genetic Algorithm)

The genetic algorithm (GA) originated with J. H. Holland's initial proposal in 1969. GAs belongs to the category of evolutionary algorithms that use concepts derived from natural selection to perform searches for solutions to optimization problems. To apply GA to the modulation problem in DAB converters, it must first be represented as an optimization problem with defined objectives and constraints. The objectives may be to minimize current stress, maximize efficiency, or minimize circulating power, depending on the application. With the optimization problem phrased, one could then use the GA to identify the candidate solution's phase shift ratio that meets the specified objectives. The GA will then evaluate the fitness of each of the candidate solutions in the population to either be chosen (or not) on behalf of reproduction, the most "fit" candidates will be selected, and the next generation will perform an operation that mimics "Crossover" and/or "Mutation" to create new candidate solutions. Reference [142] proposed a multi-objective efficiency optimization strategy based on a genetic algorithm with TPS modulation, defined by three objectives: minimizing RMS current, minimizing current stress, and achieving ZVS performance.

The genetic algorithm can handle the multi-objective modulation of DAB systems as a non-convex optimization problem. Reference[143] proposed a droop control method based on a genetic algorithm and minimizing DAB converter power losses to maximize transmission efficiency. Reference [144] also proposed the use of a genetic algorithm to multi-objective optimization modulation of modular DC-DC converters. The search process of genetic algorithms requires an excessive number of iterations and evaluates the population's fitness. Therefore, evolving solutions can be computationally and potentially real-time expensive.

The proposed model in article [145]has the advantages of efficient charging and discharging for V2G and G2V using an optimized PID controller's coefficients using enriched GA. The suggested PSO based PID has a rise time of 2.9 s and an efficiency of 87.4%, and the ITASE has a rise time of 2.5 s and an efficiency of 92.5%,overall flow of the proposed model is illustrated in figure 20.

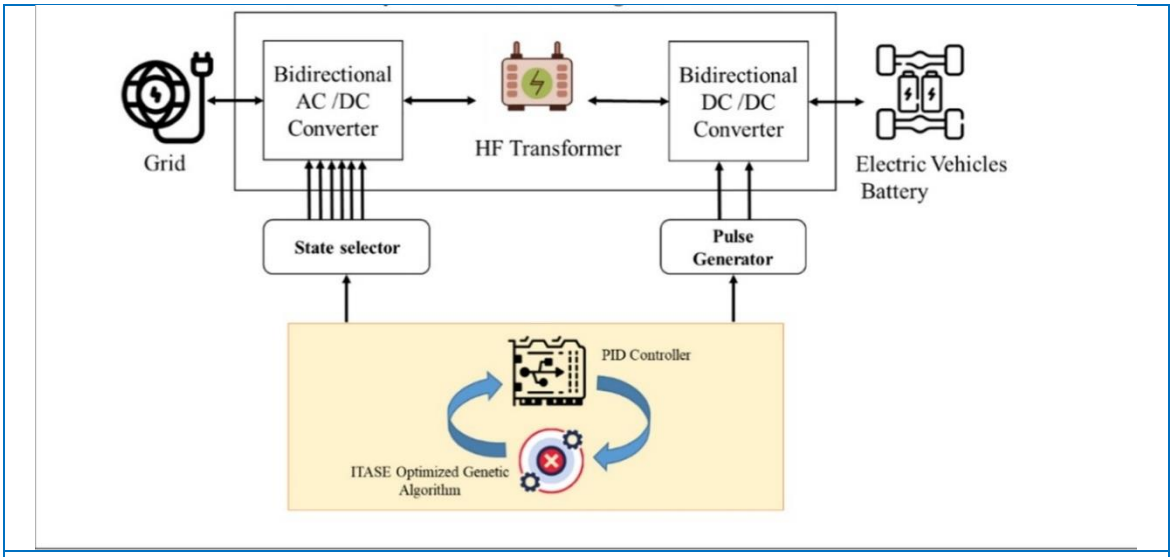



Fig.20 Block diagram of model predictive control.

### 6.3.3. Model-Predictive + Intelligent Hybrid Control

Finite set model predictive control (FS-MPC) is a practical and viable control method for power electronic converters. The challenge with FS-MPC, as with conventional feedback methods, is that the design of the weight factor can be tedious and time consuming. In[146] the authors propose the use of reinforcement learning (RL) to solve the challenges described above because they believe RL has the potential to improve the FS-MPC design of power converters in two distinct ways. The first role of the RL algorithm would be for the automated design of the weight factor for the FS-MPC with the goal of minimizing total harmonic distortion (THD) and/or average switching frequency. The second role is to create the incentive for the RL agent to be designed with the cost function of the predictive algorithm so that the RL agent learns to find what is the optimal switching policy for the power converter in modeling that the RL agent would replicate the use of prediction against the model without the RL agent knowing the system model ahead of time. We show through simulation results, that there is a strong balance in the correlation of the controller that is based on model-free RL and the predictive controller. The block diagram of the proposed RL-based framework for the converter system is shown in Figure 21.
This study [147] proposes a model predictive voltage control (MPVC) for dual-active-bridge (DAB) dc-dc converters using a generalized averaging model (GAM). The GAM structure presents an approach in which the high-frequency transformer current can be approximated as two components representing the real and imaginary axes. Using the estimated state, an MPVC is developed based on the state feedback law with a constant controller gain. An algorithmically based tuning procedure is presented to find an optimal controller gain. Simulation results compare the new MPVC to an improved.

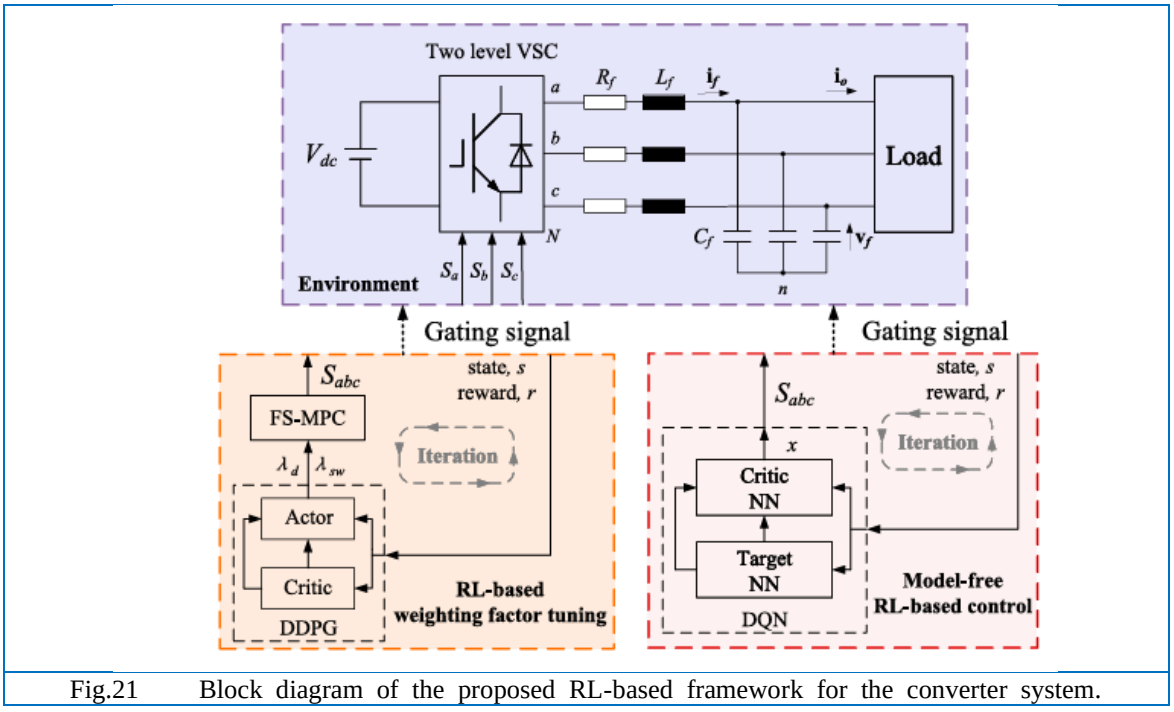



Fig.21 Block diagram of the proposed RL-based framework for the converter system.

### 6.3.4. Adaptive AI-Assisted Hybrid Control) RL or NN + Classical Control)

There has been increasing interest in utilizing model-free deep reinforcement learning (DRL)-based controllers as an option to improve the dynamic behavior, efficiency and other features of DC–DC power electronic converters known to be controlled traditionally by small signal models. Conventional controllers cannot adapt to uncertainty or disturbances, and this paper[148] presents a design methodology based on proximal policy optimization (PPO), a common and efficient DRL approach for informing near-optimum decisions for areal buck converters in both continuous conduction mode (CCM) and discontinuous conduction mode (DCM) operating under resistive and inductive loading.

The results show that testing conditions and models provided demonstrate the robustness and efficiency of the controller in a real scenario. The authors anticipate that these results will be a significant step in the application of DRL controllers in real-time scenarios, as well as provide indications and pathways to design controllers by the same methodology as it pertains to this power electronic converter topology or any other configuration of power electronic converter topology. The general control scheme of the proposed DRL controller for a buck converter is presented in Figure 22.

This research [149]proposes a comprehensive approach utilizing model predictive control (MPC) and a multi-agent system (MAS), allowing for adaptive, scalable, and cooperative control solutions in scenarios with uncertain renewable energy. This paper first illustrates a restructured Model Predictive Control (MPC) framework that has a primary goal of enhancing total system performance. Second, the multi-agent system framework applies reinforcement learning in an effective way to improve the accuracy and adaptability of control coefficients, enhancing performance in aggregate as well. The performance of the systems performance was successfully tested within MATLAB Simulink, including real-world verification of the accuracy of the methodology by running common validation tests.

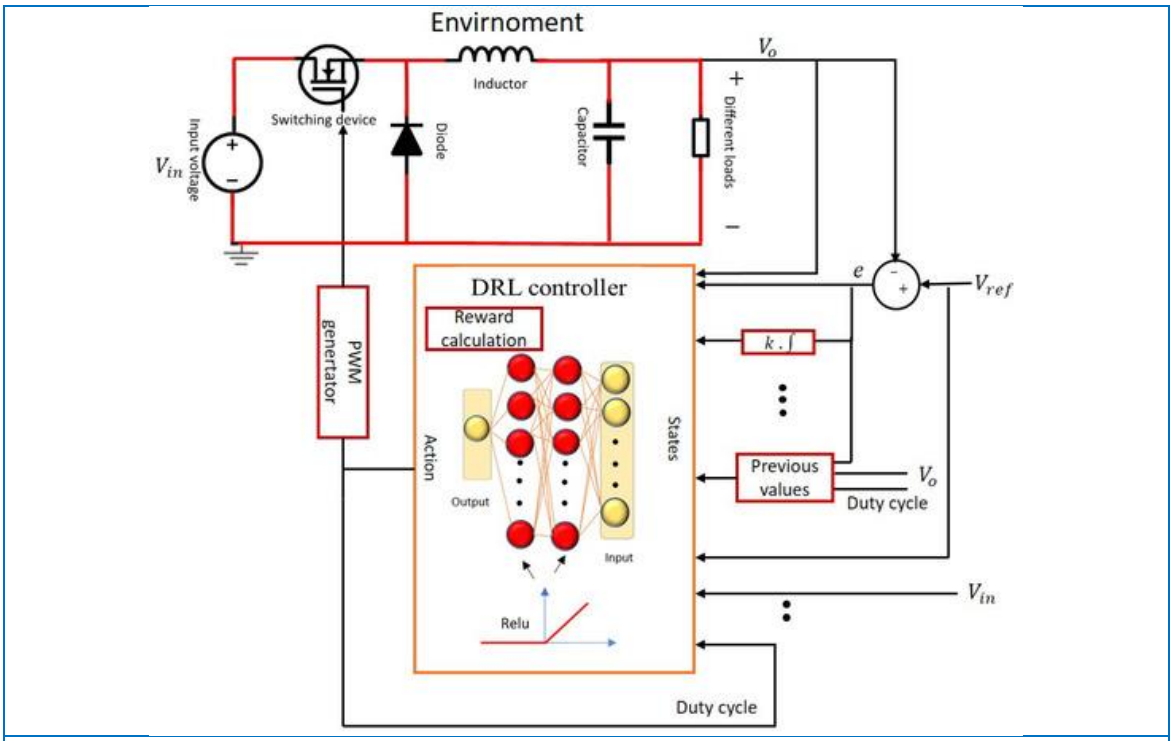



Fig.22 The proposed control DRL scheme for a buck converter.

## 6.4 Practical Comparison of Control Strategies under Realistic Constraints

Conventional Control Systems Versus Sliding Mode Control The most widely used implementations of electricity-related technology today fall under the category of conventional controllers. The two most used types are Proportional-Integral (PI) and Proportional-Integral-Derivative (PID) controllers. These two types of conventional controllers are popular because they are easy to set up and use, require a low amount of computing power, and can be implemented in real-time. However, traditional PI and PID controllers do not perform well when subjected to wide variations of voltage levels, nonlinear behavior of batteries (e.g., when charging/discharging), and rapidly changing operating conditions that occur frequently in electric vehicle charging systems[85], [107], [150].

Sliding Mode Control Techniques Offer Robustness To improve the robustness of a system to external disturbances (e.g., wind, road surface bumps) and the uncertainty in the parameters of a device or system, a sliding mode control technique should be used. However, while sliding mode control techniques may

offer increased robustness, they also create additional complexity in the control of the system and can cause the system to experience "Chattering" phenomena.[112], [151], [152].

Superior Dynamic Performance with MPC Compared to PI/PID Control and Sliding Mode Control, Model Predictive Control (MPC) can provide superior dynamic performance by explicitly handling system constraints and thus, is better suited for quality control and rapid, accurate feedback. However, model-based predictive control will only work well when applied to well-developed models of the system that have been accurately developed and, therefore, will likely require significant amounts of computational resources [113][115].

In contrast, intelligent and hybrid control approaches provide a greater degree of adaptability and can learn about their external environment. This creates a more robust system, and the use of knowledge obtained will allow these systems to overcome constraints imposed on them by physics. These approaches enhance the performance of an electric vehicle charger by increasing charging efficiency, reducing current stresses on the battery, improving dynamic response times, and extending the overall life of the battery. Although these types of systems are more complex than other control methods, recent studies have demonstrated that using reinforcement learning combined with hybrid control architecture is a feasible and scalable way to develop next-generation electric vehicle charging systems [121], [122], [123][129].

An evaluation of electric vehicle charging control methods published in the literature is usually performed following a consistent, systematic method. This guarantees that the evaluation of one's control method is identical to others. Typically, most studies evaluate their method by using common evaluation metrics (charging efficiency, current stress minimization, dynamic response time, voltage regulation accuracy, robustness to operating condition variation, and battery life). By using these common metrics to evaluate different control methods, researchers can better understand and objectively compare the strengths and weaknesses of traditional, intelligent, and hybrid controllers in realistic operating environments.

A comparative summary will be presented to summarize the reviewed control methods in a clear and organized manner. The summary of the comparisons will provide information on the main benefit, limitations, and usefulness in practice of each of the three control techniques (traditional, intelligent and hybrid) used in dual-active-bridge-based electric vehicle chargers as shown in table 3.

Table 3. Comparative summary of control strategies for DAB-based EV charging systems.

| Control Strategy | Key Advantages | Main Limitations | Practical Applicability |
|---|---|---|---|
| PI / PID Control | Simple structure and low computational burden, making them easy to implement in real-time EV charging systems[6]. | their lack of robustness when faced with variations in the batteries' nonlinear characteristics as well as the batteries' wide range ([7] | used for conventional and low-powered electric vehicle chargers when focusing on cost and simplicity |
| Sliding Mode Control | Provides a high degree of Robustness to parameter uncertainty and disturbance from outside; thereby, providing a steady-state operation within a large variation of the input and environmental conditions.[8] | Chattering Phenomenon and increased complexity of the control system may create problems for the switching-components and decrease system reliability [9] | Medium-Power EV Charges must have Robustness against disturbances. |

| | | | |
|---|---|---|---|
| Model Predictive Control (MPC) | MPC Models have strong specifications of System limit constraints and improved system dynamic response for fast charging applications [10]. | high computational complexity and the requirement for highly accurate system models for the real-time implementation of MPC [11] | For high-speed Charging EV systems to perform well, they must have adequate computational capacity. |
| Fuzzy Logic Control | The ability to control models for operating conditions without reference that are not clearly defined, or the ability to effectively control the nonlinear dynamic properties of the electric vehicle [12]. | A knowledge base, membership function, and a set of systematic tuning rules are required and developed by an expert [13] | The fuzzy logic controller will work on different nonlinear charging systems under different, uncertain operating conditions. |
| Artificial Neural Networks (ANN) | Artificial Neural Networks (ANN) allow for strong non-linear mapping and the ability to learn from the data to enhance control performance [14] | ANN requires large training datasets to train properly and there are generalization issues when using ANN[15] | Electric Vehicle (EV) charger applications use adaptive and/or data-driven techniques. |
| Reinforcement Learning / Hybrid Control | Learning by doing and being the best choice when faced with all the unknown possibilities will allow for more efficient operation of batteries and longer life[16] | The complexity of training and the amount of time it takes to converge can make it difficult to implement in real time. [17]. | Next-generation electric vehicle chargers will require intelligent control solutions. |

## 7- Future Research Directions

In the future, Electric Vehicle Charging Systems will most likely begin to develop and implement Adaptive Data-driven Control Strategies (ADCS) that meet the real-time requirements of the Electric Vehicle Charging System (EVCS). One method of overcoming uncertainties in EV Charging Systems is using Reinforcement Learning. Not only does Reinforcement Learning allow for the modeling of the non-linear behavior of batteries, but it also allows for the modeling of different operating conditions of the grid and for the relationship that exists between them. In a combined operation Hybrid systems that include Optimal Control (OC) and either Reinforcement Learning (RL) or another Adaptive Control Strategy will provide more reliable and stable operations and the capability to complete real-time operations.

In addition to the above-mentioned methods, Prototyping and Hardware-In-the-Loop testing will be important as the transition from Simulation based analysis of the EV charging system to Field deployment occurs. The effects of battery aging, state of health and safety will be prime factors in the EV Charging System development and research as this industry continues to develop and evolve. Additionally, the demand for scalable Electric Vehicle Charging Systems will continue to increase as more Electric Vehicle Charging Systems are created and developed. Additionally, the construction of coordinated connections to Vehicle-to-Grid and Smart Grid uses will continue to increase as the number of Electric Vehicle Charging Systems and Electric Vehicle deployments increases.

## 8. Conclusions

This paper detailed in this document is a comprehensive and systematic review of control strategies for dual converter-based charging systems of electric vehicle batteries (specifically lithium-ion batteries) through the Constant Current to Constant Voltage (CC-CV) charging strategy. By synthesizing many existing studies, the overview shows how Control Strategies have progressed from Standard Linear Controllers (PI/PID Controllers) to Advanced Intelligent and Hybrid Control Methods.

In addition to our thorough review of the existing state-of-art control methodologies, we provide insights into the differences identified from the comparative evaluation based on the reviewed methodologies. For instance, although the benefits of using Standard PI or PID Controllers include their simplicity, low computational power requirements, and ease of real-time implementation; these benefits diminish considerably with non-linear battery behavior, wide operating range, and rapidly varying conditions. Subsequently, other methodologies (Sliding Mode Control, Predictive Control, etc.) offer improvements with respect to robustness and dynamic performance; however, these methodologies require significantly more resources (Computational Power) when compared with Standard Controllers. Therefore, cost-sensitive practical applications of EV charging may limit their use. Finally, Intelligent and Hybrid Control Solutions (Reinforcement Learning-Based Control) demonstrated superior (1) adaptability in terms of adjusting the charging rates, and (2) improved efficiency, (3) reduced current stress, and (4) longer battery life under practically limited conditions.

In conclusion, Intelligent and Hybrid Control Strategies provide superior results to all other Control Techniques regarding Advanced EV Charging Solutions such as rapid charging, reverse power flow, and unknown operating parameters. However, there are many issues, including the complexity of training, real-time viability, and implement ability on hardware's that still need to be solved through future research. Therefore, future directions for research should be to find ways to create scalable, battery aware, real time capable Intelligent Control Frameworks, validated using hardware in a loop testing and experimental prototypes so that next generations of EV Charging Technologies can be deployed in practice.

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**Conflicts of Interest**: The authors declare no conflict of interest.

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