Design of a DC Net Meter in Vehicle to Grid Technology

A thesis submitted in fulfillment of the requirements for the award of the degree of

DOCTOR OF PHILOSOPHY

in

ELECTRICAL & INSTRUMENTATION ENGINEERING

submitted by

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CERTIFICATE

I, Kratika Yadav, Registration No. 901904014, hereby declare that the thesis entitled, **"Design of a DC Net Meter in Vehicle to Grid technology"** submitted to the Electrical and Instrumentation Engineering Department at Thapar Institute of Engineering and Technology, Patiala, Punjab (India) is an authenticated record of my own work for the reward of the degree of **"Doctor of Philosophy"** under the supervision of Dr. Mukesh Singh. This Thesis has not been submitted to any other Institute or University for the award of any other degree or diploma.

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ABSTRACT

The growing acceptance of electric vehicles as a sustainable transportation solution has led to higher demand for efficient and reliable charging infrastructure. However, multiple challenges need to be addressed before the seamless integration of EVs with the existing grid can be achieved. Firstly, the current grid infrastructure may not be fully prepared to meet the increasing electricity demand resulting from widespread EV adoption. Charging multiple electric vehicles at once, particularly during peak hours, can strain the system and result in power outages or voltage instability. Another important consideration revolves around the requirement for smart metering infrastructure capable of monitoring the bidirectional flow of electricity between the grid and the vehicles. Further, this infrastructure plays a pivotal role in enabling vehicle-to-grid technology to provide a more accurate and comprehensive overview of electricity consumption. Furthermore, the conventional centralized charging infrastructure raises concerns regarding scalability, availability, and accessibility. In response to these challenges, four distinct methodologies and schemes have been proposed.

In the first approach, a bidirectional DC net metering system has been proposed for V2G technology. The study focusses on addressing the challenges associated with AC-side metering in EV charging system. The objective is to provide precise measurements for end customers by placing the DC net meter on the battery side. Further, the proposed metering system is designed to comply with international standards and incorporates bidirectional power transfer, real-time data communication, and a net metering scheme for accurate cost calculation. Additionally, the research emphasises the potential for integrating dynamic pricing structure and utilizing the Internet of Things (IoT) to manage data from multiple DC net meters. The outcomes of this study contribute to the development of a smart DC net meter for V2G that enhances billing accuracy for EV charging operations and creating opportunities for future enhancements.

The second study investigates the role of dynamic pricing in optimizing power grid operations in the face of increasing EV adoption. It introduces a time-of-use (TOU) pricing framework that incorporates critical peak pricing (CPP) and peak time rebate (PTR) to coordinate

EV charging and reduce electricity expenses. The research underline the significance of factors such as peak/off-peak hours, state of charge (SOC), dynamic pricing, and the presence of V2G-enabled stations in achieving efficient charging and discharging. The proposed approach demonstrates better performance compared to previous models in terms of benefits, cost savings, and accuracy. Furthermore, the study seeks to emphasize the feasibility and advantages of the TOU-CPP/PTR tariff structure and the important role of dynamic pricing in managing EV charging.

Moreover, in the third study, a decentralized charging scheduling approach is put forth as a solution to address the challenges arising from the rapid expansion of electric vehicles. The proposed approach optimizes the charging schedules in a decentralized manner with the goal of minimizing the electricity costs. In addition, the findings marked the influence of EV charging on overall consumption of electricity and highlights the importance of understanding the dynamics between decentralized charging and the base load curve. Additionally, it is highlighted that ongoing research and development in charging algorithms are essential to seamlessly integrate EVs into the grid and explore advanced technologies for enhancing grid flexibility.

Lastly, an attention-based deep learning model for load forecasting has been introduced to address the challenges posed by the growing prevalence of EVs. The proposed model offers utilities the capability to dynamically adjust energy supply in real-time, thereby preventing system overloads or underutilization. With the increasing adoption of EVs, power grids face greater difficulty in maintaining a delicate balance between supply and demand. Additionally, the fluctuations in demand resulting from EV charging can strain the grid's infrastructure. The study showcases the substantial improvements achieved in energy management for public EV charging infrastructure through efficient data preprocessing and the utilization of cutting-edge deep learning algorithms such as LSTM and GRU. The demonstrated accuracy and effectiveness of these models open doors for further exploration in energy management, predictive maintenance systems, and real-world testing, collectively addressing the evolving landscape of electric vehicle integration and grid stability.

LIST OF PUBLICATIONS BASED ON THESIS

1. Kratika Yadav, Mukesh Singh,"Design and development of a bidirectional DC net meter for vehicle to grid technology at TRL-9 level", ***Measurement***, 207, 2023, 112403, https://doi.org/10.1016/j.measurement.2022.112403.
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2. Kratika Yadav, Mukesh Singh,"Implementation of DC net metering scheme in off-board EV charging systems with time of usage (TOU) capability", ***Electric Power Systems Research***, 224, 2023, https://doi.org/10.1016/j.epsr.2023.109690.
   (Impact factor: **3.9**)

3. Kratika Yadav, Mukesh Singh,"A novel energy management of public charging stations using attention-based deep learning model", *under review at* Electric Power Systems Research.

4. Kratika Yadav, Mukesh Singh,"Dynamic scheduling of electricity demand for decentralized EV charging systems", *under review at* Sustainable Energy, Grids and Networks.

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List of Abbreviations

δ	Time interval of the selected slot
c_i	Charging rate of each EVs
P_g	Power demand from the grid
P_{ev}	Power demand from all the EVs
P_{ev}^{max}	Maximum power that can be drawn from the grid to charge EVs
P_{max}	Maximum power that can be consumed at time *t*
P_{sr}	Power generation from the solar panels
P_{sr}^{max}	Maximum power that can be generated from the solar panels
P_S^{max}	Maximum power capacity of the selected slot
P_{v2g}	Power discharge from EVs to the grid
P_{v2g}^{max}	Maximum power that can be discharged from EVs to the grid
r_c	Reward for discharging electricity
SOC_{max}	Maximum allowable value of SOC for each EV
SOC_{min}	Minimum allowable value of SOC for each EV
T_d	Charging duration of each EVs
t_i	Start time of each EVs

ADC	Analog to digital converter
BEV	Battery electric vehicles
BTM	Behind-the-meter
CPP	Critical peak pricing
DG	Distributed generation
EMC	Electromagnetic compatibility
EMI	Electromagnetic interference
EV	Electric vehicles
EVSE	Electric vehicle supply equipment
G2V	Grid to vehicle
GRU	Gated recurrent unit
IEC	International Electro technical commission
INA	Instrumentation amplifier
LSTM	Long short-term memory
MSE	Mean squared error
O	Set of ongoing EVs
OCPP	Open charge point protocol
p	Price of electricity from the grid
PTR	Peak time rebate
PV	Photovoltaic generation
RNN	Recurrent neural networks

RTP	Real time pricing
SOC	State of charge
TOU	Time-of-use policy
V2G	Vehicle to grid

Chapter 1

INTRODUCTION AND THESIS OUTLINE

1.1 Introduction

Electric vehicles have emerged as the future mode of transportation, as environmental concerns become more prominent around the world. The Global EV outlook 2023 provides some appealing insights related to EVs. According to the report, in the year 2022 alone, the introduction of electric SUVs led to a reduction in oil consumption of about 150,000 barrels per day [1]. In addition, the accompanying tailpipe emissions that would have resulted from burning the fuel in traditional combustion engines have been prevented. Moreover, the report emphasizes the rapid expansion of the global electric vehicle market over the past few years. From roughly 2 million units in 2018 to more than 4 million units in 2021, sales have increased substantially. Further, China solidifies its position as the world's largest EV market, accounting for approximately 40% of the global sales share in 2021, followed by Europe and the United States [2].

Battery electric vehicles (BEVs) continue to dominate the EV landscape, accounting for approximately 75% of all global EV sales in 2021 [3]. The rising price of conventional fuels and the steadily falling price of batteries have contributed to this paradigm shift by making electric vehicles more affordable to own than their internal combustion engine (ICE) counterparts. Beyond cost-effectiveness, electric vehicles are showcasing their ability to support the grid during emergencies. They effectively function as battery storage systems when parked and idle for a few hours, contributing to grid stability.

Furthermore, EVs have the flexibility to get charged via diversity of methods, subject to their location and individual requirements. In accordance with this, the infrastructure for charging EVs exists in a variety of forms, each designed for a specific purpose. However, the conventional charging infrastructure incorporates the electricity supply infrastructure, which includes distribution transformers, energy meters, cables, and distribution panels. Together they provide a reliable input power supply to the Electric Vehicle Supply Equipment (EVSE), a fundamental component of the EV charging infrastructure. The EVSE employs a control system and wired connections to guarantee the safe and efficient charging of electric vehicles, serving as a vital link between the local electricity supply and the EV.

At the core of the EVSE, the control system performs a range of essential tasks. Among these functions are user authentication, authorization for payment, data recording and sharing for the purpose of network operations, and the protection of data privacy and security. The integration of appropriate networking and communication between grid operators, EVSE, and electric vehicles themselves is necessary for the development of a seamless charging ecosystem. By allowing these components to operate in unison, they act as a valuable grid resource, enabling not only efficient charging but also real-time monitoring and comprehensive management.

1.1.1 Global overview of EVs and charging infrastructure

In recent times, the global EV market has grown at a remarkable rate. As mentioned earlier, sales have increased from approximately 2 million units in 2018 to over 4 million units in 2021 [1, 2]. However, as the majority of charging requirements are presently met by home charging set-ups, there is an increasing demand for publicly accessible charging stations. It is essential to ensure that the ease and accessibility of refuelling conventional vehicles are extended to the domain of electric vehicles. Moreover, charging infrastructure for the public plays an essential role in promoting widespread EV adoption, particularly in densely populated cities where home charging accessibility is restricted.

Consequently, a total of 2.7 million public charging stations had been installed around the world by the end of 2022. Surprisingly, more than 900,000 of them were installed in that very year, marking a significant 55% increase from the stock in 2021. The growth trajectory closely resembles with the pre-pandemic expansion rate of 50% observed between 2015 and 2019 [1, 4]. On a global scale, the year 2022 saw the installation of over 600,000 public slow charging points, with China contributing around 360,000 of these installations. In conjunction with slow chargers, public fast charging stations play a crucial role in facilitating the charging needs of individuals who lack access to safe private charging options. Henceforth, the number of fast chargers globally increased by 330,000 in 2022. The worldwide electric vehicle market will continue to expand at a rapid pace, with many countries are coming in the forefront of this growth. Further, as the EV landscape evolves the proliferation of public charging infrastructure will continue to play a crucial role in encouraging broader adoption in diverse communities [1, 2, 5].

1.2 Electric-propulsion vehicles

EVs, also referred to as electrically powered vehicles, have acquired popularity in recent years due to their positive effect on the environment. These vehicles predominantly utilize electric power for propulsion, thereby reducing or eliminating the need for conventional internal combustion engines that rely on fossil fuels. There are several types of electrically driven vehicles, each with its own unique characteristics and applications. As illustrated in Fig. 1.1, the EVs can be classified into three primary categories [6]:

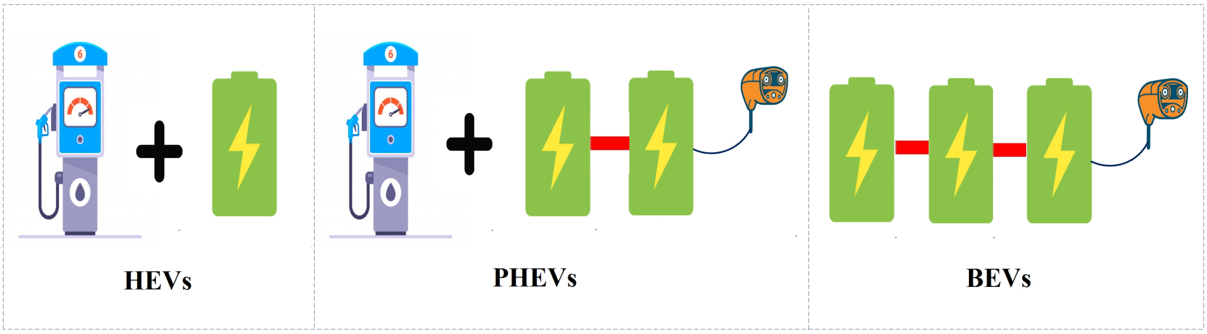


Figure 1.1: Types of Electric Vehicles

1. **Plug-in Hybrid Electric Vehicles (PHEVs)**

   Plug-in Hybrid Electric Vehicles, or PHEVs, combine an electric power train and an internal combustion engine. In addition, these vehicles have larger batteries than conventional hybrid vehicles and are capable of being charged by an external power source [7]. Further, PHEVs can travel short distances in all-electric mode and rely on their internal combustion engine for longer journeys. Therefore, this dual power train configuration allows PHEVs to achieve higher fuel efficiency and lower emissions when compared to standard gasoline-only vehicles. Some examples of plug-in hybrid electric vehicles include the Porsche Cayenne S E-Hybrid, Ford C-max energi, Mercedes C350e, Mini cooper countryman, Audi A3 E-tron, Chevy volt, Hyundai Sonata, Kia Optima and Volvo XC90 T8.

2. **Hybrid Electric Vehicles (HEVs)**

   HEVs, which stands for hybrid electric vehicle, are auto mobiles that power their wheels using a combination of an internal combustion engine and an electric motor. In contrast to PHEVs, HEVs do not have the possibility to be charged externally [8]. Instead, they generate electricity through regenerative braking and the internal combustion engine. Hence, HEVs can improve their fuel economy and reduce their emissions by switching back and forth between the two power sources. The Toyota Prius and the Honda Insight are both examples of highly successful hybrid electric vehicles that do not use plug-in technology.

3. **Electric vehicles (EVs) or Battery Electric Vehicles (BEVs)**

   Battery Electric Vehicles, or BEVs, are electric vehicles that are solely propelled by electricity stored in large-capacity rechargeable batteries. The electric motor that powers the wheels of the vehicle is powered by these batteries. Further, BEVs are a sustainable choice due to their zero tailpipe emissions and outstanding fuel economy. They need to be plugged into charging stations to charge their batteries, which can take varying amounts of time based on the charger's capacity and the size of the battery. The Tata Tigor, Tata Nexon, MG ZS, Mahindra E20 plus, Hyundai Kona, Mahindra Verito and the Chevrolet Bolt EV are all notable examples of battery electric vehicles.

In addition, there are FCEVs, commonly referred to as zero-emission vehicles, which use fuel cells to generate electricity. The chemical energy of the propellant is directly converted to electricity. Some of the examples of fuel cell electric vehicles are Toyota Mirai, Honda Clarity Fuel Cell, Hyundai Tucson FCEV, and Hyundai Nexo. In an effort to lessen greenhouse gas emissions, air pollution, and reliance on fossil fuels, the various kinds of electrically powered vehicles support the movement toward sustainable mobility.

1.3 Modes of EV charging and power specifications

Electric vehicles rely on specialized charging infrastructure to charge their batteries, and the methods of recharging can vary depending on the available power sources and technologies. In addition, the charging speed and time required to achieve a full or partial charge are affected by the power rating of the charging stations [9]. Moreover, there are two primary charging systems employed for charging the EVs: AC charging and DC charging. Perhaps, AC charging makes use of on-board chargers that are able to transform alternating current into DC power within the car. In contrast with this, DC charging converts power prior to its entry into the vehicle. Once the electricity has been converted, it is subsequently delivered to the battery of the vehicle, thus avoiding the use of the vehicle's internal on-board converter, as illustrated in Fig. 1.2.

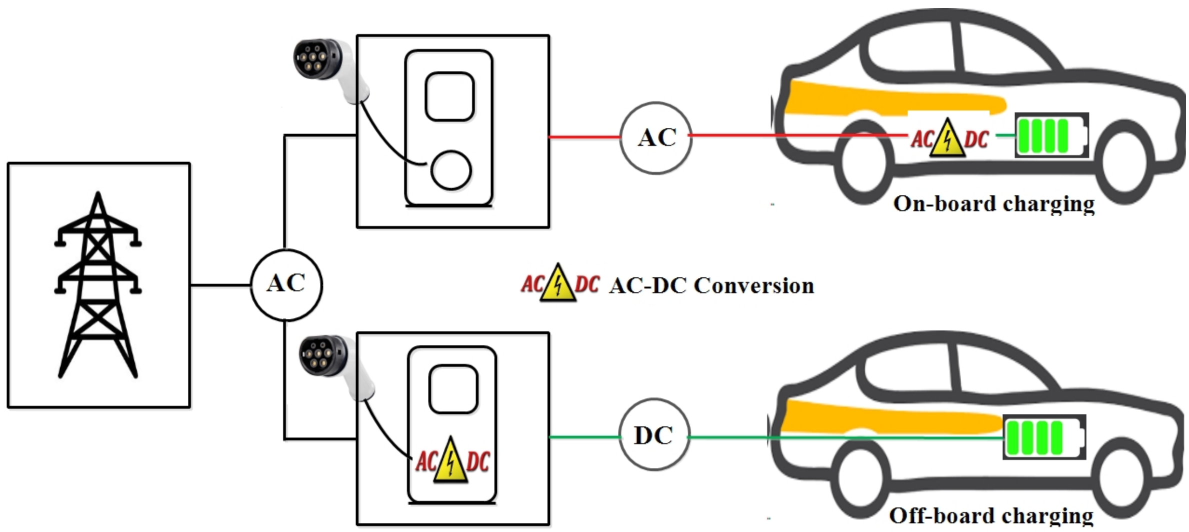


Figure 1.2: AC and DC charging architecture

Different charging arrangements, often referred to as 'charging levels', correspond to different voltage and current ratings. In addition, the number of hours required to charge the vehicle depends on the level of charging. The Society of Automotive Engineers (SAE) provides a classification to each of these charging levels, as can be seen in Table 1.1 [10].

Table 1.1: AC charging specifications at a glance.

AC Charging	Current (A)	AC Voltage (V)	Power Output (kW)	Primary Use
Level 1	12-16	120/230	$P \leq 3.7$	Residential and workplace charging
Level 2	12-80	208/240	$3.7 \leq P \leq 19.2$	Residential, workplace and public charging
Level 3	150-400	208/480/600	$P \geq 19.2$	Residential, workplace and public charging

The capacity of an on-board charger is an important feature to take into consideration when purchasing an EV. The rate at which an electric vehicle can be charged is proportional to the charger's ability to draw AC power from the grid and to make use of the available phases. For instance, if a vehicle is equipped with a 4kW on-board charger, its charging rate cannot exceed 4kW per hour. Therefore, to enhance charging speed the transition from AC to DC charging stations becomes necessary. DC chargers perform the conversion from AC to DC externally, hence avoiding the need for EV's on-board charger. As a consequence of this, DC chargers are capable of producing far more power than their AC counterparts.

Similar to AC charging, DC charging is categorized based on the power levels, as outlined in Table 1.2 [10]. In particular, charging in mode 3 requires a high amount of power and is highly associated with the concept of rapid charging. It is a type of charging in which users are willing to pay a premium fee to charge their vehicle as soon as possible [11]. Additionally, the charging cost, charging time, cost of charging stations, voltage level, current level and other factors vary depending on the various charging levels. Further, IEC 61851-1 international standard also classified charging modes for EVs similar to ones mentioned in Table 1.2 [12].

Table 1.2: DC charging alternatives for electric vehicles.

DC Charging	Current (A)	DC Voltage (V)	Power Output (kW)	Primary Use
Level 1	$I \leq 80$	200-450	$P \leq 36$	Residential, workplace and public charging
Level 2	$I \leq 200$	200-450	$P \leq 90$	Residential, workplace and public charging
Level 3	$I \leq 400$	200-600	$P \leq 240$	Public charging

Charging stations are designed to fulfil the purpose of supplying electricity to charge the EV batteries. Initially, the EV charging station will establish communication with the electric vehicle to guarantee a safe and efficient connection for the flow of electricity. In the case of slow charging, no interaction with the on-board charger is required beyond connecting the vehicle into a conventional 3-pin 5-amp or 15-amp outlet. For moderate EV charging, power rating typically start at 2.5kW and can scale up to 30kW. Further, power ratings of currently available DC chargers range from 25kW to 60kW, with even more powerful models expected to become available in the near future.

Despite the fact that high-power DC charging for EVs reduces the time to charge the vehicle, it requires a more reliable energy grid with additional infrastructure [13]. Therefore, standard charging stations are sufficient for majority of charging needs, along with overnight or slow charging of EVs. Apart from this, swapping batteries is a relatively new technique for recharging batteries that is gaining popularity on an international scale. In this approach, a wasted EV battery is removed from the vehicle and interchanged with another that is completely charged. This technology is being explored for application in numerous types of EVs, including two-wheelers, four-wheelers, and even electric-buses.

1.3.1 Stages of electric vehicle charging

Charging an electric vehicle requires a series of complex processes that convert electrical energy from the grid into usable energy stored in the battery. In order to ensure that there is an adequate transfer of power, the process may involve on-board or off board conversions. Meanwhile, when an electric vehicle is plugged into a charging station, be it a standard household outlet or a fast charging station, the charger establishes a two-way data link with the EV's on-board circuits [14]. The alternating power that comes from the grid is converted to direct current by the charger, regardless of whether it is on-board or off board. As it may be seen in Fig. 1.3 below, the charger, which is commonly referred to as an AC/DC converter, plays an essential part in the conversion process.

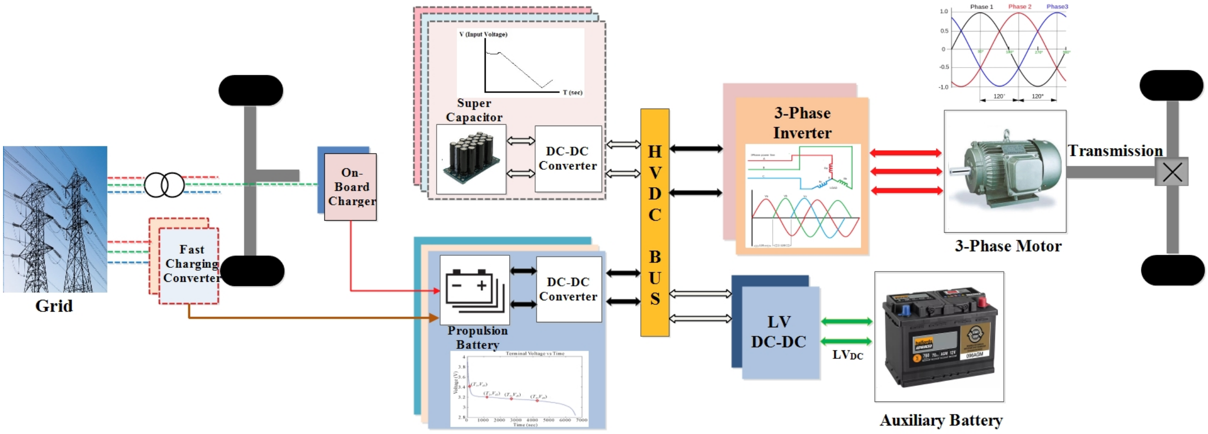


Figure 1.3: EV charging process

Further, the HVDC bus transfers the converted power to the on-board converter within the charger. At this stage, some of the power is typically sent to charge the vehicle's auxiliary battery, which supplies electricity to features like the stereo and the climate control system [15]. Thus, the primary battery is preserved for longer by being used mostly for propulsion. The charging process also involves the Battery Management System (BMS), which monitors the state of the battery, temperature, and voltage levels to ensure secure and optimal charging. The BMS maintains communication with the on-board control unit, thereby mitigating the risk of either overcharging or overheating the battery.

During rapid charging, which is made possible by high-powered fast charging stations, both the charger and the vehicle must be able to manage higher levels of power. Henceforth, the heat released during rapid charging generally necessitates more advanced cooling technology. The charging of an electric vehicle requires a wide variety of specialized equipment, including off-board AC to on-board DC conversion, HVDC buses, inverters, auxiliary batteries, and advanced management systems.

1.4 Electric mobility and grid integration

The provision of electricity for charging EVs operates within a regulated framework that spans various levels. There are sets of regulations and practices, some of which are generic in nature, while others are specifically designed for charging set-ups [16]. More importantly, the integration of EVs with the power grid represents an important bridge between the transportation and energy sectors. Further, this integration involves multiple dimensions, with the initial step being the physical connection of EVs to the grid [17]. To enable this, a suite of compatible charging infrastructure is required, ranging from the convenience of standard household outlets (Level 1) to the rapidity of DC fast chargers.

Furthermore, it is essential to consider the harmonization of EV charging with the existing grid infrastructure. The Vehicle-to-Grid (V2G) concept advances this integration by enabling a two-way energy exchange between EVs and the grid as shown in the Fig. 1.4. Equipped with V2G capabilities, EVs become versatile energy storage units, capable of not only drawing power from the grid but also injecting excess electricity back into it [18]. In addition, this technology has the potential to enhance grid stability, optimize renewable energy utilization, and ensure a more balanced energy ecosystem as mentioned in Table 1.3.

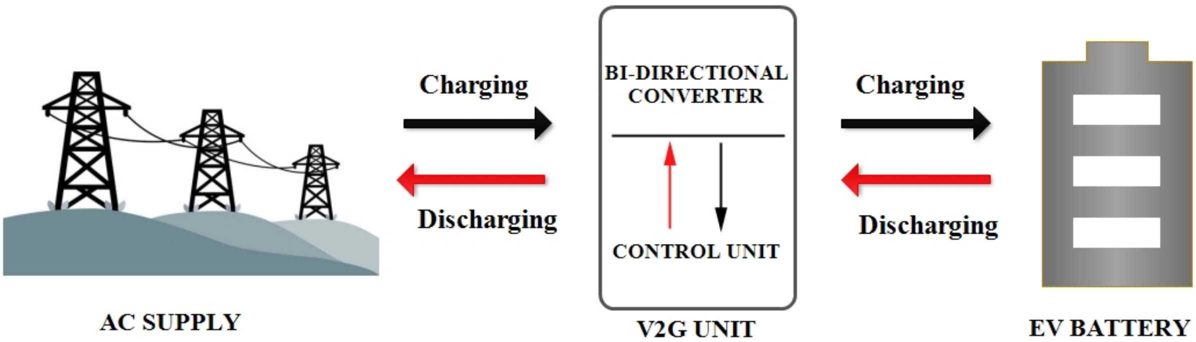


Figure 1.4: Vehicle-to-Grid Technology

During times of high energy production, V2G-enabled EVs can absorb surplus energy. Subsequently, during peak demand periods, they can release stored energy back into the grid. To facilitate this, V2G introduces sophisticated vehicle energy management systems that prioritize battery health and efficiency, all while accommodating user preferences and grid necessities. Beyond its technical capabilities, V2G presents economic opportunities through ancillary services. Moreover, aggregators can orchestrate groups of EVs as a virtual power plant, actively participating in tasks like frequency regulation and enhancing grid stability [19]. This dynamic engagement benefits both EV owners and the overall grid, offering potential revenue streams while reinforcing the resilience of the power network. However, implementing V2G requires meticulous attention to factors such as battery lifespan, charging cycles, and user convenience, ensuring a harmonious balance between grid support and vehicle sustainability.

Table 1.3: V2G Characteristics

System	Definition	Services	Benefits	Drawbacks
Unidirectional	Power flow from grid to EVs	Ancillary Service-load levelling	Maximum profit minimized power loss, operation cost and emission	Service range
Bidirectional	Power flow between vehicle to grid in both the directions	Peak power shaving, reactive power support, voltage regulation, harmonic filtering, Integration of renewable sources, spinning reserve	Maximum profit, improved load profile, maximization of renewable generation, minimized emission and power loss, prevent grid from overloading	Fast battery degradation, complex hardware, social barriers

Likewise, tariff plan implementation is also an important concept for EV charging integration. Pricing models such as time-of-use (TOU) and demand-based rates provide incentives to EV users to charge during periods of lower electricity demand. Hence, it not only optimizes grid utilization but also mitigates strain on the grid during peak consumption hours [20]. Moreover, the collaborative approach is further enhanced by demand response mechanisms, enabling utility companies to communicate with charging stations, temporarily adjusting charging speeds to align with grid stability and fluctuations in electricity demand.

1.4.1 Metering Infrastructure

Advanced metering systems serve as the cornerstone for smart grids, which allow utilities and customers to communicate in both directions. In addition, the possibilities for real-time load management, demand response programs, and effective energy distribution are made possible with the help of smart metering. Also, the customer participation in energy management programs can be increased by the integration of bidirectional meters and EV charging infrastructure [21]. Access to data in real time gives consumers the ability to make educated decisions about when and how to charge their EV, which in turn contributes to the conservation of energy and the reduction of associated costs.

Furthermore, metering requirements for EV charging infrastructure are crucial for accurate measurement, efficient management, and transparent billing. For charging stations, particularly those located in public spaces or business settings, precise metering is essential to track the electricity consumption associated with each charging session. In this way, customers can receive accurate bills and have a better understanding of the costs incurred. In addition, advanced metering systems are able to record factors such as charging duration, voltage levels, and charging rates to detect the amount of energy that is consumed. Hence, it provides a more comprehensive understanding of the charging process.

Additionally, there is a significant role for metering on the DC side of the electric vehicle charging infrastructure, particularly for fast-charging stations. As shown in Figure 1.5, DC side metering results in measuring the amount of DC power that is supplied to the vehicle's battery while the battery is being charged [22]. This measurement not only ensures accurate billing but also aids in load management and infrastructure optimization. With the proliferation of high-powered DC fast chargers, accurate DC metering is more crucial than ever. The information gathered via direct current metering has the potential to contribute to a better understanding of the influence that fast charging has on the grid and to facilitate improved grid planning.

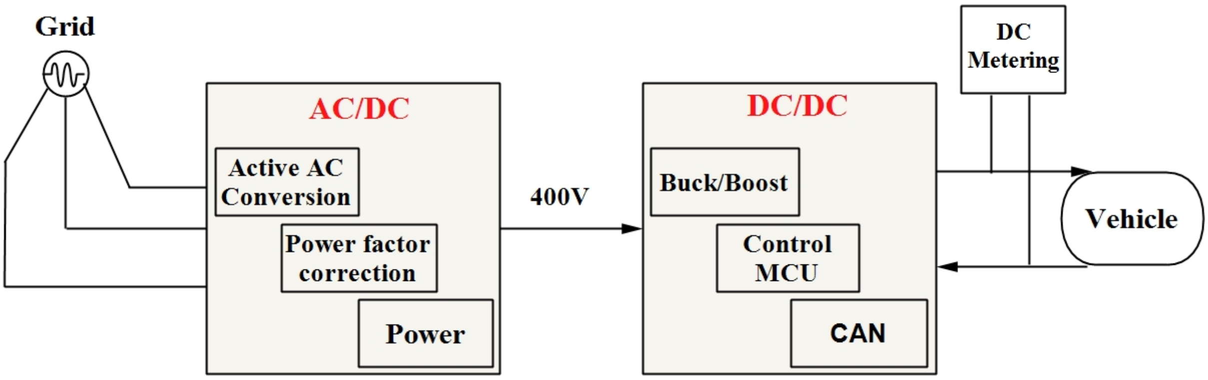


Figure 1.5: DC metering

In addition, a significantly more advanced concept in metering is known as ”net metering,” and it involves a bidirectional measurement of energy. This measurement not only takes into account energy consumption, but it also takes into account energy that is supplied back into the grid via V2G interactions. Further, it facilitates a comprehensive evaluation of the energy flow, allowing EV owners to offset their electricity bills by contributing excess energy from their charged vehicles to the grid [23]. Hence, the adoption of renewable energy sources is well-aligned with this two-way energy exchange. For example, excess energy generated by sources such as solar panels can be stored in EV batteries and then returned to the grid during high demand periods. As a result, the utilization of renewable resources is increased to its full potential, and grid efficiency is improved.

Not to mention, bi-directional metering facilitates the development of V2G technology, which uses EVs function as distributed energy resources. Meters that are equipped with V2G capabilities may record both the energy drawn from the grid and energy supplied back to it [24]. In order to promote a more balanced and resilient energy network, this gives utilities the possibility to pay consumers for their grid contributions, especially during periods of increased demand or system instability. The incorporation of advanced metering infrastructure into EV charging systems lays the groundwork for a dynamic energy ecosystem, empowering consumers to become active participants in energy generation, consumption, and management.

1.4.2 Net metering

Net metering is an approach that allows the customers with their own electric generation capacity to receive financial compensation for the energy they produce as shown in Fig. 1.6. Furthermore, net metering is first introduced in terms of Photovoltaic (PV) generation. In addition, it is the policy first implemented in the US in the 1980s [25, 26]. It is widely recognized that net metering plays a pivotal role in promoting distributed generation (DG), particularly solar energy. In 2018, a remarkable 97% of the generation capacity aligned with net metering program was comprised of solar photovoltaic modules (such as rooftop solar). According to information from the U.S. Energy Information Administration (EIA) [27], net metering participation nearly quadrupled between 2013 and 2018. Moreover, it is important to note that the term ”net metering” is commonly used to refer to an approach known as net energy metering (NEM). Under NEM, electricity supplied to the grid by a net metering consumer is compensated on one-to-one basis for electricity purchased from the grid [28]. However, the manner in which consumers of net metering are reimbursed varies significantly between states.

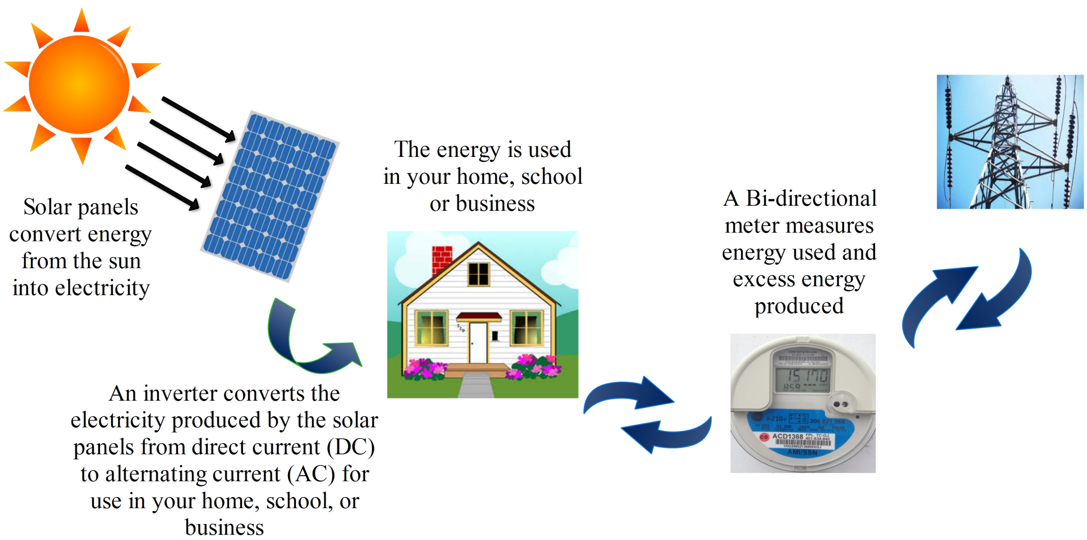


Figure 1.6: Bidirectional flow of power from home to grid

For billing purposes, each unit of electricity a customer generates is deducted from the quantity of electricity they consume (usually expressed in kilowatt-hours, kWh). It is common practice to refer to this phenomenon as ”the meter running backward. Moreover, as of April

2019, 45 states have regulations regarding net metering that mandated utilities must provide customers with the option to participate in net metering. According to the EIA, nearly 2 million users took part in the net metering programs in 2018, compared to approximately 153 million total electricity customers [28, 29]. In other terms, roughly 1% of electricity customers in the United States participated in net metering in 2018 but the numbers are predominantly increasing.

Meanwhile, the concept of vehicle-to-grid includes a number of significant components, one of which is net metering, which serves as a mechanism for the dynamic exchange of energy between EVs and the grid. However, it is still very early in the implementation process for V2G. In this innovative system, EVs equipped with bidirectional charging capabilities become more than just mobile batteries; they transform into integral components of the electricity network. In the context of V2G technology, net metering allows EV owners to not only draw energy from the grid to charge their vehicles but also to feed excess electricity into the grid during times of high demand. This bidirectional flow of electricity is monitored by smart metering systems, which measure the energy consumed from and supplied to the grid. In turn, the utility account of the EV owner is adjusted based on the net difference between energy drawn from the grid and energy injected into it.

Nevertheless, net metering is the concept which is often got confused with the bidirectional metering or dual metering. In dual metering, there are two separate meters but they do not communicate with each other. However, both the meters (usage meter and generation meter) are tied to the electric company account. Perhaps, net meter will measure the bidirectional flow of power and customers need to pay the net amount of their electricity consumption [30].

1.5 Achieving smooth electric vehicle integration

Efficiently incorporating EVs into the broader ecosystem requires a comprehensive strategy that aligns transportation, energy, and infrastructure sectors. The following sections will delve into the major aspects that play a critical role in attaining successful integration of electric vehicles.

1.5.1 Distributed Infrastructure for EV charging solutions

Concentrating charging stations, especially high-power chargers at a single point escalates the demand for EV charging. Further, it may necessitates infrastructure changes when the permissible capacity of a feeder is surpassed [31]. Therefore, it is advisable to deploy charging infrastructure in a distributed manner to lower the power demand for charging individual site. Moreover, a strategic approach that aims to efficiently integrate electric vehicles into the existing energy grid is a decentralized electric vehicle charging infrastructure. By dispersing charging stations into different areas, prevents an accumulation of charging demand that might overburden local grids during peak hours. Henceforth, the strain on the grid is lessened and the likelihood of power outages is decreased by equally distributing charging infrastructure.

Beyond its grid-related advantages, decentralized charging infrastructure offers tangible benefits for EV owners and the broader community. The convenience and accessibility of charging stations in various locations reduce ”range anxiety” concerns and encourage wider EV adoption [32]. Placement of charging stations in public areas, workplaces, and businesses not only improves the usability of these areas, but also correlates with sustainability initiatives by promoting the use of clean transportation. Furthermore, the decentralized infrastructure integrates seamlessly with renewable energy sources, such as solar panels, which can augment the use of clean energy during EV charging. It makes use of the resources that are available locally, which helps to reduce the carbon emissions that are caused by transportation. In addition, the balanced distribution of charging loads reduces the effects of sudden demand spikes, benefiting utility companies and grid operators by reducing the need for rapid changes to compensate for fluctuations [33].

1.5.2 Dynamic load management for electric vehicle charging stations

The growing adoption of EVs bring-forth increased charging demand, which pose various challenges at multiple levels, including utilities service area and feeder networks. On one hand, aggregated demand for charging has the potential to either worsen the peak demand or create new demand peaks (also known as secondary peaks) [34]. Conversely, intermittent increases in EV charging loads can have adverse effects on the distribution network, especially in areas where electricity feeders have limited available capacity. In addition, uncontrolled or uncoordinated EV charging, also known as simple or dumb charging, can disrupt the efficient operation of the electrical distribution system. This disruption can manifest as voltage fluctuations, harmonic distortions, increased power losses, and a decline in reliability inductors [35]. In instances where EV charging stations draws power from an existing connection, uncoordinated charging can lead to voltage instability within the host establishment's electrical system.

A vital strategy for maximizing the integration of EVs into the electric grid is EV load management, which guarantees efficient energy usage, system stability, and affordable charging options. In order to balance the growing demands of EV charging with the capacities of the grid, this approach employs a number of methods, such as load forecasting and decentralized charging. The success of load management for EVs relies on the accuracy of the load forecasts. Forecasting future charging demand assists grid administrators and utilities in anticipating peak load periods and planning grid resources accordingly. In order to deliver real-time and accurate future demand, advanced data analytics and machine learning algorithms assess previous charging patterns, weather conditions, and other variables [36].

Furthermore, demand response approaches make it possible for utilities to communicate with electric vehicle charging stations in order to alter charging prices dependent on the state of the grid. During times of high electricity demand, utilities can temporarily slow down or halt charging to lessen the stress on the grid. In exchange, EV owners may receive financial rewards for taking part in demand response initiatives, which reduces the cost of charging EVs [37]. This two-way communication helps to ensure the stability of the grid while also preserving the convenience for owners of electric vehicles. The critical requirement to find solutions to the challenges that are being caused by the integration of electric vehicles, renewable energy sources, and current electrical grids is the motivation behind this research.

1.6 Research objectives

With various challenges considered, the research seeks to achieve the following objectives::

1. To model a DC net meter for vehicle-to-grid technology at 15kW level.

2. To design and develop a DC net meter for off-board EV charging systems with a time of usage (ToU) capability

3. To develop and demonstrate a DC net meter on 15kW level charging systems.

The first objective involves the detailed modelling of a 15kW-level DC net meter that has been designed exclusively for V2G applications, allowing seamless energy exchange between the grid, EVs, and other energy sources. By simulating various scenarios and configurations, the proposed design effectively measure the bidirectional energy flow in V2G that contribute to grid stability while maximizing benefits for both EV owners and the entire energy system. Further, the second objective focuses on the development and implementation of a DC net meter capable with time of use (TOU) capabilities, which is essential for maximising energy consumption and grid stability.

The proposed TOU-enabled DC net meter has the potential to greatly reduce the pressure on the grid during peak load periods by allowing EVs to operate as flexible storage units that adapt to grid demands and supply changes. Last but not least, the research aims to establish the practical demonstration of the DC net meter on 15kW-level charging systems, showing its effectiveness, reliability, and potential to contribute to a more efficient energy ecosystem.

1.6.1 Thesis organization

The thesis is structured into seven chapters, each designed to fulfil a distinct role in the research.

1. Chapter 1 provides an introduction that outlines the objectives of the study and presented key concepts such as EVs, their charging infrastructure, V2G technology and the DC net metering system. It is important in laying the groundwork for the research since it clarifies the necessity of understanding the aim and objective of the study.

2. Chapter 2 presents a comprehensive overview of the existing literature related to DC meter design for various applications, dynamic pricing, EV load forecasting and EV charging infrastructure. Furthermore, based on the research challenges outlined in this

chapter, suggestions for constructing the foundation of the research methodology are presented.

3. In Chapter 3, the development of DC net meter has been presented for V2G technology. This chapter includes information on international standards, parameter selection, hardware development and software modelling of the DC net meter. Further, a developed DC net meter of upto 30kW power measurement tested on the real-time bidirectional environment. The results and findings of the experiments are explained in detail.

4. In Chapter 4, a TOU-based pricing structure specifically proposed for off-board EV charging systems has been introduced. Along with this, the implementation of DC net metering policy in conjunction with TOU scheme has also been discussed. An in-depth description of the system framework is provided and a case study is used for simulation. The simulation results are shown to validate the proposed pricing structure. Further, the developed DC net meter is also tested in a bidirectional lab environment utilizing the same pricing structure.

5. In Chapter 5, the optimization of electricity demand is discussed within a decentralized charging infrastructure. The proposed scheduling algorithm is intended to help with the effective management of EVs and to deal with any unexpected arrivals. Further, results from simulations are used to validate the proposed algorithm and to show how effective it is. The chapter ends by summarizing the key findings and and contributions covered.

6. In Chapter 6 a novel approach for energy management of public charging stations employing an attention-based deep learning model is discussed. Comprehensive discussion of dataset selection, data preparation, and intricate modelling strategies is provided in this chapter. To assess the efficacy of this novel method, the results obtained are compared to those generated by conventional machine learning algorithms, highlighting the improved accuracy achieved.

7. Chapter 7 is the conclusion chapter. It summarizes the research, including the literature review, research methodology, results, and analysis. The chapter also discusses the impli-

cations of the research findings, provides suggestions for future research, and concludes the study.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

The phenomenal rise in energy demand led to the integration of the existing grid with renewable sources. Another factor that promotes the use of non-conventional resources is the worsening of the ecological environment. Many researchers are working on the reduction of greenhouse gases, low fuel consumption, alternatives to crude oil, etc. However, still today in India, 70% of the electricity generation is thermal or coal-based. Hence, it is quite evident that the dependency on fossil fuels is very prominent in the country. Globally, various countries have started to shift themselves to the eco-friendly generation or its consumption like solar rooftop generation, wind power generation, etc. However, to store the electricity a large battery packs are required. In order to eradicate the dependency on the large battery packs, the concept of direct export of energy to the grid came into existence. Furthermore, the export of energy to the grid can be measured by the smart metering infrastructure. Smart metering infrastructure includes two-way measurement, an advanced cloud platform for the exchange of information, and controlled equipment. Hence, this type of framework is required where there is a bidirectional flow of power. Presently, the integration of EV with the smart grid has emerged the opportunities in the metering infrastructure. However, the meter designed for various applications are different from the V2G meter in terms of power ratings and dynamic rating based on Time of Use (TOU). Consequently, the meters are different on the basis of single-phase or three-phase or DC meters.

2.1.1 Advanced metering framework

Nowadays, smart meters are considered as an essential part of the smart grids and it will enable bi-directional communication between the utility and the consumer. A smart grid would be successfully implemented by the deployment of advanced metering infrastructure (AMI) through smart metering systems (SMS). However, AMI is defined as an organized infrastructure that facilitates two-way communication between utility providers, consumers and smart meters [38]. The foremost requirements for AMI are higher bandwidth and low latency. Furthermore, it can be used to validate power outages, connect and disconnect services remotely, send load management and facilitate automated net metering system [39]. The architecture of advanced metering infrastructure has been shown in Fig. 2.1.

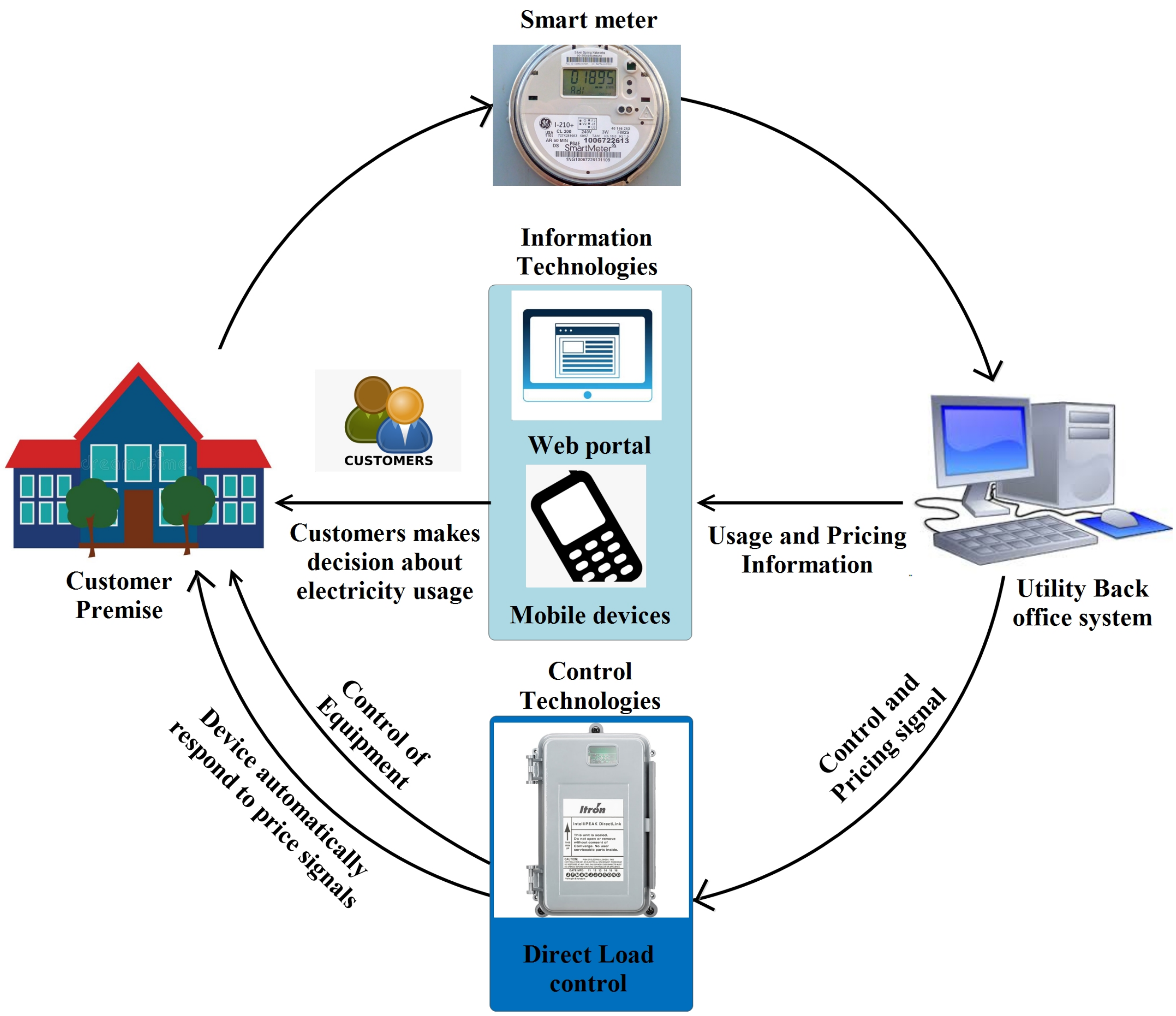


Figure 2.1: Architecture of the advanced metering infrastructure.

AMI goes beyond traditional metering systems by incorporating cutting-edge technologies, including smart meters, communication networks, and data management systems. Smart meters are at the core of AMI, replacing conventional electro-mechanical meters. These smart meters are equipped with advanced sensing capabilities, communication modules, and computational power. They measure electricity, gas, or water consumption with greater accuracy and at shorter intervals, often in real time or near-real time. Meanwhile, the data collected by these meters is then transmitted securely through communication networks, which can vary from wireless technologies like cellular networks, radio frequency (RF) mesh networks, power line communication (PLC), to wired options like Ethernet or fiber optics.

Once the consumption data is transmitted to the utility's data management system, it undergoes various processes to ensure accuracy, privacy, and effective usage analysis. Moreover, data encryption and authentication protocols safeguard sensitive information during transmission. The utility's data management system processes and aggregates the data, allowing for detailed consumption analysis, demand forecasting, and identification of potential issues such as energy theft or anomalies. One of the pivotal features of AMI is its bidirectional capability. Equally important, consumers can access their consumption data through web portals or mobile apps, fostering greater awareness of their energy usage patterns. Therefore, the real-time feedback empowers consumers to make well-informed decisions regarding energy conservation and peak demand management. Thereby, potentially reducing their bills and environmental impact. Furthermore, AMI facilitates the seamless integration of renewable energy sources, electric vehicles, and demand response programs into the grid, thereby enhancing its overall resilience and sustainability.

Moreover, net metering is the concept first introduced in the terms of PV generation, the majority of solar rooftop panels are installed behind-the-meter (BTM) [26, 40]. However, in this, only the net demand is registered which means the export of power minus the import of power. In the research conducted by [41], a novel approach is introduced to address the challenge of disaggregating BTM solar generation from the net demand. The proposed approach, known as Repeated Games with Vector Payoff (RGVP), stands out for its non-intrusive nature. By identifying and combining demand and generation patterns, the RGVP approach progressively enhances its accuracy in distinguishing between solar-generated electricity and actual grid demand, thereby providing valuable insights for energy management.

However, the effective operation of PV systems is not solely limited to accurate disaggregation but extends to considerations of power loss within the network [42]. Pragash et al. [43] delve into the impact of PV sizing and operating power factors on the total active power losses experienced in the power network. Using tools like the digsilent power factory, a detailed load flow and stability analyses has been conducted to quantify these power losses. By understanding the correlation between PV system characteristics and network power losses, the research contributes to the optimization of PV system design and integration, ensuring not only efficient energy generation but also minimal power wastage in the distribution system.

Furthermore, the integration of EVs into the energy landscape brings forth its own set of challenges and opportunities. In the study conducted by [44], the focus lies on effectively managing the charging of a large fleet of EVs within the context of a net-metered PV parking lot. The challenge here is to accommodate the charging needs of numerous EVs without overwhelming the grid or compromising the operation of the net-metered PV system. Through the proposed algorithm, the study explores strategies to ensure balanced and optimal charging across the fleet. The results emphasize the need for a sufficient number of charging stations that can accommodate the maximum battery capacities of EVs. This demonstrates the importance of careful infrastructure planning and management in realizing the full potential of renewable energy-integrated EV charging systems.

The studies conducted by [41,43–45] offer crucial insights for designing a specialized meter for V2G applications. As V2G systems often involve EVs as mobile storage units, effectively managing their charging and discharging is paramount. The algorithms proposed in the above studies can offer valuable insights into developing strategies that optimize energy flows and utilization within the V2G ecosystem.

2.2 Need for DC metering in V2G technology

The current architecture of the grid controls the unidirectional flow of energy from the central plant to the end users. With the introduction of distributed energy sources, power management becomes a very difficult task. As a result, the end users have to bear the consequences of poor energy quality [46]. In the above viewpoint of bidirectional grid transfer, the measurement of power at the utility and consumers' end becomes more necessary. Therefore, in V2G technology the measurement of power at the battery end is also essential. So far, smart meters have been developed to measure the power flow on the grid side. For instance, the smart meter developed in [47] for V2G technology can measure the power on the grid side by using energy measurement chip ADE7758 and microprocessor S3C2440. Likewise, a smart AC power meter with voltage and current rating of 0-300Vrms and 0-20A is developed in compliance with IEC 61000-4, 62052-11 and 62053-21 [48]. In addition, an AC net meter has also been developed to measure the net import of electricity in the V2G technology [49]. It is worth noting that several smart meters were designed to measure the power on the AC side of the system.

Few studies have been conducted to evaluate the power on the DC side of the smart grids including the solar panels and other equipments. Perhaps, the designed meter for these applications cannot satisfy the need of the charger energy measurement due to its high voltage and current charging ratings [50, 51]. Further, the losses in the converters throughout the rectification process must be measured precisely as power measurement accuracy is a critical requirement for grid-tied systems. As a result, the transmitted energy must be separated from the losses experienced in the converter stations to provide a fair distribution of grid operation expenses. Furthermore, it is estimated that a considerable amount of the energy is lost in the rectification process [52]. Also, it is to be said that what is not measured cannot be controlled thus cannot be improved. Therefore, to improve the power transfer capability and to share the energy resources efficiently, bidirectional DC measurement is required.

Various DC meters have been developed to reduce the consequences faced by the end users with different electrical ratings. For example, a DC revenue meter for nanogrid is developed to measure the losses caused by DC/AC and AC/DC conversion up to 140V DC [53]. Correspondingly, a dual-core energy meter for DC charging station has been designed based on an organization of legal metrology R46 International recommendation [54]. The proposed system adopts the SoC chip with the microcontroller in a dual-core design. In DC, a perfect isolation is required between the input and output to avoid any discrepancies in measurement. Almost all the meters are developed with the basic current and voltage sensing techniques [52, 54, 55]. For example, a DC meter is being developed with a range of 400V DC and 80A [52] by using the low pass filters, resistor divider circuit and current sensor. Hence, to make the hardware circuit perfectly isolated an advanced circuit design is needed.

Additionally, it will be easier to assess power losses in a V2G system if it is equipped with both AC and DC meters. By keeping this in mind, power losses were extensively measured in [56] between grid and vehicle by using the Acu DC 243-C DC meter manufactured by Acuenergy and DM II plus power quality analyzer under different conditions. Both AC and DC measurements will give an accurate picture of the measurement. On the other hand, DC measurement is also less popular due to a lack of written standards for voltage and current transducers for DC meters [57]. IEC is currently in the process of developing the standard IEC 62053-41, aimed at delineating specific requirements specific for DC static meters used in measuring active energy with an accuracy class 0.5% and 1%. Similar to this, the DC meter designed in [50] for electric vehicle chargers has a maximum voltage and current deviation of 0.081% and 0.064% respectively. Further, the DC meter has been designed for EV charging application in [52] with the maximum current deviation of less than 1%, thus, claiming the Class 1 accuracy.

2.3 TOU pricing for efficient EV charging

The traditional power system has faced many challenges in managing higher electricity demand. With the advancement of technology, the current power system is transforming into a self-automated grid known as a ”smart grid”. Many researchers are actively involved in the field of smart grids. One notable work is conducted by [58] by proposing a smart power plant utilizing various battery storage systems. In addition to the research mentioned above on smart grids, there is also a significant focus on other critical aspects of power systems. Researchers such as [59] are actively working on developing restoration strategies for power systems to ensure quick recovery and resumption of services after blackouts or disruptions. In terms of EVs, the smart grid offers an intelligent charging solution that incorporates a V2G-enabled advanced metering infrastructure along with a dynamic pricing policy. Numerous studies have explored the integration of dynamic pricing in V2G applications. Some researchers have optimized electricity charges based on real-time pricing as it provides high rewards to the consumers [60]. However, RTP is considered uncertain and risky due to its hourly changing tariff rate.

Interestingly, the TOU rate structure relies on the historical data collected from the various smart meters [61, 62]. It aims to balance inefficient pricing strategies that charge a single tariff for an extended period and overly complex real-time pricing systems that dominate the wholesale market. Other benefits of the TOU policy in terms of EV charging include peak load shifting, battery optimization, EV route optimization, improved market operation, and so forth. For instance, in [63–65], an optimal charging and routing of EVs with the help of TOU pricing have been proposed. The research aims to reduce the electricity cost, the used number of cars, and the distance traveled. The proposed model shifts the load and reduces the electricity cost by 3.1%

Likewise, in [66], a model has been proposed to reduce the charging cost while ensuring all the EVs are fully charged. In addition, the research highlights the formulation of a bi-level programming model to resolve the scheduling issue. Similarly, a research conducted by [67] proposes a technique for EVs to adjust their charging schedule in response to TOU prices and the state of charge (SOC) curve. It also presents a heuristic approach to solve the optimized model and includes numerical simulations that compare the improved charging model to a traditional charging pattern. Further, the TOU pricing model has been implemented to study the impact of EVs on the distribution network, transformers, low energy consumers, and energy storage investments [68–71].

It is worth noting that TOU pricing systems are designed to regulate power demand. Several articles have examined how TOU schemes may be linked with or complement demand response schemes. With the help of V2G technology, the TOU policy offers significant advantages to EV customers. It enables them to lower their electricity charges by allowing their EV to deliver the power back to the grid during periods of high demand. The utility tariff rate will be determined by the time the energy was utilized (this includes hours of the day/night and seasonal rates).

2.4 Predictive modelling for EV demand

The rise of electric vehicles has ushered in a new era of transportation, with a greater emphasis on energy efficiency, environmental sustainability, and cost savings. However, the success of EVs relies heavily on the the accurate prediction of electric vehicle load [72]. The state-of-the-art load forecasting models can be classified into two distinct types: traditional statistical models and artificial intelligence (AI) models. The time series method, autoregressive integrated moving average, regression analysis, and Kalman filtering are the mainstays of conventional forecasting [73, 74]. While AI employs artificial neural networks, support vector machines, and deep learning techniques [75, 76]. Each algorithm has its own strengths and weaknesses, and the choice of algorithm will depend on the specific requirements of the application and the nature of the data [73, 75, 76].

Further, machine learning algorithms have been employed to analyse EV sales and public attitude's towards EVs based on a aggregation of neural network, a Long Short-Term Memory (LSTM) network, and a decision tree algorithm [77]. Moreover, the research conducted by [40, 43, 78], predicts the charging behaviour of individual EV drivers and multi-time scale EV load prediction by using the LSTM network with other ML algorithms, such as decision trees and SVM and ANN. The research reflects that the LSTM, as a deep learning algorithm is capable of capturing the time-series characteristics of the charging data more efficiently than any other algorithm.

Similarly, the study conducted by [79] proposed a hybrid machine learning approach based on real-world historical driving data to anticipate the remaining driving range of EVs. The mixed model combines the Extreme Gradient Boosting Regression Tree (XGBoost) and the Light Gradient Boosting Regression Tree (LGBoost) effective machine learning algorithms (LightGBM). Furthermore, an ensemble-based learning model has been studied in [25] by merging three base learners including the ANN, recurrent neural network (RNN), and long short-term memory (LSTM) algorithms. A dataset of electric vehicle charging loads from all city-owned electric vehicle charging stations in Boulder, Colorado, from 1 January 2018 to 31 July 2020, was used. This dataset, in particular, contains a summary of 20,562 random transactions.

Additionally, a clustering based EV charging infrastructure on UCLA campus and city of Santa Monica has been chosen as testbeds [80]. The research method combined the K-Means clustering and multilayer perceptron. The study summarizes a study on clustering electric vehicle (EV) drivers based on their driving behavior and preferences. Similarly, a research has been conducted by [81] to predict individual EV departures using regression models trained on historical data.

Machine learning algorithms are typically trained using smaller datasets and require less less computational resources. However, deep learning algorithms require large amounts of data and are specialized in solving problems related to large amount of data and complex non-linear relationships. Also, deep learning algorithms can handle unstructured data (such as audio, images and text), have many layers of interconnected nodes and can automatically pull characteristics out of the data. Several researches have been made in the field of deep learning for EV user behviour prediction.

For an instance, a comparative study has been made in [26,41,82] with other machine learning algorithms to accurately predict the driving patterns and charging behaviors of EV drivers. Moreover, [45] proposes cost predictions for an electric car battery based on LSTM. It has been discovered that LSTM outperforms typical backpropagation neural network algorithms. Other studies [23, 83–85] used LSTM to anticipate load demand, whereas [38] used gated recurrent units and obtained more accurate findings. The experimental results of these investigations reveal that deep learning models outperform traditional methods in terms of load forecasting accuracy.

2.5 Approaches for decentralized charging infrastructure

In recent years, EVs have garnered a lot of attention due to their potential to reduce greenhouse gas emissions and lessening dependence on fossil fuels. Nonetheless, the widespread adoption of EVs encounters several challenges, such as the expense related to charging stations, the investment needed to expand distribution systems, and the social cost incurred by users on the way to charging stations [86]. To address these challenges, recent research proposes various models and techniques to minimize the costs associated with EV charging infrastructure. One such proposal utilizes the Voronoi diagram and adaptive genetic algorithm to calculate the service range and charging load of charging stations for reducing the overall cost of EV charging infrastructure [87]. Another approaches involves the creation of a Centralized Management System (CMS) software designed to facilitate seamless EV charging [88, 89]. Similarly, an optimal planning of centralized charging and multipoint distribution networks has been proposed, which considers the battery logistics system [90].

Furthermore, a number of multi-objective optimal operating techniques have been proposed to improve the centralized battery swap charging system's (CBSCS) economic effectiveness while reducing its influence on the power grid. One such method involves the modification of the non-sorting genetic algorithm III (NSGA-III) to address the scheduling problem in CBSCS [91, 92]. In addition, a framework known as CCS-PV-EBS that integrates solar photovoltaic energy and an Echelon Battery System (EBS) made of retired EV batteries has been proposed to lower the cost of owning an EV [93]. To achieve optimal results in this framework, a Multi-Objective Natural Aggregation Algorithm (MONAA) has been developed. Moreover, a centralized system based on integer linear programming has been put forth to minimize the charging price per EV [94].

The main drawback associated with the centralized algorithm is that they are less effective in handling the communication disturbances, such as delays or packet losses as compared to decentralized approach. In addition, the computation time for the scheduling optimization took longer to complete when there were more EVs [95, 96]. Therefore, several researchers has shift their focus in analysing the decentralised form of EV charging infrastructure. For an instance, the charging fee of all cars at the charging station with constant charging demand has been minimized using the consensus algorithm in a decentralized fashion [97]. Moreover, to address challenges related to the potential lack of global information about the charging needs of all EVs and the computational burden posed by an increasing number of EVs, an EV-based decentralized charging algorithm (EBDC) and mobile edge computing (MEC) supporting architecture have been developed [98–100]. Further, an improved alternating direction method of multipliers (ADMM) algorithm has been proposed for promoting the power sharing between EV charging station in distributed framework [101].

Some researchers have also investigated the model that involve both centralized and decentralized architectures for the day-ahead optimal scheduling of EVs [102, 103]. For an instance, the distributed transactive model in [104] calculates the real-time willingness to pay (bid) for EVs and HVAC units to maximize social welfare and preserve households' privacy. Further, a novel approach called centralized allocation and decentralized execution (CADE) reinforced by a reinforcement learning (RL) framework has been proposed to maximize the profit of charging stations [105]. It is worth noting that various optimization techniques, such as model predictive control, reinforcement learning, and pricing schemes, are proposed to minimize charging costs and maximize profits.

2.6 Research Gap

Despite significant advancements in smart meters for monitoring power flow in V2G technology, there is a substantial research gap when it comes to measuring power on the DC side of smart grids. Existing meters that were developed for DC applications have restrictions on the voltage and current charging limits, which makes them unsuitable for measuring power in circumstances that include high-voltage and high-current charging. Additionally, a thorough evaluation of the losses caused during the rectification process is required to guarantee accurate power measurement and a fair allocation of grid operation costs.

Furthermore, the broad acceptance and application of DC measurement systems is hampered by the absence of established standards for voltage and current transducers especially created for DC meters. The incorporation of both AC and DC meters would also significantly aid in the measurement of power losses in V2G systems. However, there is a lack of study on this integration, and in order to provide a more precise understanding of power flow and losses in V2G systems, extensive studies that incorporate both AC and DC measurements are required.

Meanwhile, a lot of research has been conducted on dynamic pricing policies like RTP and TOU pricing in the context of V2G technology. However, it is important to acknowledge that there are some research gaps in this area that require further investigation and exploration. For an instance, additional research is required to determine how to manage the risk and uncertainty associated with RTP. Additionally, the integration of TOU pricing with variables such as state of charge, demand response, and the effects on the distribution network requires further investigation. Comprehensive case studies and real-world implementations are necessary to validate TOU pricing models and provide practical insights for their adoption. For the evaluation of TOU pricing, there is also a need for more precise and understandable projections of EV load.

Likewise, load forecasting techniques available today include both traditional statistical and artificial intelligence (AI) models, each of which has benefits as well as drawbacks. The time-series characteristics of EV charging data have been successfully captured using deep learning techniques, especially Long Short-Term Memory (LSTM). In addition, machine learning algorithms have been applied to the study of EV sales, public perceptions, and charging behaviour. However, there is a gap in the field of attention-based deep learning algorithms, which have the potential to generate predictions that are more precise and understandable than those conventional deep learning models.

In order to schedule EVs optimally, researchers examined at both centralized and decentralized designs. They take variables into consideration such as real-time willingness to pay, maximizing societal welfare, and maximizing charging station profit. Nevertheless, these strategies frequently experience increased complexity, constrained scalability, and inadequate consideration of renewable energy sources and net metering. Based on the literature review and research gap identified, the broad areas for further research in EV charging infrastructure can be summarized as follows:

1. There is a need for DC net metering solution for EV charging infrastructure. It should involves the measurement of bidirectional power flow, dynamic pricing capability and interoperability standards.

2. An artificial learning based load forecasting model tailored to EV charging infrastructure is required to capture the complicated time-series data of EV charging.

3. A decentralised EV charging infrastructure scheduling ought to be studied for better scalability, resilience, and communication. To optimize charging station scheduling, consensus algorithms, decentralised control techniques, and peer-to-peer coordination mechanisms has been already explored. As a result, there is a growing demand for innovative decentralized EV charging algorithm that not only reduce costs but also alleviate the burden on the system.

Chapter 3

BIDIRECTIONAL DC NET METER

3.1 Introduction

The global transportation system depends on the internal combustion engine (ICE) which runs on petroleum fuels. Petroleum consumption increases from 32.5 million tons in 1981 to 184.7 million tons in 2015 [106]. Accordingly, the harmful emissions in the environment constitute about 36% NOx due to the vehicles itself. This suggests that conventional vehicles contribute to the issues such as depleting fuel resources, global warming, greenhouse gas emissions, and climate change. The electrification of vehicles is a crucial step in reducing the dependency on fuel imports and tackling the alarming situation of greenhouse emissions. It is also said that EVs are 4 times more efficient than ICE and has 50 times lesser moving parts [106]. The widespread adoption of electric vehicles (EVs) remains low due to the high initial cost, insufficient charging infrastructure, battery degradation and range anxiety. After a decade of phenomenal expansion, there were 10 million EVs worldwide on the road by the end of 2020 [107]. In fact, the International Energy Agency's 'Global EV Outlook 2021' research predicted that there would be 130 million electric vehicles on the road by 2030 [108]. Major automobile manufacturers have begun to introduce their electric vehicles and soon can be recognized as the future mode of mobility.

Moreover, the EV owners can utilize the energy stored in the electrical storage system (ESS) for additional benefits. The electric vehicle is often parked rather than driven by the owner. Meanwhile, this will provide an opportunity to use EV as a reserve to meet the demand and provide incentives to the customers. Since the ESS of the vehicle allows the bidirectional exchange of power, it can further be employed to import and export the energy from the grid. The idea is also known as 'Vehicle to Grid Technology', seeks to optimize electricity generation, its usage, and transportation by converting electric vehicles into "virtual power stations" [109]. This technology aims to reduce the pressure on the current grid at peak hours and offers a window to the consumers to save their money [110]. Additionally, the concepts such as vehicle to home, V2G, vehicle to vehicle have become increasingly vital in a grid-connected operation where there is a high energy requirement. For instance, the research has been conducted in [111–114] to ensure that the appropriate location is chosen while stopping to charge or discharge an electric vehicle by using the VANET-based communication. In addition, the research also investigates the implementation of vehicle-to-vehicle ad hoc wireless connection to optimally identified best charged/discharged EV pair to operate the V2V charging scheme.

However, for the successful implementation of V2G, a bidirectional meter is required to measure the export and import of power. In fact, various smart energy meters have been developed for the bidirectional measurement in vehicle-to-grid integrated technology [47, 115]. The designed meters measure the AC side of the conventional chargers and hence, there is no measurement of power lost in the rectification process [56]. For instance, the charging or discharging of high-capacity EV batteries is guided by the losses in the DC system [10, 12]. These losses are associated with the system due to the high current and need to be measured precisely. Alternatively, DC metering will help to measure the power delivered directly to the battery, ultimately leads to precise billing at the consumers' end.

Similarly, the new European Union Regulations 2019 are advising energy suppliers to only charge customers for the energy transmitted to the electric vehicle. Consequently, holds the energy service provider responsible for the power conversion and other losses [52]. This would undoubtedly lead to effective measurement and accurate invoice generation. Several studies have been carried out to implement DC side metering in various applications, including fault detection, HVDC, and V2G [57,116,117]. Furthermore, DC metering is still in its nascent stage due to measuring problems caused by high current and a lack of defined standards [52, 57]. In V2G transmission, if DC side metering will implement in addition to the net metering scheme, the energy cost and present net worth of the power system can be reduced [26]. EV owners can make extra money by selling excess power to the grid while compensating for grid inadequacies using the net metering system. The developed meter is one-of-its-kind and would measure the power flow while charging/discharging the battery.

3.1.1 Motivation

Electric vehicles are being offered as a cleaner form of transportation. By charging the vehicle at non-peak hours and return the energy at the peak demand period, V2G system could help to tackle the inconsistency of grid-connected operations. Furthermore, to measure the net energy transferred between the grid and EV, a bidirectional meter is required. Existing measurement method includes the detection of electricity at the grid side. However, prominent losses exist in the system due to the presence of power electronic devices for AC-DC conversion. Monitoring of power on the battery side will help to determine the losses that occurred in the charger [118]. With these considerations in mind, this research focuses on developing an integrated DC net meter of automotive-grade that essentially measures power on the DC side and depicts charger losses. The suggested technique integrates a widely used net metering scheme with the DC charging mechanism of electric vehicles [10]. In future work, a ToU based tariff regime can be implemented with the real-time clock (RTC) for adequate electricity consumption. It is designed in such a way that it can pass EMI/EMC testing with less effort.

3.1.2 Contribution

The contribution of the net metering policy is quite evident in terms of PV generation. It promoted the usage of renewable sources as well as provided incentives to the customers. The implications of the proposed DC net metering in terms of V2G are as follows:

1. The proposed DC net meter is one of its kind for V2G technology. It is designed for level 1 DC charging system in compliance with IEC 61000/60255/62052 and other international standards.

2. The DC net meter technology has been thoroughly tested in an actual operational environment. Hence, the proposed meter is in its final stage for commercial deployment.

3. The current state of knowledge regarding the development of DC meters is lacking in functional safety. Therefore, a proposed meter is developed by selecting components that are automotive electric council (AEC) qualified.

4. The net meter is ratified in the real-time V2G infrastructure in order to insure the functionality in the operational environment.

3.2 Proposed scheme for the DC net meter

The measurement and sensing techniques have been evolved in the recent years. Power measurement has progressed from unidirectional to bidirectional, and now to net metering. The goal of the technology is to measure the net amount of energy transported between the grid and the consumer [25]. Under V2G technology, the proposed net meter will measure the charging and discharging power from the vehicle to the grid at subsidized rates. However, the meter installed on the grid side is unable to monitor the losses that occur in the charger. Subsequently, if a separate meter is installed on the battery side, loss calculation must be simpler. Fig. 3.1 depicts the location of the AC and DC net meters in the bidirectional V2G system.

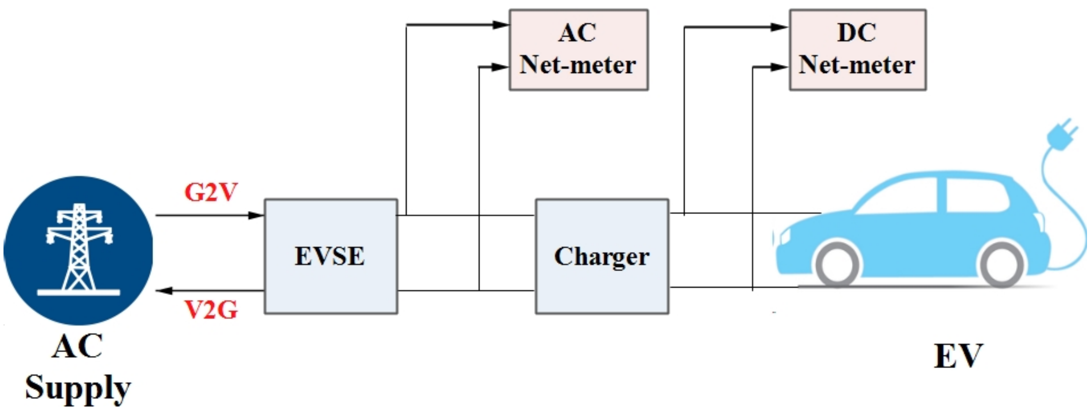


Figure 3.1: AC and DC net meter integration in Vehicle to Grid power transfer.

It is clear from the figure, the AC net meter will be installed on the grid side, while the proposed DC net meter will be installed on the battery side. Electric vehicle supply equipment guarantees that the charger and the vehicle are connected safely. Furthermore, the current will only flow from the charger to the car when a secure connection has been established.

In this research, a DC net meter will be designed for the V2G application at 30kW power level to derive a cost-effective solution. Despite being designed for a voltage range of 150V, the proposed net meter it can be configured upto 1000V without requiring significant changes to the PCB layout. By connecting EV as a storage device along with a net-metering plan, EV owners will be able to minimize their electricity consumption. Further, the net power drawn or delivered, P_{ev} by the EV is the difference between the charging, P_{ch} and discharging, P_{dch} power units. Mathematically, it can be written as:

$$P_{ev} = P_{ch} - P_{dch} \tag{3.1}$$

3.3 Designing Aspects of DC Net Meter

3.3.1 Standardisation of the DC net meter

The model of the DC net meter is developed in two stages: hardware designing and software implementation. Further, the hardware of the proposed meter is designed in two stages- analog and digital boards. Both boards have been designed in compliance with a number of international standards. For example, according to the IEC 61000-4 standard, a DC net meter is designated as level 3 since it can withstand a surge of 3.5kV. Table 3.1 [48, 52, 119, 120] lists the additional requirements that are taken into account while developing the meter.

Table 3.1: International standards.

Standards	Reference number	Remark
IEC/EN Standards	IEC 61000-4-4 IEC 61000-4-5 IEC 61000-4-6 IEC 61000-4-8 IEC 61000-4-17 IEC 61000-4-29 IEC 60255-22-3 IEC 60255-22-4 IEC 60255-22-5 IEC 60255-26 IEC 60255-27 IEC 62052-11	IEC 61000 deals with the requirement of fast load current variation, conducted differential mode current disturbance, fast transient/burst immunity, surge immunity, radio frequency, and electromagnetic field immunity tests to check the meter accuracy under certain disturbances. Whereas, IEC 60255 includes the test rules to ensure the protection within the power system environment. However, IEC 62052, particularly deals in the conditions associated with the type testing of DC meters
Standards related to Automotive vehicle & its charging	AIS 004, EN 50463-2	Automobile vehicle-Electromagnetic compatibility. EN 50463-2 is an old railway standard sometimes used for EV charging application

DC energy metering standardization appears to be less difficult than the present ac metering standards. However, the industry stakeholders are currently in dispute regarding the criteria for various applications. Consequently, in some instances, standards such as the German standard VDE-AR-E 2418 or the older railway standard EN 50463-2 are being employed for DC metering in EV charging applications [52]. As a result, the net meter is built according to the standards outlined in the above table. The technical specifications of the DC net meter are mentioned in Table 3.2 below.

Table 3.2: Ratings of the proposed DC net meter.

Parameters	**Ratings**
Voltage Range	0-150V
Current Range	0 to 200A
Resolution	100mV or 100mA
Accuracy	Class 1
Dimension	20 x 17 x 7cm

3.3.2 Architecture of the DC Net Meter

The basic architecture of the proposed net meter is primarily composed of DC current & voltage sampling, communication module, power supply, data storage, display and other units shown in Fig. 3.2. Individual sensors for the voltage and current are required to calculate the power absorbed by the load. The greater value resistor ($1M\Omega$) in the system suppresses any type of disturbance occurred in the form of noise. Further, the measured voltage or current will then be amplified and digitised after going through the resistor divider circuit, as shown in the diagram below. However, the accuracy of the measurement depends upon the processing and computation of the voltage and current sensor data.

3.3.3 Hardware Architecture

Voltage Measurement

A resistance potential divider is commonly used to measure high voltages. A series of resistors are employed to lower the voltage proportionate to a level that the ADC input can handle. Fur-

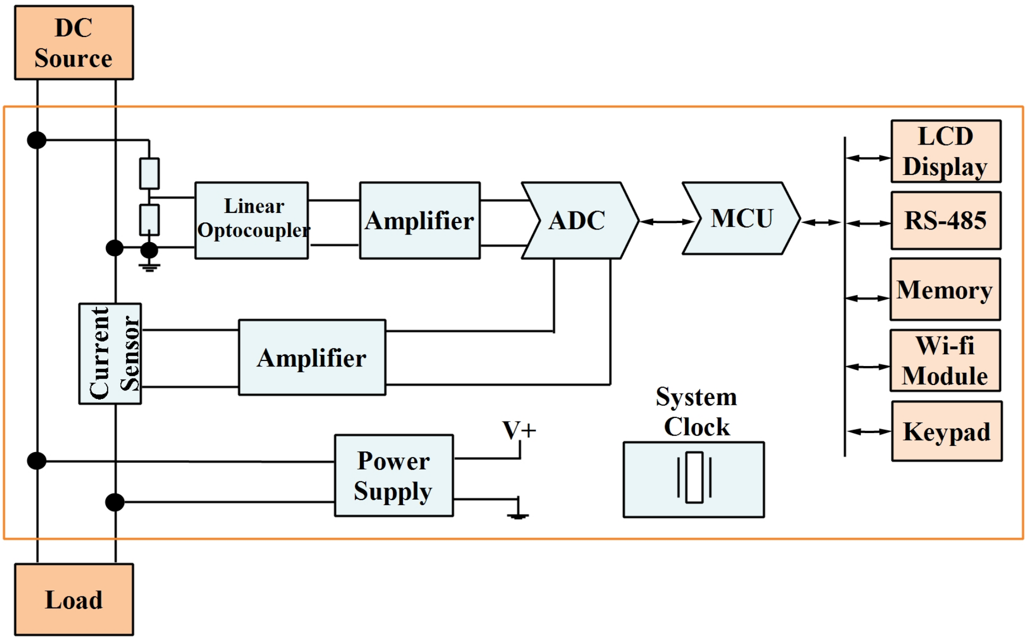
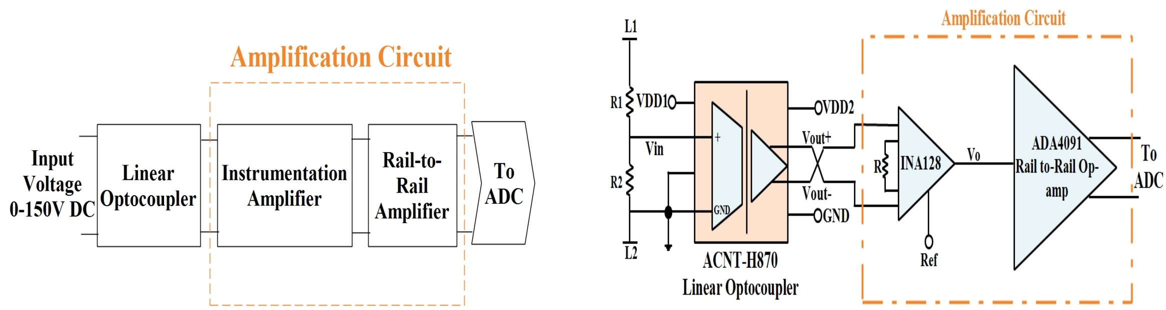


Figure 3.2: Basic architecture of the DC net meter.

thermore, standard components may be used to correctly assess high amplitude input signals, as shown in Fig. 3.3. The temperature coefficients of the desired component must, however, be taken into account to ensure the requisite precision at various voltage levels. The signal conditioning circuit for the incoming voltage is described in detail below.



(a) Block diagram for voltage conditioning circuit.

(b) Circuit diagram for signal conditioning process.

Figure 3.3: Voltage conditioning circuits.

i) Linear Optocoupler

As mentioned earlier, high value resistors are used to suppress the noise. Further, a resistor divider is used to scaled-down the DC voltage by choosing suitable *R1* and *R2* following the input range (0-2V) of the sensor. Here, the ACNT-H870 linear optocoupler is selected to pass a digital or analog signal, from input to output across an isolation barrier. It is specifically designed to provide a complete barrier between the input and output. However, a differential output voltage on the other side of the optocoupler is generated in proportion to the input voltage. The supply voltage given to the device is 5V and the differential outputs of the coupler *(Vout+, Vout-)* can be directly coupled with an op-amp to alter the single-ended output.

ii) Amplification Circuit

The output of the linear optocoupler is coupled with the input of an instrumentation amplifier INA128. The device works in the range of $\pm 2.5V$ and $\pm 18V$; however, the typical supply voltage of the device is $\pm 15V$. In addition, a single resistor pin R_g decides the gain of the amplifier in the range of 1 to 10000.

The simplified output voltage of the instrumentation amplifier is given below:

$$V_o = (1 + \frac{2R}{R_g})(V_{out+} - V_{out-}) \tag{3.2}$$

Since the device has a built-in protection circuit and buffer amplifier, there is no need for input impedance matching. The reference pin should be connected to the ground to ensure better common-mode rejection. The gain of the instrumentation amplifier INA128 is given in Eq. (3.3):

$$G = 1 + \frac{50k\Omega}{R_g} \tag{3.3}$$

where, gain resistor R_g is equal to 30kΩ and is connected between pins 1 and 8, the gain of the device is calculated as:

$$G = 1 + \frac{50k\Omega}{30k\Omega} = 2.66 \tag{3.4}$$

Further, the INA128 has a high input impedance and a common-mode rejection ratio which helps to reduce the noise in the system. As a result, it can be used for any measuring application. The single-ended output of the instrumentation amplifier is given to the rail-to-rail opAmp

ADA4091. The ADA4091 is a four-channel or dual-channel operational amplifier with rail to rail inputs and outputs. The INA128 produces single-ended differential output, which must be converted to rail-to-rail output before being fed to an ADC.

Current Measurement

The magnetic field intensity created by the flow of electricity can be used to determine the current. However, it can be estimated either by using direct or indirect connections, such as shunt resistors, Rogowski coils, current transformers, magnetic field-based transducers such as Hall effect sensors and fluxgate sensors. The direct connection includes the measurement of current by using the shunt resistor. By using the shunt resistor, both AC and DC currents can be determined. Furthermore, the measured voltage is quite low and can be amplified before being sent to the other devices. Although, it is a low-cost and reliable procedure, it does have some disadvantages. Therefore, this current measurement technique is generally used for low or medium power applications [121].

Additionally, a Hall effect-based or Fluxgate current sensor operates on the same concept, except the presence of the magnetic coil in the air gap in the latter. The exciting current present in the fluxgate becomes the prevalent source of noise and therefore, it exhibits more noise in the system [122]. For our application, WCS1500 linear hall effect-based current sensor is used to measure the current in the circuit. It can provide a large sensing range of up to 200A at 5V supply voltage. The output of the sensor is in the range of 0-5V or $\pm 2.5V$.

Further, the current sensor's output is transmitted to the input of the instrumentation amplifier INA128, where it is amplified or level shifted to provide the desired output as depicted in Fig. 3.4, which was designed in Altium Designer 17. The figure depicts the schematic layout of the proposed DC net meter, which includes voltage & current signal conditioning, 3V/5V voltage regulators, and switch mode power supply. Moreover, the analog-digital converter is then used to sample and digitize the output of the signal conditioning circuit.

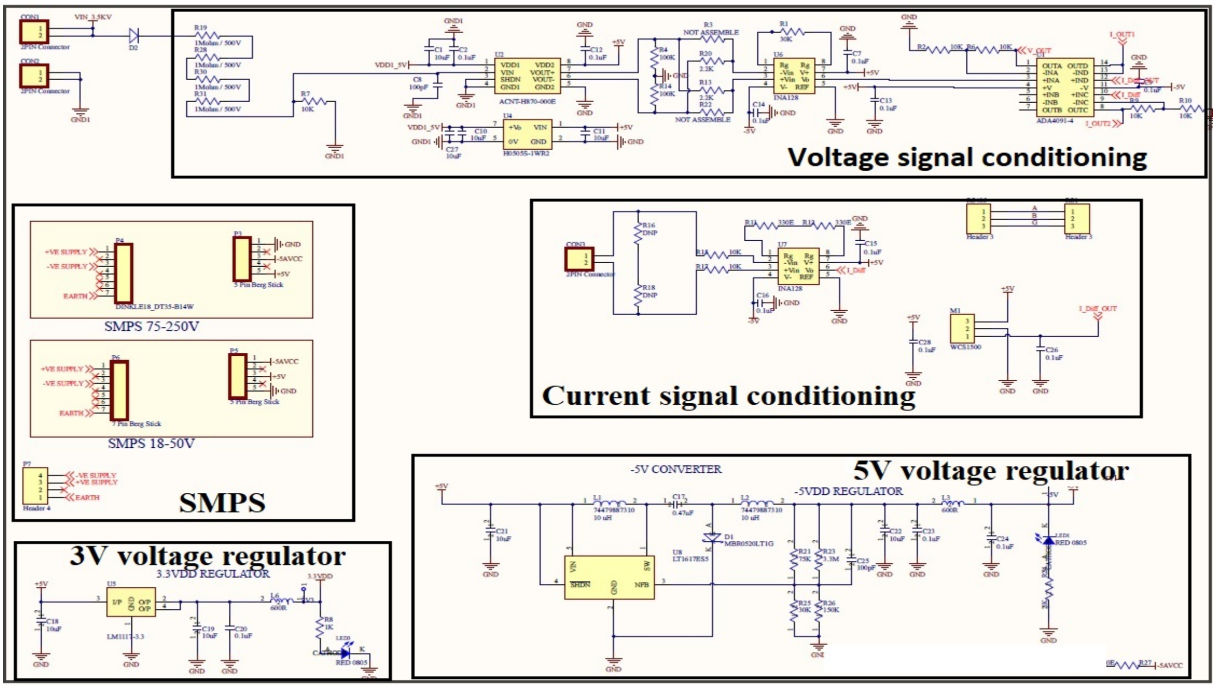


Figure 3.4: Schematic design for the DC analog board created in Altium 17.1.

Digital Design

ADCs (analog-to-digital converters) are employed in a wide range of electronics and commercial applications. The selection of an ADC is an important aspect of any electronic design. Microcontrollers launchpad typically have on-chip analog-to-digital converters (ADCs). In C2000 TMS320F28069M *Launchpad*, a 12-bit ADC is provided with around 16 input channels. For 12-bit internal ADC of input range 0-3.3V, the step size or minimum voltage that can be detected is computed as [123]:

$$S_z(N) = \frac{V_{in}(FS)}{R(2^N)} \tag{3.5}$$

where, $S_z(N)$ is the step size for N-bit. For 12-bit internal ADC, full scale input voltage $(V_{in}(FS))$= 3.3V and N=12

Then,

$$S_z = \frac{3.3}{4096} = 0.8mV \tag{3.6}$$

The on-chip ADC on the microcontroller is used for all general purpose applications. For specific applications, external ADC is required. The power losses are higher since the DC net meter operates on a high-valued current signal. Therefore, 16-bit ADC AD7606 supports the sampling of all the channels simultaneously with a throughput rate of 200ksps. Further, the conversion time on all the channels is around 4μsec. In addition, the device is integrated as it exhibits 152.6 μV resolution which is more than any other on-chip ADC. The step size or minimal voltage detection of 16-bit external ADC is calculated as:

$$S_z = \frac{5}{2^{16}} = \frac{5}{65536} = 0.07mV \tag{3.7}$$

The external ADC converts the incoming analog signal into the discrete signal and hence is interfaced between the incoming signal conditioning circuit and the C2000 MCU for further data processing. The 100-pin MCU has been chosen to design the digital board for the net meter, and it is programmed through the Code Composer Studio (CCS) to assess the various electrical parameters. Moreover, it is a cost-effective, real-time MCU of 90 Mhz CPU that exhibits minimal noise and distortion as it impacts the measured responses. It has an advantage in terms of input data processing since they are designed to perform intense numerical calculations including complex formulas [49, 124]. The digital board is designed in such a way that it supports FRAM for storage, a Wi-fi module & RS485 for real-time communication purposes, and an LCD for display as shown in Fig. 3.5.

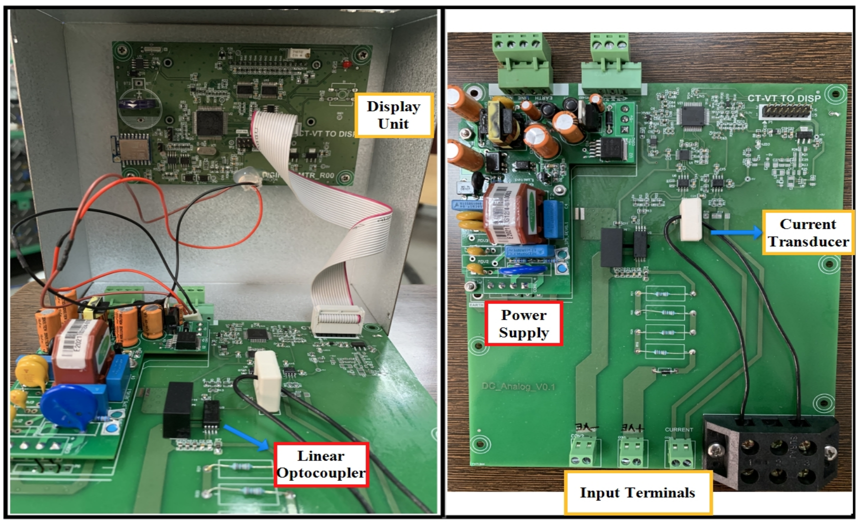


Figure 3.5: Hardware of the proposed DC net meter.

Further, a real-time clock (RTC) is also interfaced with the MCU to provide date & time information along with alarm signals. It will also be useful in implementing the ToU in the future.

3.3.4 Software Implementation

The measurement steps involved in computing and displaying the parameters at the end of the payment cycle is shown in Fig. 3.6. The voltage and current signal conditioning circuit processes the data before sending it to the 16-bit ADC to create a digital representation for further processing. Further, the microcontroller is programmed using C language in order to provide compatibility among C2000 series. The LCD panel displays the measured electrical parameters. Further, the clock will then synchronise and the parameters will be sent via communication modules. Finally, self-checking of parameters & components will be performed and the procedure will get repeated.

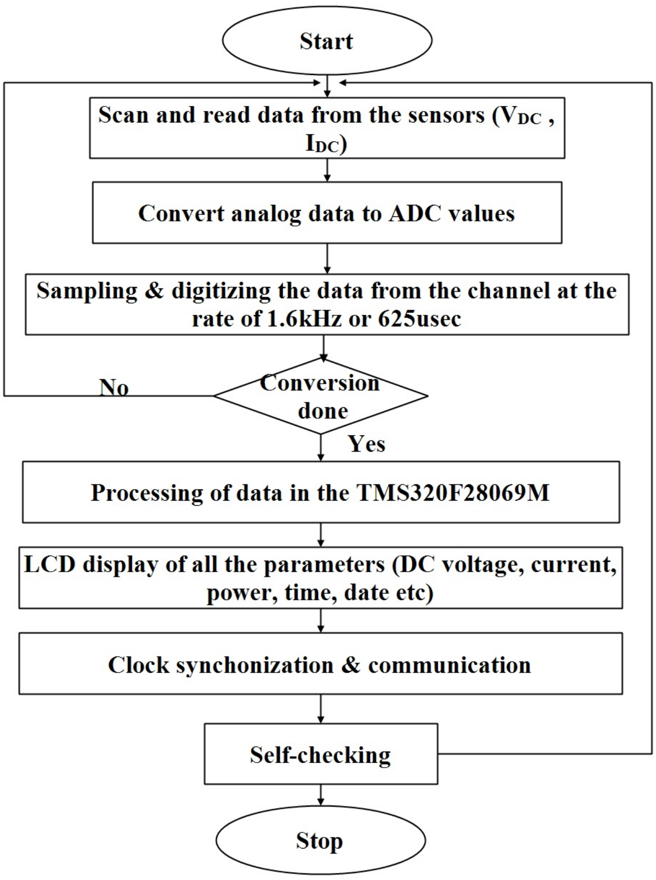


Figure 3.6: Process flow for the implementation of software.

The software implementation code is transferred to the hardware by using the XDS110 debugger. By implementing the code in the microcontroller, various electrical parameters such as I_{dc}, V_{dc}, P_{dc}, RMS component of ripple (I_{rms}, V_{rms} and P_{rms}) and frequency can be determined. Additionally, the built-in metrics enable the smart meter to characterize the bi-directional power flow through the node. For instance, the direction of current flow can be used to discern whether the node is supplying power (power generation) or absorbing power (power consumption). Likewise, such data is crucial for understanding the power dynamics between the grid and EV [125].

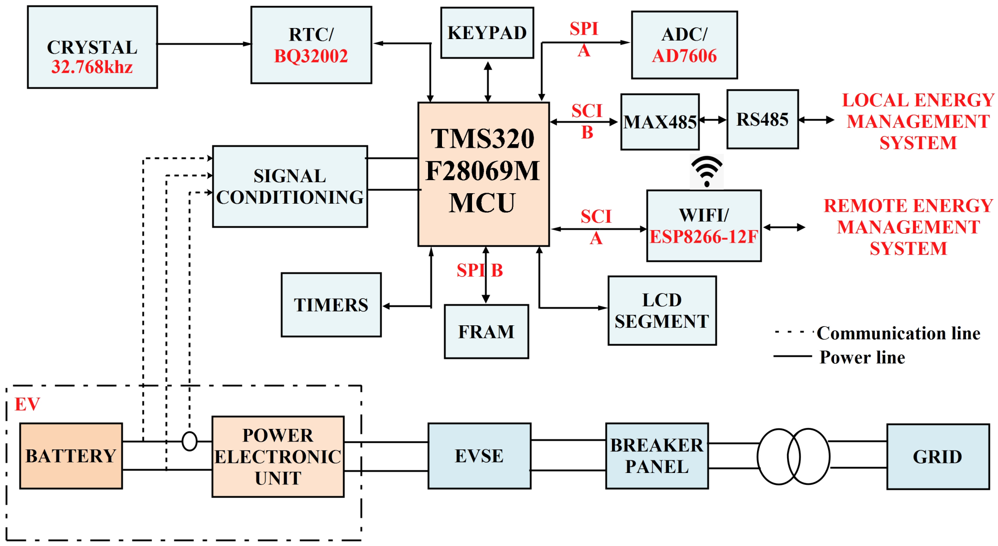


Figure 3.7: DC net meter communication with other peripherals.

The measurements obtained from the meter are further communicated with the help of RS485 interface as shown in the Fig. 3.7. The figure shows the integration of C2000 DSP core microcontroller unit with the other peripherals. The device communication allows the internet access for internet of things (IoT) operation and data management of metering systems in future. The data is serially transmitted from the meter to the local energy management system via the MODBUS protocol. However, to establish a communication with the remote energy management system, an IEEE 802.11 standard [126] based Wi-fi module ESP8266-12F is used to offer medium distance coverage. As a result, a DC net meter can communicate with other devices and send/receive command signals both locally and remotely. Measurements obtained from the meter is useful to multiple parties including energy providers, traders and consumers in order to analyze the demand, monitor each customer's electricity usage, and save money on their electricity bills [127]. Along with this, the developed net meter uses the 32k x 8bit flash RAM to solve the large amounts of data, memorize functions under power outage, and other issues.

3.4 Hardware Testing and Results validation

In this section, the tests were conducted on the aforementioned DC net meter to validate the desired results. Primarily, a test bench has been created to perform the hardware testing on the meter in order to verify the voltage and current signal conditioning circuit. Furthermore, a second test evaluation validates the meter operation in the V2G application. In this test, the experiment is carried out to ensure the accuracy of the meter in the real time bi-directional environment. In detail, a test setup configured in Fig. 3.8 examined the performance of signal conditioning circuits.

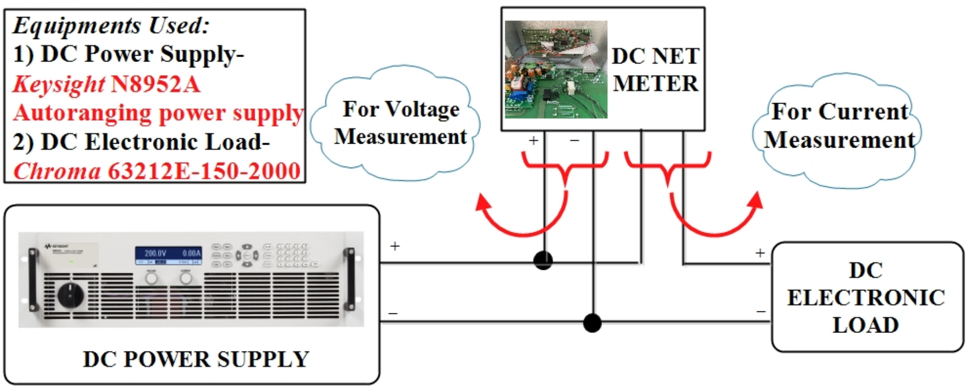


Figure 3.8: Test bench configuration for hardware testing.

As shown in the figure, a DC net meter is connected across the DC electronic load to validate the measurement results over the specified range. Typically, the environmental temperature was kept constant at 24°C while obtaining the measurements. The meter is manually calibrated for accurate measurement. At the beginning of the test, a steady current of 10A is maintained and a DC voltage signal with a step of 10V is generated in accordance with the measurement range. In the next, voltage has been kept constant at 48V and current has been swept from 0 to 200A. Fig. 3.9 and Fig. 3.10 display the results obtained from both the proposed DC net meter and

FLUKE 434 series power analyzer, allowing for a comparison between the two. The graphs are plotted between the reference DC voltage/current and the observed deviation in percentage.

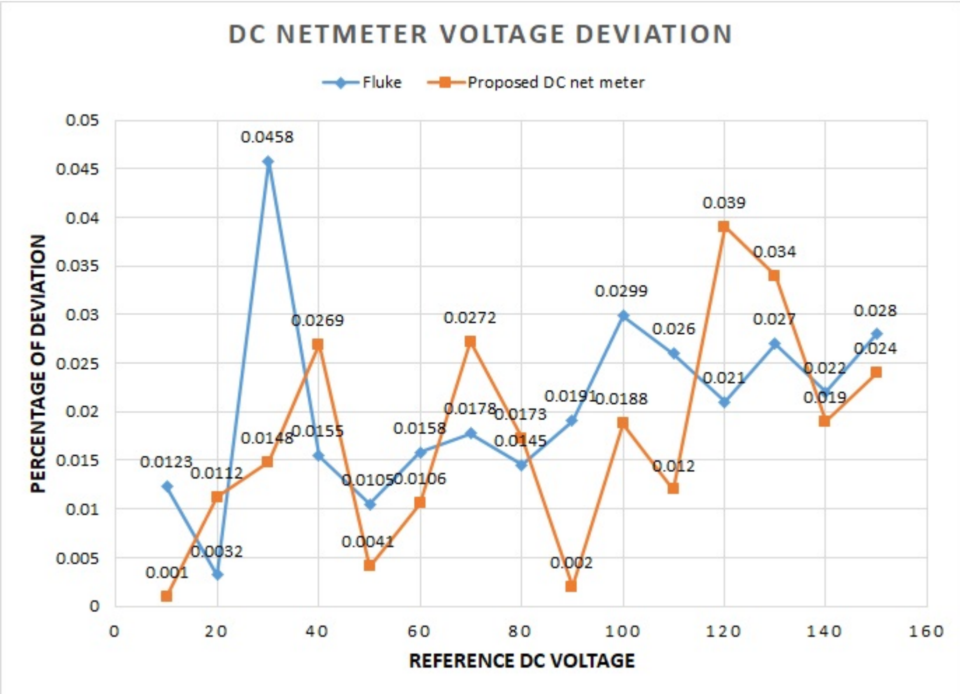


Figure 3.9: Percentage deviation of voltage.

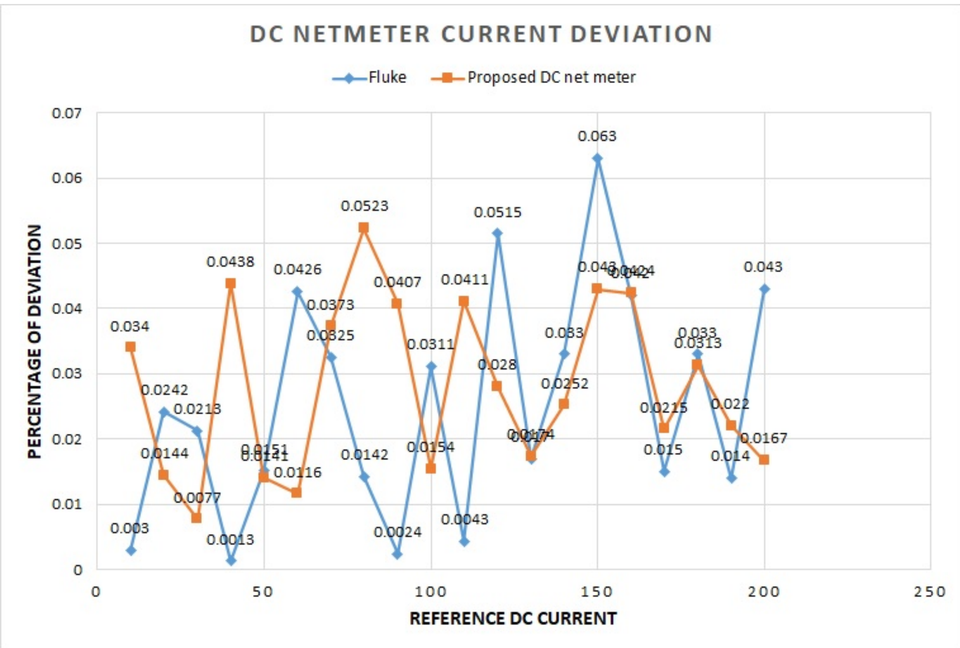


Figure 3.10: Percentage deviation of current.

The error or maximum deviation (E) is obtained by calculating the difference between observed and reference value and is given by:

$$E = y^p - x^p \tag{3.8}$$

where, x^p and y^p are the reference and observed value at any point p. Further, it is attributed from Fig. 3.9 and Fig. 3.10 that the voltage calibration curve has a maximum percentage deviation of 0.039%, while the current curve has a maximum percentage variance of 0.0523%. The error limit caused by voltage and current range is specified in Table 3.3 [52] in accordance with the international standards. For instance, the marginal error for Class 1 accuracy devices is typically less than 1%. However, the voltage marginal error in such case is limited to 1-2% adhering to the voltage range.

Additionally, the voltage and current error in the developed DC net meter is relatively low when compared to the DC meter designed in [50], which is 0.081% and 0.064% respectively as shown in Table 3.4. Similarly, a DC meter has been designed in [52] with a maximum current deviation of less than 1% stating the Class 1 accuracy. The outcomes obtained from the proposed DC net meter align with the standards requirements, thereby substantiating its class 1 accuracy classification.

Table 3.3: Maximum percentage error as per the standards.

Current range	**Marginal error (%)**		**Voltage range**	**Marginal error (%)**	
	Class 0.5	Class 1		Class 0.5	Class 1
1 to 10% $I_{nominal}$	1	1.5	less than 66% $V_{nominal}$	1	2
10 to I_{max}	0.5	1	66% to V_{max}	0.5	1

Table 3.4: Comparative results of the proposed net meter with the existing research work and Fluke analyzer.

	Proposed DC net meter	**Fluke power analyzer**	**DC meter in [22]**	**DC meter in [15]**
Maximum current deviation	0.0523%	0.063%	0.064%	Less than 1%
Maximum voltage deviation	0.039%	0.0458	0.081%	Less than 1.5%

Similarly, a second test bench configuration has been developed considering a specific V2G application, as shown in Fig. 3.11. The test bench comprises of a Keysight N8952A DC power supply, a Chroma DC electronic 63212E load, a battery, a DC net meter, and a switch. It is quite evident that a DC net meter is connected across the battery in order to measure the charging/discharging electrical parameters. A test bench set up of the proposed meter in the laboratory is shown in Fig. 3.12. The net meter performance is validated in both the charging and discharging modes. In the beginning, a battery is allowed to get charged up to a specific level by using the DC source. In a while, the battery is allowed to get discharged with the help of DC load [128]. In both conditions, the proposed net meter is connected across the battery to measure the current and voltage.

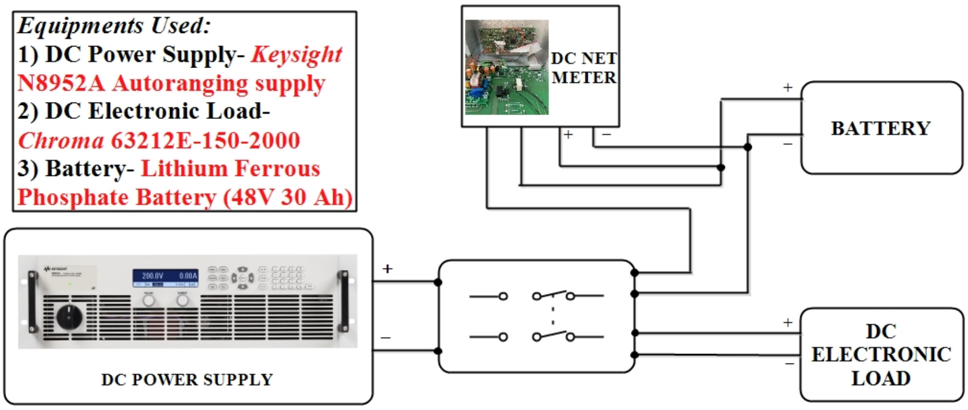


Figure 3.11: Test bench configuration for bidirectional measurement.

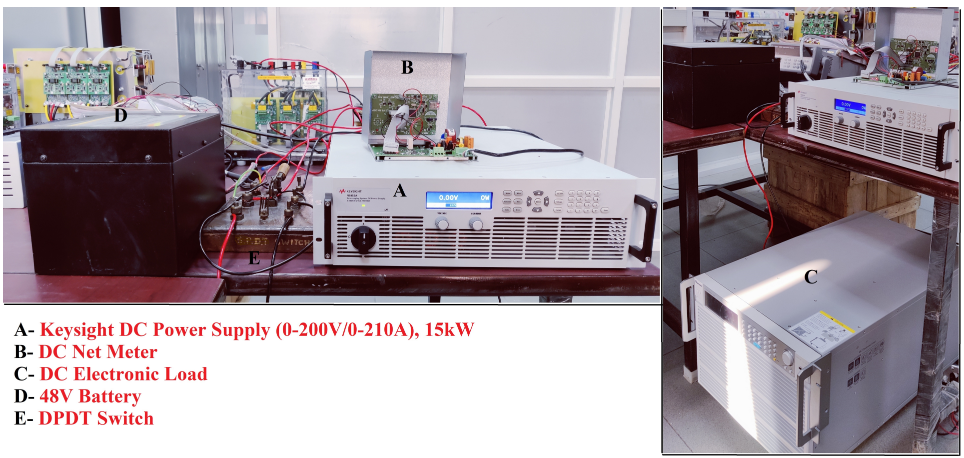


Figure 3.12: Test bench configuration of the proposed DC net meter.

The variations in the battery energy, denoted as $\triangle E$, throughout a charge/discharge cycle [129] can be expressed as:

$$\triangle E = \int_0^t \eta P dt \tag{3.9}$$

where, η represents the charging/discharging efficiency. Within charging stations, V2G can be implemented as a power reference in the feedback loop for regulating EV power. In this scenario, the calculation of EV power is defined as follows:

$$P_{EV}^{C/D}(t) = \begin{cases} -P_{EV}^{D} & V2G \\ P_{EV}^{C} & G2V \end{cases} \tag{3.10}$$

where, $P_{EV}^{C/D}$ indicates the EV charge/discharge power in V2G, P_{EV}^{D} is the EV discharging power and P_{EV}^{C} is the charging power of the EV. The battery involved in the experiment has the nominal voltage and current capacity of 48V and 30Ah respectively. Initially, the battery is allowed to get charged with a standard charging current of 6A. The initial voltage of the battery is measured around 43.5V form the net meter. Further, a constant current of C/5 rate is supplied to the battery. The CC/CV controlled algorithm is implemented inside the DC power supply. The measurement on the battery side is taken after 5hrs and it is recorded as 52.14V. On the contrary, a battery is allowed to get discharged by using the 1C-rate in the same test bench. In the end, the discharged voltage as recorded by the proposed DC net meter is 43.19V. The CC/CV characteristics of the battery are shown in the Fig. 3.13.

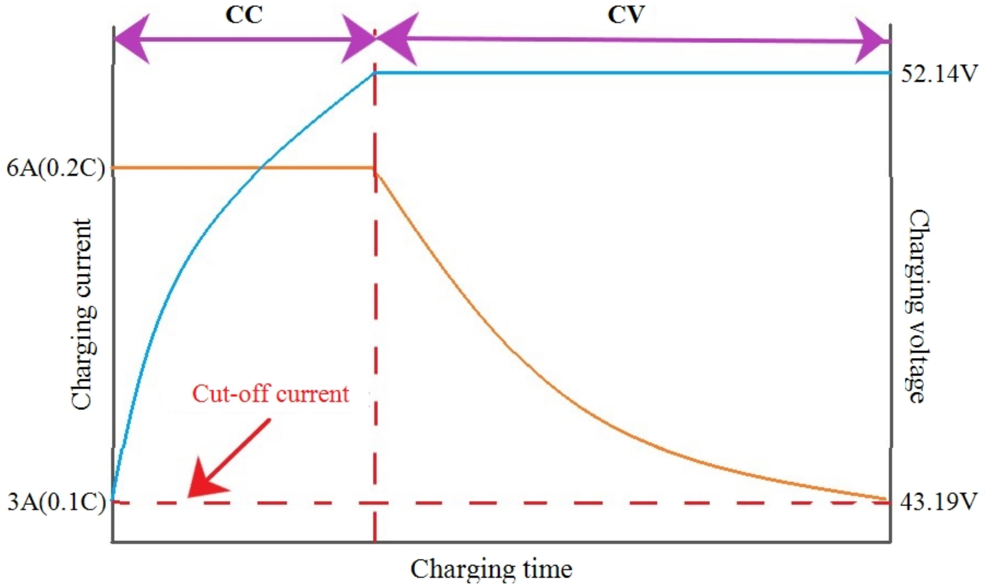


Figure 3.13: Battery charging and discharging characteristics.

By analyzing the results, it is evident that the DC net meter records the measurement with high precision. Each measured value as showcased in Fig. 3.9 and Fig. 3.10 has been compared with the reference value. This framework, however, can benefit from time of usage tariffs in the future when the regulator includes EV charging under the dynamic pricing regime. Furthermore, the proposed DC net meter has been tested in the real-time 2kW bidirectional charging infrastructure as shown in Fig. 3.14.

To better ensure the performance of the net meter for the V2G operation a 2kW bidirectional charging system has been setup in the lab facility. A 120V lead acid battery bank served as the load for a real-time charger, with a three-phase supply serving as the energy source. The charging system also comprises a transformer, buck-boost converter, voltage and current sensing module, Fluke power analyzer, and 2kVA voltage source inverter. Most of the parameters within the requirements are accurately measured by the DC net meter.

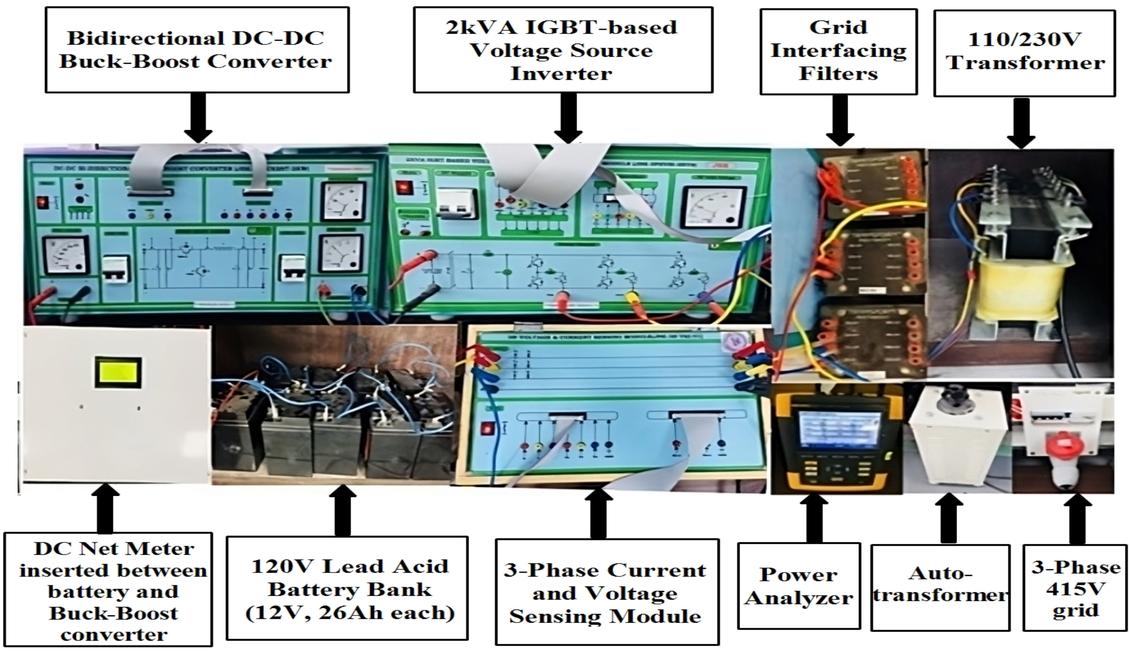


Figure 3.14: Experimental set-up of DC net meter in a bidirectional 2kW environment.

It is also worth noting that a single vehicle with a small kWh capacity has a minimal effect on the grid. However, as the number of electric vehicles grows, the impact on the grid operations may become severe. Due to the global goal of replacing traditional fossil fuel-based cars with electric vehicles, the capacity might range from mega-watt-hour to giga-watt-hour. As a result, in grid-connected systems V2G structures have become more prominent. On the other hand, the integration of V2G with a net metering scheme helps the EV owners to get paid by the distribution companies for transferring surplus power to the grid.

3.5 Conclusion

This chapter highlights the challenges associated with AC side metering and explores the research on DC measurement systems. The goal of this study is to present a V2G-enabled smart DC net metering system. The proposed net meter has been designed and developed in line with IEC 61000/60255/62052 and other international standards. The system has been presented through detailed sections covering both its hardware and software design. Compared to the traditional meter, the DC net meter has bidirectional power transfer capability via RS485 and Wi-fi. Besides, software implementation can guarantee the communication of data in real-time. The experimental results have demonstrated the net meter's compliance with the standard requirements. Following the software calibration, the percentage error of voltage and current measurements remain consistently below 1%, aligning with the stringent measurement standards applicable in electrical stations. In addition, the proposed meter can be further extended with the implementation of various dynamic pricing schemes such as, real-time pricing, time-of-use, critical-peak pricing and peak time rebates. Looking ahead, the integration of the internet of things (IoT) technologies holds promise for managing data from numerous DC net meters efficiently. Moreover, the integration of measuring device into the pre existing network to assure the inter-operability is yet another concern.

Chapter 4

DC NET METERING WITH TOU CAPABILITY

4.1 Introduction

Globally, the adoption of plug-in electric vehicles (EVs) has been observed to alleviate greenhouse gas emissions and the requirement for fossil fuels. In the years ahead, there will be an enormous rise in the population of electric vehicles on the road. The broad adoption of EVs alters the load profile, worsening the gap between energy demand and supply. Additionally, it leads to overloading of the system, increased losses, and other power-related issues. On the other hand, EVs are considered as a type of flexible load that can be switched over at different times of the day. However, the uncoordinated EV charging may necessitate the power system expansion and network reformation. To overcome this issue, a cost-effective solution involves strategically scheduling the charging and discharging of vehicles during off-peak or peak hours of the day. The charging pattern not only contributes to reducing peak loads but also facilitates valley filling, ensuring a more reliable operation of the power system [130].

The discharging of the vehicle is also represents a valuable source of on-peak electricity. In other words, "vehicle-to-grid technology" enables the unused power stored in the EV batteries to be pushed back to the grid when needed. Furthermore, dynamic pricing is necessary to encourage consumers to use their EVs' implicit storage capacity while determining the best charging schedule. Dynamic pricing strategies consist of inclined block rate, time of use (TOU), critical peak pricing (CPP), real-time pricing (RTP), and peak time rebates (PTR) [131]. Some other variants of the above mentioned pricing schemes include seasonal block rate, super peak TOU, and others. Since the price fluctuates every hour, the RTP pricing technique is considered to be most risky [132]. Further, the variation of prices in RTP has increased the odds of rewarding users. However, TOU is one of the widely used strategies in power systems due to its specific nature. TOU-based pricing can successfully shift the customers' demand in off-peak hours, avoiding the need for any unanticipated grid expansion.

Customers are compensated under the TOU plan for charging/discharging their vehicles during designated off-peak, mid-peak, and on-peak hours of the day, avoiding market fluctuations [131]. Additionally, the TOU rate can be fixed based on EV customers' historical load profile data. Furthermore, after reviewing historical data, an EV aggregator implements the TOU pricing structure for the year. It may be visible to customers in the form of tariffs. Time of use-based demand response is considered the most viable strategy for encouraging EV owners' active involvement and improved electricity market operations [133]. Several studies have been conducted on deploying a TOU-based pricing plan to coordinate EV charging patterns and improve power system operation [134–136]. In order to make the system more customer-centric, TOU based pricing scheme must be implemented along with a net metering policy. The net metering policy allows the customers to manage their net electricity import/export from the grid.

Net metering is introduced to transmit the surplus power the photovoltaic (PV) system generates to the grid. However, the concept of net metering in V2G technology is in its very early stage. Further, to avail the full benefits of net metering in V2G infrastructure, a meter should be kept at the battery side to account for rectification losses in the charger [52, 56]. In addition, DC net meter will measure the power that is only transferred to the EV [137]. Thus, in the context of V2G technology, the research intends to examine the impact of implementing a TOU-CPP/PTR pricing scheme and DC net metering policy. Further, it aims to understand how this pricing scheme can coordinate EV charging patterns, optimize power system operation, and maximize net metering benefits in V2G infrastructure. Moreover, a substantial gap in the field is a lack of a comprehensive and cost-effective solution to deal with unorganized EV charging. Therefore, this research examine the TOU-CPP/PTR pricing structure to demonstrate how well it reflects changes in energy prices and capacity costs, especially during peak seasons. Meanwhile, TOU can be used to indicate changes in the average daily energy prices, whereas CPP/PTR can be used to reflect capacity cost during the peak of the seasonal system.

The optimization of the microgrid-based case studies proves the effectiveness of the proposed research.

4.1.1 Motivation

EVs can also operate as a dynamic load in smart grids if used appropriately. The coordinated scheduling of the EVs aids the existing power infrastructure in reducing stress and average electricity consumption. This research examines the socio-economic benefits of a net metering-based TOU pricing scheme, focusing on EV charging/discharging strategies to lower the power cost. Further, the approach considers two significant factors: implementing dynamic pricing to charge/discharge the EV during low/high electricity demand to generate profit. Second, discharging an EV during a period of high electricity consumption can effectively decrease the demand for purchasing power from the grid. Thereby, it lowers the yearly capacity charge. Furthermore, the study analyzes the load profile by including the EV impact on the TOU-based pricing structure. Also, it proposes the DC net metering policy for EVs, which is an integral part of cost-cutting.

4.1.2 Contribution

Keeping the aforementioned literature in mind, the significant contributions are outlined as follows:

1 The proposed model assessed the adjustment charging and discharging schedules for EVs to lower customers' power expenditures, allowing them to achieve the lowest net-present cost.

2 In real time, a DC net metering based TOU scheme has been proposed based on EV demand and surplus energy available (stored in EV batteries).

3 The proposed scheme minimizes energy reliance on the grid, passing the benefits on to end customers in the form of lower energy costs.

4.2 Proposed Scheme

Electric vehicles are designed to provide a ecofriendly transportation alternative by minimizing the dependency on fossil fuels and reducing greenhouse emissions. Nevertheless, the unregulated charging of auto-mobiles puts a lot of strain on the power system. However, it may be possible to reduce the supply-demand imbalance and flatten the load curve by implementing coordinated charging in tandem with a time-of-use-based net metering policy. The proposed study has examined techniques for managing EV charging and discharging with the objective of lowering power costs for users and obtaining rewards. Further, this research determines the technical and financial benefits of using TOU-CPP/PTR-based pricing scheme implemented by the aggregator in charging/discharging the vehicle. Additionally, the study suggests the use of DC net metering, as depicted in Fig. 4.1, to charge or discharge an electric vehicle since it ensures precise power flow and eliminates rectification losses.

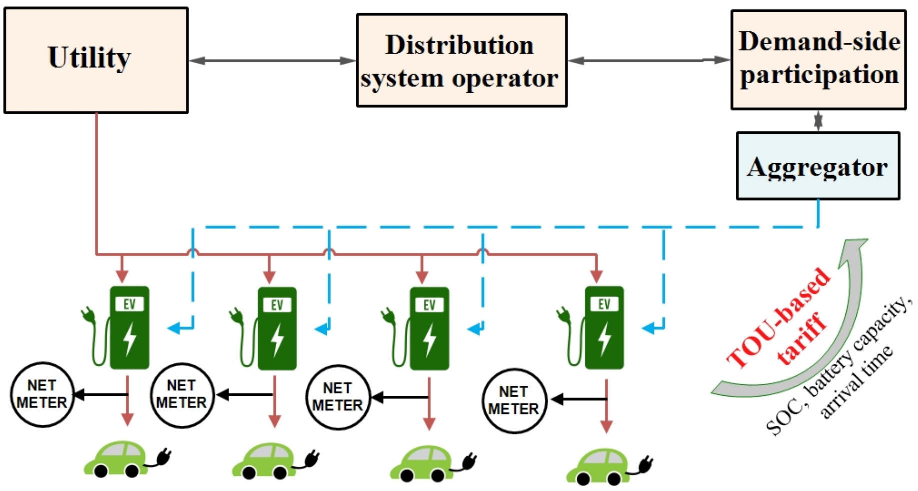


Figure 4.1: Basic architecture of the proposed system.

Moreover, the integration of DC net metering with time-of-use (TOU) policies benefits both users and service providers since it eliminates any hidden costs and instead promotes savings. The results of the pricing mechanism are explored using the functional microgrid case studies. However, the performance of the pre-designed DC net meter in relation to the same billing method is investigated in a 2kW bidirectional scenario.

4.3 Methodology of the proposed research

4.3.1 Overview of the proposed research

The average electricity cost of any building includes the cost of the imported grid power and the installation of any distributed energy and battery storage system. This can be illustrated as:

$$c_e = \sum (G_{im} + DG_{I,I,B} - DG_{ex}) \tag{4.1}$$

Here, c_e represents the cost of electricity, G_{im} is the cost of power coming from the grid and $DG_{I,I,B}$ is the injected renewable power cost, if any, or their installation with battery system, minus DG_{ex} which represents the export of surplus energy to the grid. If the inhabitants have an electric vehicle, the cost of charging the vehicle (EV_{ch}) must be included in the electricity bill. Eq.(3.1) can be rewritten as follows:

$$c_e = \sum (G_{im} + DG_{I,I,B} - DG_{ex} + EV_{ch}) \tag{4.2}$$

In order to fulfil the hourly demand, the infused electricity from the grid must be combined with the power generated by renewable sources and battery system. For balancing the equation, the average demand supplied for any building is defined as:

$$P_d = P_{DG} + P_G + P_b \tag{4.3}$$

Where, P_d represents the demand power, P_G is the grid power, P_{DG} is the power from the distributed generation and P_b is the power from the storage system. However, Eq. (3.3) can be rewritten if there is additional load in the form of EV charging.

$$P_{d_{new}} = P_{ch} + P_{d_{old}} \tag{4.4}$$

It has been highlighted that as more electric vehicles become available, demand will surge. Uncoordinated EV charging puts a large strain on the power system and widens the load curve's gap between peak and valley filling. To avoid this, it is necessary to coordinate vehicle charging and to use it as a regulated load to provide energy back to the grid. Meanwhile, there are some boundary constraints that limits the charging/discharging of EV and can be written as:

$$0 \leqslant P_{ch} \leqslant P_{ch}^{max} \tag{4.5}$$

$$0 \leqslant P_{dch} \leqslant P_{dch}^{max} \tag{4.6}$$

$$SOC_{min} \leqslant SOC \leqslant SOC_{max} \tag{4.7}$$

The charging and discharging power are represented by P_{ch} and P_{dch}, each with a set level of limitations (P_{ch}^{max}, P_{dch}^{max}). Subsequently, the operating modes (i.e. V2G or G2V) of EV can be chosen depending on their state of charge, SOC (SOC_{min}, SOC_{max}) and time. For instance, if an EV's SOC is less than 20%, the vehicle will cease discharging and charge during non-peak hours as shown in Fig. 4.2. The EV also rapidly discharges to balance the predetermined capacity if the SOC is more than 20% and the load demand exceeds the contract capacity [138, 139]. Nonetheless, an EV also has the ability to discharge when demand for power is lower than contracted capacity and energy prices are high. In such instances, instead of a flat pricing structure, a time-of-electricity-usage plan is used to effectively coordinate the charging and discharging of EVs.

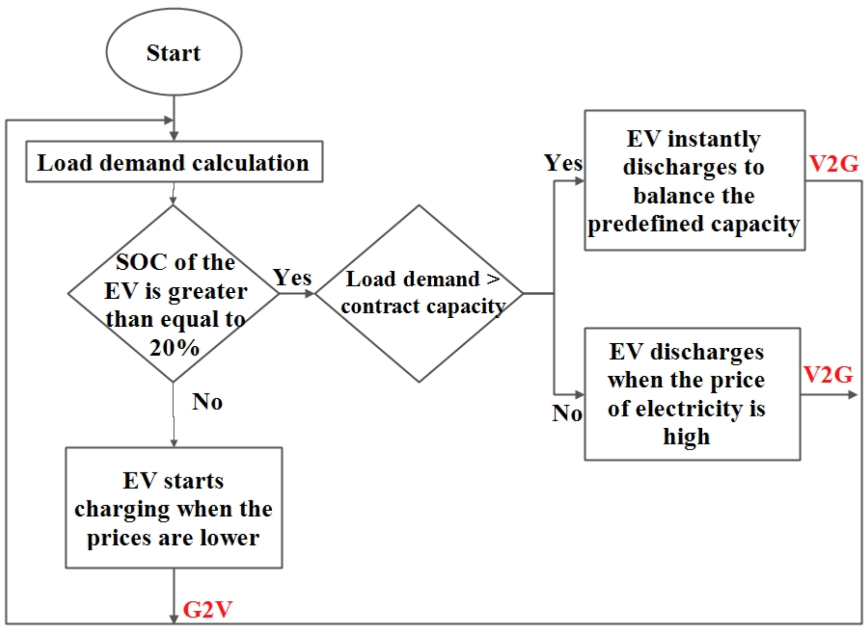


Figure 4.2: EV power dispatch based on their SOC level.

In order to maximize the advantages of the pricing scheme mentioned above, a few key criteria must be addressed. The time duration for varying energy prices, operations of various appliances, and most importantly, a meter that measures overall energy usage and when it is utilized, hence, the time of usage capability.

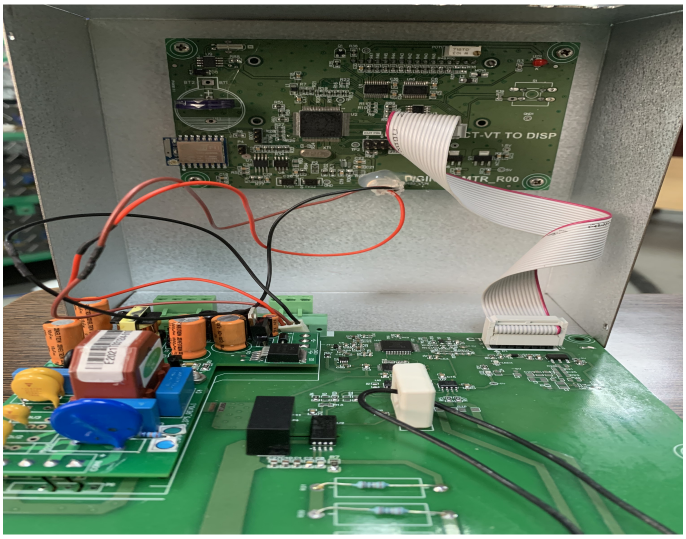


Figure 4.3: Developed DC net meter for V2G-enabled EV charging.

The DC net meter as shown in Fig. 4.3 has been designed in compliance with international standards of up to 30kW power level. The IEC 61000/60255/62052 has served as a basis for developing DC net meter. Further, standards such as AIS 004 and EN 50463 pertaining to automotive charging requirements have also been considered [137]. The DC net meter measures the net energy consumption on a timely basis. Moreover, the net meter is specifically designed for V2G-enabled EV charging and is equipped with a real-time clock (RTC) to synchronize with the time-based tariffs. Consequently, EV owners will receive better structured, accurate, and error-free data on their power import and export with the help of a DC net meter. The physical components of the DC net meter consists of a linear optocoupler (ACNT-H870) for isolation, a hall-effect sensor (WCS1500) for current sensing, an analog-to-digital converter (ADC 7606) and microcontroller (TMS320F28069M) for computation. It also comprises an LCD and ESP8266 Wi-fi module for wireless connectivity.

4.3.2 TOU-CPP/PTR based tariff structure

In this research, the optimization of case studies was carried out using the energy charges mentioned in Tables 4.1 and 4.2. Specifically, Table I represents the energy charges applicable during the summer season, which runs from June to October in Borrego Springs, USA. Similarly, Table II mentions the winter season charges that span from November to May. Additionally, the tariff rates are divided into three categories: on-peak, off-peak and super-off peak (early morning/midnight) hours. It is worth noting that the super-off-peak hours may vary on weekdays and weekends.

Table 4.1: Tariff rates for summer season

Months	**Days**	**Hours of day**	**Time of day (hrs)**	**Energy charges ($/kWh)**
June-October	Weekdays	On-peak	16:00-21:00	0.141
		Off-peak	21:00-00:00 06:00-16:00	0.112
		Super-off peak	00:00-06:00	0.085
	Weekends	On-peak	16:00-21:00	0.141
		Off-peak	21:00-00:00 14:00-16:00	0.112
		Super-off peak	00:00-14:00	0.0852
	All days	CPP	Critical peak hours	1.95
	All days	PTR	Critical peak hours	-1.4

Customers can benefit from peak rebates and net metering incentives through the aforementioned TOU-based pricing structure. Furthermore, it is expected that the rate structure will undergo specific changes during the crucial peak hours. As a result, Tables 4.1 and 4.2 presents

Table 4.2: Tariff rates for winter season

Months	**Days**	**Hours of day**	**Time of day (hrs)**	**Energy charges ($/kWh)**
Nov-May	Weekdays	On-peak	16:00-21:00	0.112
		Off-peak	06:00-10:00 14:00-16:00 21:00-00:00	0.095
		Super-off peak	00:00-06:00 10:00-14:00	0.086
	Weekend	On-peak	16:00-21:00	0.112
		Off-peak	14:00-16:00 21:00-00:00	0.095
		Super-off peak	00:00-14:00	0.086
	All days	CPP	Critical peak hours	1.95
	All days	PTR	Critical peak hours	-1.25

the the CPP and PTR tariff rates in this case study. It is important to note that these rates can only be used 15 times per year and are applicable during the peak events of the year [140]. The pricing structure as described earlier closely resembles that offered by the San Diego Gas and Electric Company in California offers, except for a special tariff known as peak rebates. The energy prices are divided into a variety of categories in order to lessen the peak load and help users limit their usage.

4.3.3 Case study

The office space in the Borrego Springs community microgrid in California, United States, served as the case study for this research [141]. The annual demand for electricity is recorded as 1.124MWh, with an average daily consumption of about 3000kWh. In Fig. 4.4, the load profile for the day with the highest demand is shown. The figure also depicts that the maximum electricity demand was noted in July, which was 272.4 kWh. Further, Fig. 4.5 displays the heat map illustrating the monthly consumption behaviour of the users.

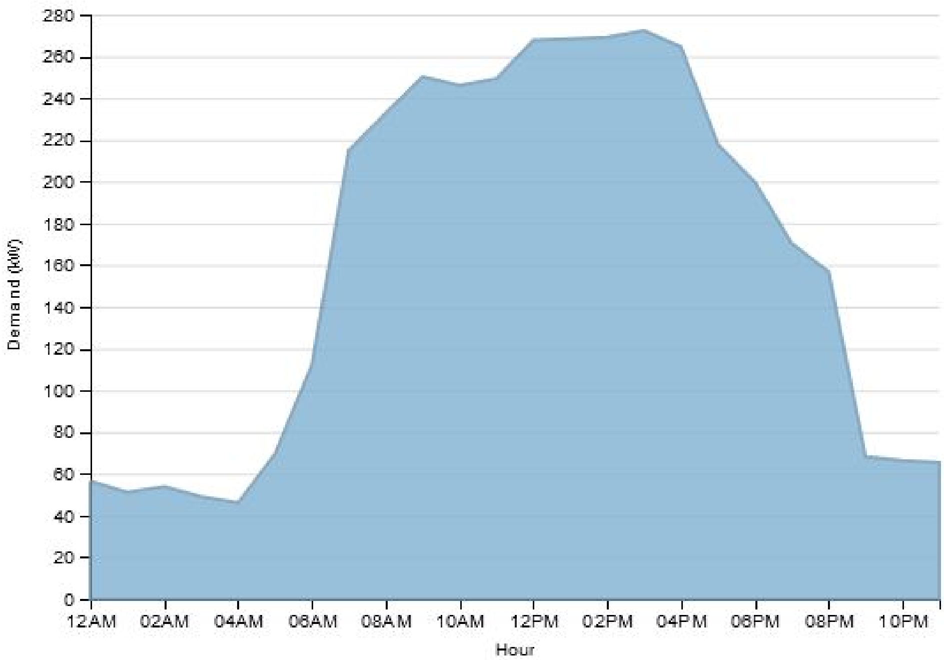


Figure 4.4: Daily load profile

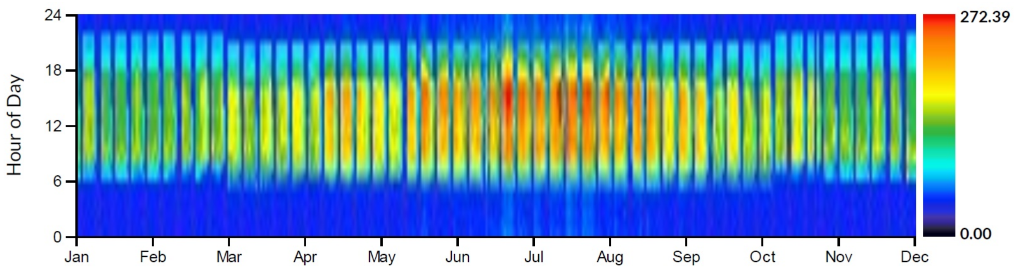


Figure 4.5: Heat map showing energy consumption pattern

According to the load profile, the demand for electricity is notably high during the forenoon hours, with the peak demand occurring between 12:00 and 16:00. However, if the users charge their vehicles during the peak hours, this will cause an increase in the electricity demand.

Therefore, a time-of use pricing mechanism must be implemented to coordinate the EV charging and reduce the stress on the power system. Further, there are occasions that the utility designates as crucial peak days, requiring consumers to pay a higher price than usual. The number of critical peak days in a year is limited and frequently restricted to hot weather [140].

On the other hand, peak time rebate (PTR) is similar to CPP as shown in Fig. 4.6, except that instead of charging the customers during critical peak hours, they will receive a reimbursement for low consumption. The utility maintains the authority to choose which program (PTR or CPP) to use to reduce capacity expenses associated with power generation sources that operate for only a few hours per year. By implementing the TOU-based pricing structure, EV customers are encouraged to organize their charging during the overnight hours, when power rates are lowest, instead of peak hours of high demand. This strategy aims to optimize charging patterns and reduce load on the power system in the time of peak hours.

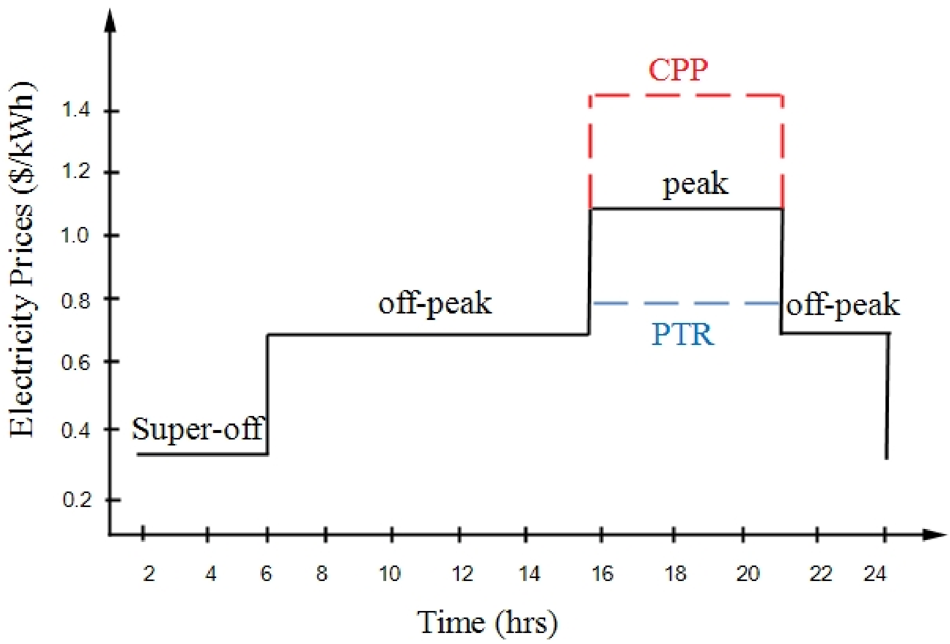


Figure 4.6: Illustration of TOU-based pricing mechanism

In section III.B, the TOU-based tariff structure has been described in detail, and the microgrid is simulated for the proposed pricing schemes. In addition, the developed DC net meter is sorely tested in the bidirectional charging/discharging environment at the proposed tariff rate.

4.4 Results and Discussion

The microgrid comprises PV generation, lithium-ion energy storage units, and converters. The model considers a cost of $3000 per kW for fully installed solar systems and a cost of $500 per kWh for battery energy storage. The base case implements the fixed pricing of $6.5 with a sell-back price of $2.5, excluding the solar panels and battery storage. Meanwhile, 40 electric vehicles are considered in the area requiring 15kWh of charge energy per EV. The maximum charging power per EV is kept below 10kW. On the other hand, the proposed optimized case implemented the TOU-based pricing structure as mentioned in Table 4.1 and 4.2. The results obtained from the simulation with respect to the base case are summarized in Table 4.3.

Table 4.3: Annual cost & savings

Annual savings	$1,24,536
System Capital cost	$14,99,870
Over the project lifetime of 25 years, savings can be	$31,11,085
Payback time	12 years

The implementation of proposed TOU-CPP/PTR-based pricing scheme resulted in significant annual savings of $124,536 in comparison to the base case. Further, the total capital cost for implementing this scheme was $14,99,870. Over the project's 25-year lifetime, the accumulated savings reached upto $31,11,085. Additionally, the estimated payback time for the proposed pricing scheme was determined to be 12 years, indicating a reasonable time frame to recover the initial investment. These findings emphasize the financial benefits and long-term cost-effectiveness of the proposed pricing model.

A comprehensive comparison of all the analyzed cases can be found in Table 4.4. Notably, the scenario where electric vehicle charging is accomplished using grid and solar electricity without utilizing battery storage, or Case II, emerged as the best case scenario. Moreover, the proposed scheme demonstrated a higher internal rate of return (IRR) which denotes the possibility of a more appealing and profitable investment over the project's lifetime.

Table 4.4: Detailed summary of all cases

Cost & Savings	**Base Case**	**PV+TOU-based tariff**	**PV+storage+TOU-based tariff**	**Storage+TOU-based tariff**
CAPEX	$0	$14,99,850	$15,02,184	$2,334
Annual total savings	$0	$1,20,444	$1,19,320	$47
Annual utility bill savings	$0	$1,24,443	$1,23,556	$124
Annual demand charges	$41,317/yr	$30,883/yr	$30,793/yr	$41,203/yr
Annual energy charges	$1,54,892/yr	$40,853/yr	$40,880/yr	$1,54,882/yr
Net present cost (NPC)	$25,36,496	$24,92,234	$24,94,618	$25,38,227
CO2 emissions	508.5t/yr	202.2t/yr	200t/yr	508.5t/yr
Payback time	na	12 yrs	12 yrs	na
Internal rate of return (IRR)	na	6.19%	6.17%	na

It is worth noting from Fig. 4.7 that throughout the day the solar panels generates electricity that may be used to charge the EVs. Hence, there is no need for a separate battery system in this configuration because the EVs can function as a kind of energy storage system. In addition, fully charged EVs can give electricity back to the grid during peak hours with the use of V2G chargers. This bidirectional energy flow maximizes the utilization of EVs and enhances grid stability. Furthermore, the adoption of time-of-use based pricing system enables consumers to effectively manage the charging and discharging of their EVs, enabling them to optimize their usage in a cost-effective and sustainable way.

The capital expenditure required for installing the system is shown in Fig. 4.8. Initially, there is a high capital expenditure associated with setting up the microgrid, leading to negative cash flow in the early year. However, as time progresses, the operating costs of the microgrid decrease due to improved efficiency, optimized maintenance, and and the benefits derived from increasing the system size. This reduction in operating costs indicates the financial benefits and potential profitability of the microgrid system after recovering the initial investment.

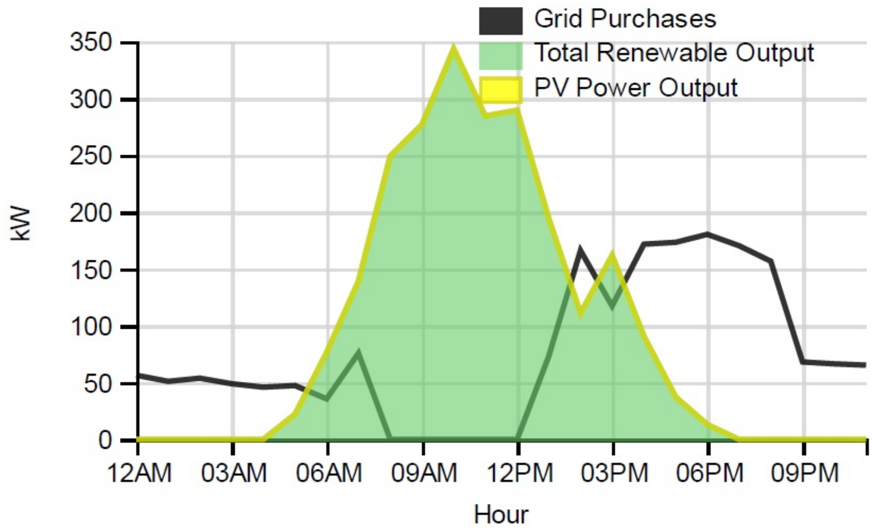


Figure 4.7: Graph plotted between PV power output and the grid purchases.

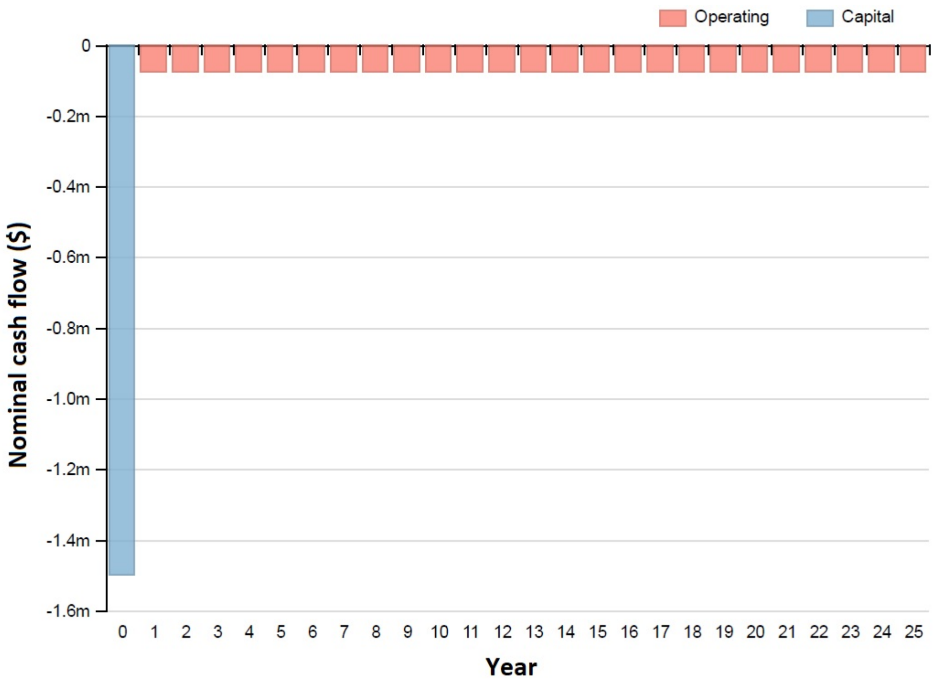


Figure 4.8: Cash flow for the system.

Meanwhile, the integrated system is projected to generate around 202 t/yr of total carbon emissions, compared to the normal grid's production of around 508.5 t/yr. This shows the reduction of 2.5 times in carbon emissions. However, it is important to note that Fig. 4.9 shows the electricity purchase from the grid on a peak day in July for both the baseline and optimized (integrated system) scenarios. Purchasing electricity from the grid is more in line with the base scenario than the integrated situation.

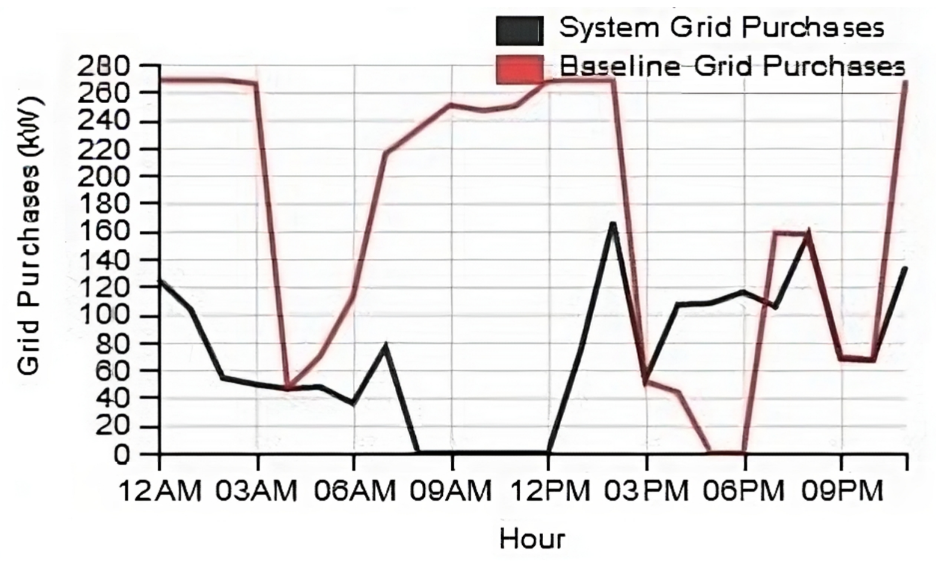


Figure 4.9: System grid purchase with respect to base case.

Additionally, the monthly breakdown of the bill in terms of fixed charges, demand charges, and energy charges is shown in Fig. 4.10. This breakdown provides insights into the different cost components associated with the electricity consumption in both the cases.

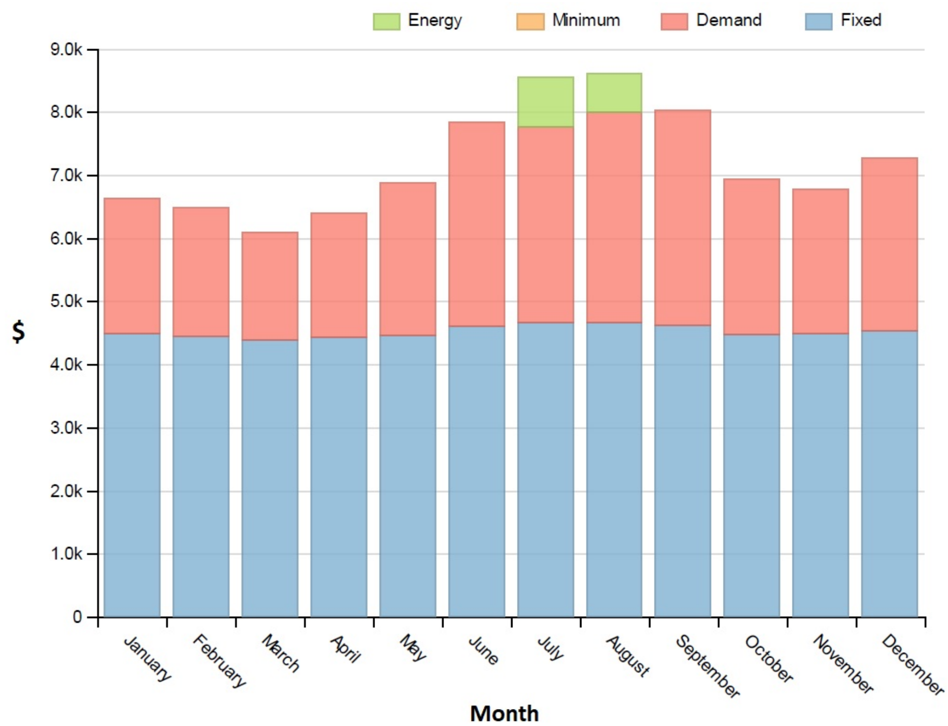
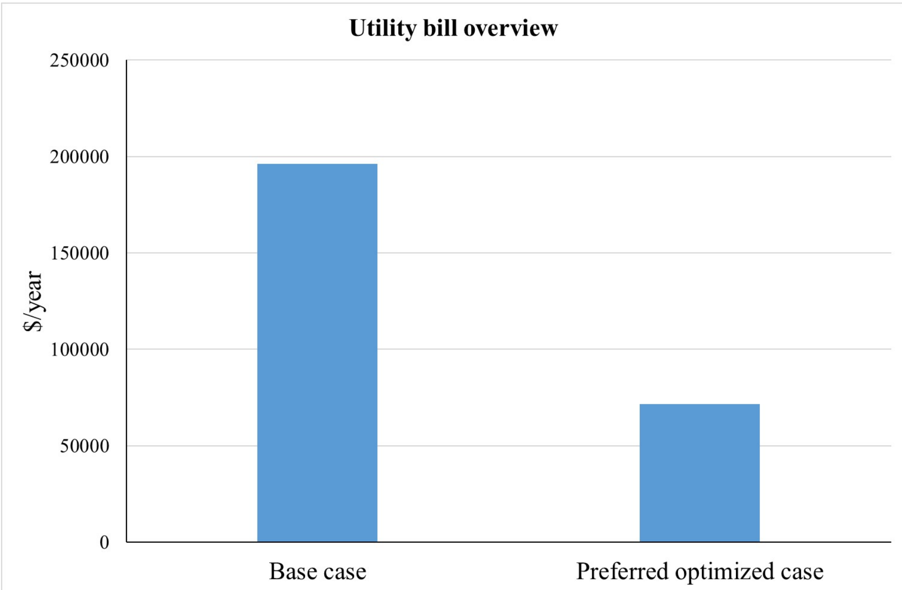


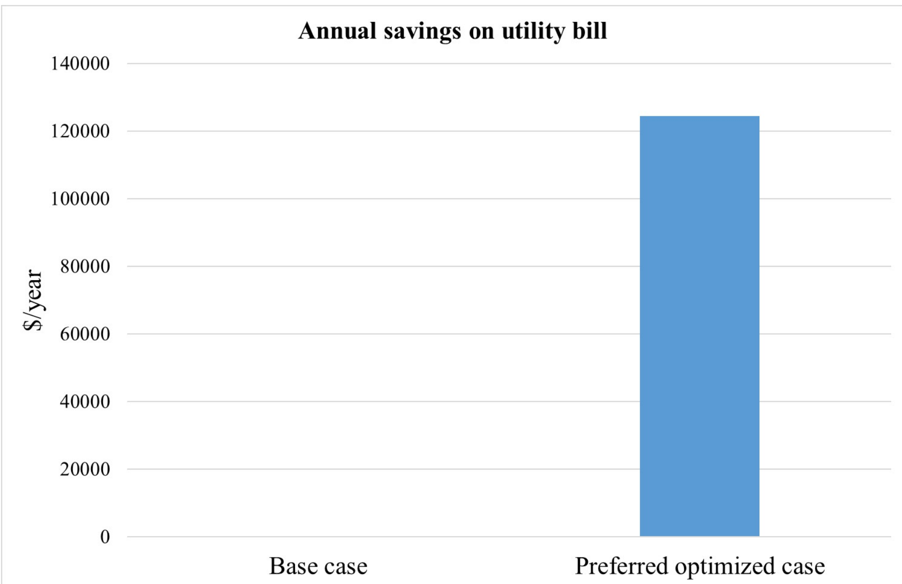
Figure 4.10: Monthly electrical bill breakdown.

The energy charges based on the total amount of energy customers used in July are decreased to \$800 under the TOU-based tariff structure. Conversely, demand charges based on the maximum amount of electricity ever used at once during a billing period and at the time of day business needs are decreased from \$4100 in the base scenario to \$3200. In the busiest month of the year, the overall electricity consumption cost, including the fixed costs, comes to about \$8500 as shown in Fig. 4.10.

Fig. 4.11(a) displays the annual utility bill calculations for both scenarios during the optimization process. Furthermore, Fig. 4.11(b) illustrates the electricity bill savings relative to the baseline case.



(a) Utility bill overview in both the cases.



(b) Depiction of annual savings on the electricity bill.

Figure 4.11: Overview of the electricity bill and the savings

By coordinating EV charging, the proposed TOU-based pricing approach minimizes power system losses. Further, balancing the load and avoiding periods of high demand encourages charging during off-peak times. This minimizes system strain, decreasing voltage drops, line losses, and congestion. It also enables the integration of renewable energy sources by aligning charging with high renewable generation periods. When the TOU base pricing structure is used, the bill will have enough savings compared to the base scenario when there were no savings. Additionally, an integrated system handles its demands and limits the amount of electricity it purchases from the grid [142]. With a smart grid, the utility is not alone responsible for meeting the demand, and as electric vehicles become more prevalent, the smart grid helps reduce the pressure.

4.4.1 DC net meter performance based on the tariff structure

The experimental lab setup of a 2kW charging system includes the following components: a bidirectional DC-DC buck-boost converter, 2kVA voltage source inverter, grid interfacing filters, 110/230V transformer, 3-phase/415V grid, 3-phase voltage & current sensing module and 120V lead acid battery bank (12V, 26Ah each). In Fig. 3.14, the developed DC net meter is connected between the battery and buck-boost converter to measure the net energy transferred. The results obtained are also verified using the Fluke 434 series II power analyzer.

Further, the simplified interconnection between the components is shown in Fig. 4.12. These components include a bidirectional DC-DC buck-boost converter, which ensures precise voltage regulation. Additionally, an IGBT-based voltage source inverter is employed for reliable power conversion, a voltage and current sensing module to measure electrical parameters and a battery bank comprising 120V lead-acid batteries. Lastly, a DC net meter is connected to the battery side to measure power transfer. The connections of all the above mentioned components are depicted in the figure.

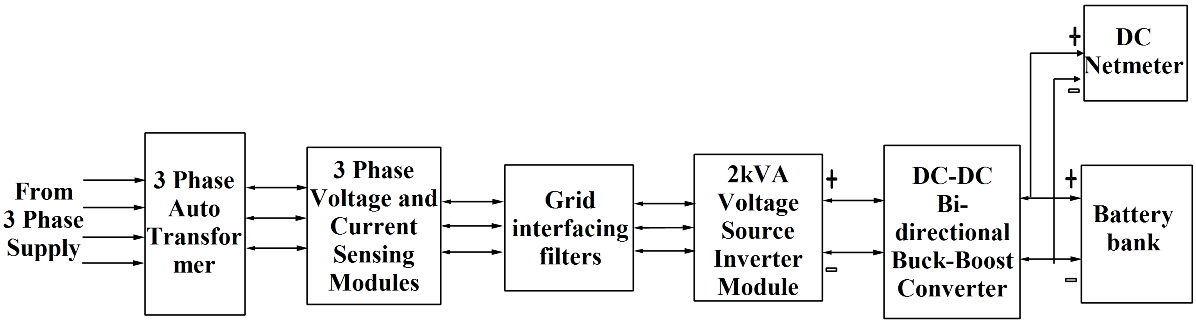


Figure 4.12: Simplified interconnection between the elements.

The net bill generated by a DC net meter is computed using net units derived by multiplying the amount of electricity purchased or sent back to the grid by the current electricity price. Further, the process of electricity bill generation in a DC net meter based on TOU-based pricing is depicted in Fig. 4.13. Beginning with the parameter initialization, the net meter measures the net charging/discharging units based on the time of the day. Subsequently, the net bill is calculated using the predetermined TOU-based pricing. If the charging or discharging occurs during peak hours, the meter will generate a bill equal to the net calculated units multiplied by the peak hour rate. Similarly, the net bill generated in off-peak hours is determined by multiplying the net consumed units by the off-peak hour rate. The same is valid for charging/discharging the EV during the super-off peak hours.

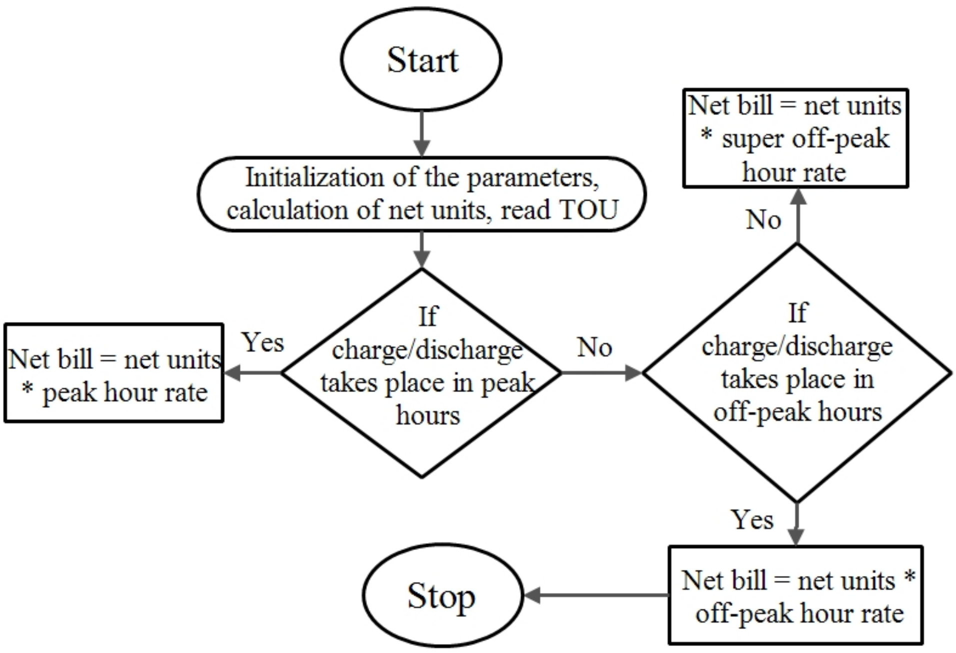


Figure 4.13: Overview of TOU-based algorithm in DC net meter

In the bidirectional lab setup, an input of 2.2kW, 230V is provided to supply a current of 9.5A to facilitate charging or discharging of the battery. However, the battery has a 12V, 26Ah lead-acid configuration and the C-rate is maintained at 0.2C. In an hour, the battery is able to charged itself by a current of 5.2A. Further, to calculate the time required for the battery to reach full charge, the battery's ampere-hour (Ah) rating is divided by the maximum current it can be charged with in one hour. As a result, the battery must be connected for 5hrs to get fully charged. Furthermore, the input current required to charge the battery at 0.2C rate is calculated as 1.9A. The required energy for the first hour of the charging is computed and displayed around 437Wh. The battery has been charged in the peak hours of the day, therefore, the net bill generated after 5hrs is displayed by the DC net meter and is mentioned in Table 4.5.

Table 4.5: Performance of DC net meter in the bidirectional environment

	Hours of the day	**Bill (in $)**	**Net bill (in $)**
Charging	Peak	0.307	0.1683
Discharging	Off-peak	0.138	

In the off-peak hours, the battery was discharged through the load continuously for about three hours under the same environmental conditions. At the end of the day, the net bill as indicated by the DC net meter shows a value of 0.1683$. It is important to note that the net meter is designed for a voltage range of 150V. However, it can be modified to accommodate voltages upto 1000V without requiring any significant changes to the PCB layout.

4.4.2 Discussion

The optimization process in the study involved numerous crucial steps. First, historical electricity consumption information was gathered from a workplace in the California microgrid of Borrego Springs. Based on this information, a time-of-use pricing strategy was developed with multiple pricing levels at different times of the day. The relationship between electricity consumption and uncoordinated EV charging was then represented using a mathematical model. The TOU-based pricing method was then improved through optimization using the HOMER software, which allowed for the specification of objectives, restrictions, and parameters. The outcomes made it possible to optimize energy consumption patterns and accomplish targeted goals. The research clarifies that EV charging and discharging can be done while considering a number of factors, including peak or off-peak hours, SOC level, dynamic pricing structure, and V2G-enabled stations.

Moreover, in microgrids, EVs can be charged when renewable energy sources are available, but they can also be charged at night when there is less demand for electricity in places without access to renewable energy sources [143]. The proposed scheme outperforms the research models presented in [138] concerning project benefits, savings, and IRR. Further, the proposed research covers a larger office space with 40EVs, in contrast to the model developed in [144], which focuses on a single residential home with an electric vehicle. In addition, the performance of the DC net meter in the bidirectional flow of electricity is better than the meters developed in [52, 145] in terms of accuracy. DC net metering is critical for monitoring and measuring the power flow in the system. In the proposed scenario, a DC net meter has been used to monitor the net charging units of the battery. Furthermore, DC net metering increases transparency and accountability in the energy exchange process. It enables users to precisely measure their energy consumption and provides an even framework for invoicing or crediting. Furthermore, the net meter's voltage range is expandable, ensuring compatibility with diverse system configurations and future scaling.

4.5 Conclusion

Dynamic pricing plays a crucial role in alleviating pressure and reducing greenhouse gas emissions within the power industry following the integration of electric vehicles. It facilitates the coordination of EV charging and discharging without the necessity for extensive network expansion. Therefore, the significance of dynamic pricing and its role in strengthening the power system has been investigated, with a special emphasis on the fast adoption of EVs. The research introduces a multi-objective approach with the primary goal of reducing electricity expenses by devising a time-of-use (TOU)-critical peak pricing (CPP)/peak time rebate (PTR) tariff structure for orchestrating EV charging. Further, a microgrid-based case study examines the designed tariff structure. Based on a combination of integrated renewable systems, several cases are examined. From the results, the designed solution has proven to be both technically and financially feasible. Furthermore, this study suggests a TOU-enabled DC net metering strategy for EV charging systems that will benefit both customers and utilities. The DC net meter has been tested on a 2kW bidirectional environment that implies the TOU pricing scheme. Customers can pay only for the energy legitimately supplied to their EVs because of the TOU-enabled DC net metering regulation. Perhaps, the research concentrated mostly on time-of-use (TOU) pricing structures for synchronized EV charging. The research can be expanded in the future by creating better charging algorithms for EVs, investigating V2G technology, and adopting demand response strategies. Furthermore, additional research might look into load management and cost-benefit analyses from diverse perspectives, such as utility companies.

Chapter 5

DECENTRALIZED EV CHARGING SYSTEMS

5.1 Introduction

Electric vehicles (EVs) are gaining popularity as a promising alternative to gasoline-powered vehicles, thanks to their environmental benefits and improved performance. The Global EV report 2022, highlights the significant progress made in the EV market despite the challenges posed by the COVID-19 pandemic [146]. Apart from the progress made in the EV market, the report also highlights the need for continued investment in charging infrastructure to support the growing number of EVs on the road. However, the widespread adoption of EVs raises concerns about their impact on the power grid. Majority of the existing grid infrastructures were constructed prior to the widespread emergence of EVs. Therefore, they perceive the load associated with EV charging as something challenging. When a substantial quantity of EVs is haphazardly linked to the electrical grid for battery charging, it notably transforms the grid's load profile. Moreover, the concern was also raised by the Electric Vehicle Integration initiative to ensure a smooth and sustainable transition to a more electric future [147].

To address the grid-related issues, a decentralized charging system has been proposed that utilizes the vehicle-to-grid (V2G) concept. The V2G systems have the potential to improve the overall stability and reliability of the power grid through their capabilities in frequency management and voltage support [148, 149]. In this system, EVs can store and return electricity to the grid, enabling them to participate in demand response initiatives and offer grid support services. In addition, V2G dispatching is divided into two categories: centralized and decentralized. The term "centralized" refers to a coordinated dispatching strategy in which the central coordinator (CC) optimizes EV charging based on grid conditions and charging requirements for a specific target [150]. However, a unified plan requires EV charging data to be uploaded to the CC, which could lead to the disclosure of critical data. Also, the solving time will increase exponentially as the number of EVs rises.

The decentralized approach is an incentive technique in which the energy price mechanism acts as an intermediary to control the charging of EVs. By decentralizing the charging process, EVs can distribute their charging load over time and reduce the impact on the grid [151]. However, it is not easy to optimally plan the EV charging and discharging processes. Firstly, it is challenging to identify the ideal scheduling approach that can reduce the overall charging cost, especially when there is a high EV population. Later, the developed optimal scheduling pattern for charging/discharging the EVs must accommodate the unpredictable arrivals of the vehicles in real time. The scheduling strategy that is being proposed should demonstrate its effectiveness in dealing with these challenges and facilitating a seamless transition toward a future that is more reliant on electric power. Furthermore, net metering and renewable sources are other crucial concepts that should be included in the decentralized system. During high demand, it encourages the customers to transmit surplus power to the grid [152]. Regarding financial gains, incorporating net metering into the V2G system can be advantageous.

5.1.1 Motivation

The enormous influence of EVs on the grid's load profile presents a significant barrier to their widespread adoption. However, a potential solution to this issue lies in the vehicle-to-grid systems. Despite this, it remains challenging to optimize EV charging and discharging especially when there is a large population of EVs. Furthermore, the centralized dispatching approach is constrained by the data security concerns and an increased solving time with a higher number of EVs. Conversely, a decentralized approach is appropriate for determining an optimal scheduling strategy that effectively lowers total charging costs while successfully handling unpredictable EV arrivals. Therefore, a decentralized scheduling algorithm has been developed in this research to optimize EV charging and discharging while reducing the load on the power grid as shown in Fig. 5.1.

5.1.2 Contribution

This research offers the following contributions:

1. The research proposes a dynamic scheduling strategy for EV charging and discharging that makes use of decentralized system to ensure effective management of charging patterns and grid stability.

2. The proposed convex optimization problem is a novel approach that can shed light on the optimal design and control of decentralized EV charging.

3. By accommodating the dynamic arrivals and departures of EVs, the proposed method improves the grid's resilience.

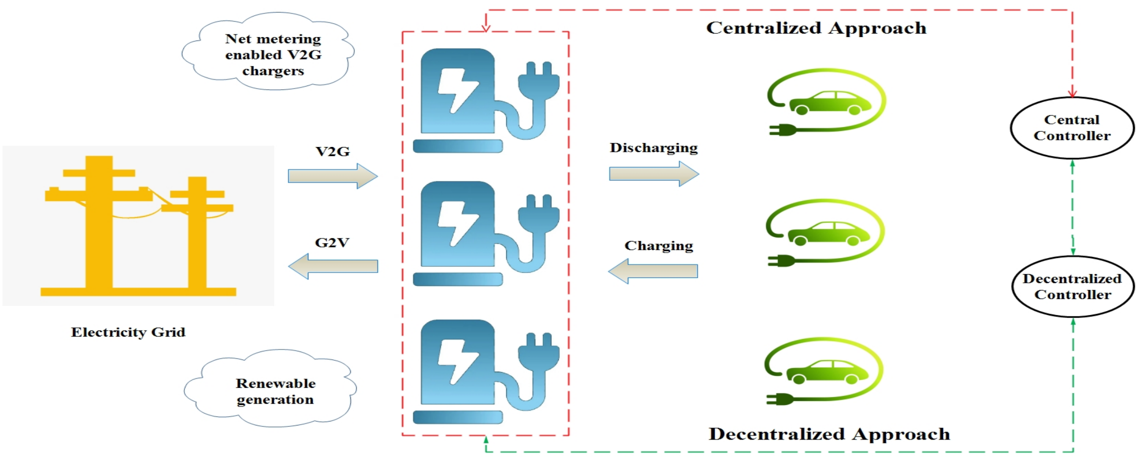


Figure 5.1: Proposed decentralized EV charging system.

5.2 Proposed Methodology

The decentralized charging system for electric vehicles implements a novel method to effectively regulate the charging procedure, taking into account the distinct attributes of each EV. The mechanism operates by dividing time into several intervals and using an advanced method to allocate charging slots fairly among electric vehicles. Further, the allocation is determined by considering various parameters such as arrival and departure time, in order to ensure fair and equal access to charging resources. Each electric vehicle in the system autonomously adjusts its charging rate during the assigned time slots, with the goal of minimizing individual charging expenses. In addition, the optimization takes into account variables such as energy prices, battery limitations, and customer preferences, allowing electric vehicles to strike a compromise between the desire for a fast recharge and cost efficiency. Moreover, the decentralized system fosters energy management and sustainability by incentivizing electric vehicles to charge during periods of reduced demand or increased accessibility of renewable energy sources. The capacity to modify charging techniques in real-time is a crucial characteristic of decentralized charging system, allowing the EVs to effectively respond and adapt to changing situations.

5.2.1 Problem Statement

The objective of the multi objective problem is to minimize a cost function that represents a weighted combination of power transferred to the EV or discharged through V2G technology. Mathematically it can be written as:

$$minC_{total} = C_e * (\sum_{t=0}^{T} E_{ev}^t + E_{v2g}^t) \tag{5.1}$$

where, C_e represents cost per unit energy, E_{ev}^t is the total energy from the EV charging and E_{v2g}^t represents the total energy from the V2G discharging. This summation represents the net energy obtained from EV charging and V2G discharging over a specified time period.

subjected to:

Demand constraints

Mathematically, it is imperative to ensure that the total power demand at any given moment is met, and this can be expressed as follows:

$$P(t) = P_{ev}(t) + P_g(t) + P_{sr}(t) - P_{v2g}(t) - P_l(t) \tag{5.2}$$

Here, $P_{ev}(t)$ represents the power demand from electric vehicles at time t, which can vary over time depending on the charging behavior of EVs. $P_g(t)$ is the power demanded from the grid which depends upon the overall electricity demand and the availability of other power sources. Further, $P_{sr}(t)$ represents the power generation from solar panels. In addition, $P_{v2g}(t)$ represents the power discharge from electric vehicles to the grid which can be used to balance the grid during periods of high demand. $P_l(t)$ are the power losses due to conversion of AC power to DC power and vice versa.

Net metering

The concept of net metering should be enforced to ensure accurate accounting of the net power exchanged with the grid, based on the power generated by solar panels, the power drawn by EVs, and the power fed back to the grid by the V2G system. Mathematically it can be written as:

$$\begin{aligned} P_g(t) =& max(0, -P_{v2g}(t))+ \\ & min(0, P_{ev}(t) - P_{sr}(t) + P_{v2g}(t)) \end{aligned} \tag{5.3}$$

In the above equation, $P_g(t)$ represents the net power drawn from the grid at time t. The term $max(0, -P_{v2g}(t))$ represents the power fed back to the grid from the V2G system, if any. Further, $min(0, P_{ev}(t) - P_{sr}(t) + P_{v2g}(t))$ represents the net power drawn from the grid, after accounting for the power generated by solar panels and the power fed back to the grid by the V2G system.

Vehicle-to-Grid constraints

The V2G constraints need to be met to ensure the stability of the power grid when electric vehicles are connected to it [153]. The constraint, $P_{v2g}(t) <= P_{v2g}^{max}(t)$, means that the amount of power that can be discharged from the EVs to the grid at any given time t should not exceed a maximum limit. The maximum limit can fluctuate, contingent on factors such as the capacity of EV batteries, the condition of the power grid, and the presence of renewable energy sources.

$$P_{v2g}(t) <= P_{v2g}^{max}(t) \tag{5.4}$$

$$P_{v2g}(t) <= -P_{ev}(t) \tag{5.5}$$

Further, Eq. (5.5) means that the power discharged from the EVs to the grid should not be greater than the power demand from the EVs themselves. It ensures that the EVs are not completely discharged and remain operable, and that the power grid is not overloaded with too much power being discharged from the EVs.

EV charging constraints

These constraints guarantee that the EV battery remains within safe charging levels, avoiding both overcharging and undercharging [154]. Additionally, they ensure that the power demand from EVs aligns with the capacity of the charging infrastructure.

$$P_{ev}(t) <= P_{ev}^{max}(t) \tag{5.6}$$

$$SOC(t) >= SOC_{min} \tag{5.7}$$

$$SOC(t) <= SOC_{max} \tag{5.8}$$

where, $P_{ev}^{max}(t)$ is the maximum power drawn from the grid to charge vehicles, SOC_{min} and SOC_{max} are the minimum and maximum allowable values of SOC, respectively. Furthermore, it is important to restrict battery degradation in a manner that ensures the EV battery's final state of charge at the end of the specified time horizon remains above a certain threshold [155]:

$$SOC(T) >= SOC_{final} \tag{5.9}$$

Renewable energy integration

Renewable energy integration is a critical element in the optimization of the power grid [156]. In this case, solar energy is the renewable source being considered. The integration of solar energy into the grid can be optimized by controlling the fraction of solar energy that is being used at any given time [157]. The fraction, denoted by $f_{solar}(t)$, is a function of time and represents the percentage of solar energy that can be integrated into the grid.

$$P_{sr}(t) = f_{sr}(t) * P_{sr}^{max}(t) \tag{5.10}$$

where, $P_{sr}^{max}(t)$ is the maximum power that can be generated from solar panels at time t.

5.2.2 Proposed decentralized scheduling scheme

Decentralized EV dispatching is a distributed approach to charge electric vehicles that incorporates multiple charging stations, each with its own set of constraints and objectives [158, 159]. In the decentralized EV charging, EVs are grouped together based on their location, and a decentralized controller (DC) is assigned to each group. The DC communicates with the centralized controller and charging stations to gather data about EVs and the forecasted load for the day [160]. Based on this data, the DC optimizes the charging schedule and directs each EV to charge or discharge the battery using the most efficient power level. If an EV's state of charge (SOC) falls below the set threshold, it can be given priority for charging. Similar to this, if an EV's SOC is high and the owner does not require it for immediate use, the DC can advise discharging it down to earn more credits. The proposed dispatch scheduling algorithm is optimized for every time frame to facilitate effective charging of the anticipated EVs and to accommodate any unexpected EV charging arrivals.

Further, the proposed scheduling algorithm works by dividing the time horizon into a number of subsequent charging slots, each of which has a fixed length as shown in Fig. 5.2. The length of a slot should be determined by the anticipated variations in the demand for EV charging and the production of renewable energy during that time. For instance, a slot length of 15 minutes would be appropriate for a situation where the demand for EV charging is very variable, while a larger frame length of 1 or 2 hours might be appropriate for a situation where the demand is more consistent. To implement the proposed scheme, the charging stations would need to share information with each other about their charging demands, renewable energy availability, and battery states. This information could be exchanged using a communication protocol such as the Open Charge Point Protocol (OCPP), a widely adopted standard for communication between charging stations and central management systems.

In order to implement the proposed mechanism, it is essential to determine the ideal duration for each time slot and allocation of EVs to these slots. Additionally, forecasting of base loads using a similar-day approach is required to optimize charging powers within the current

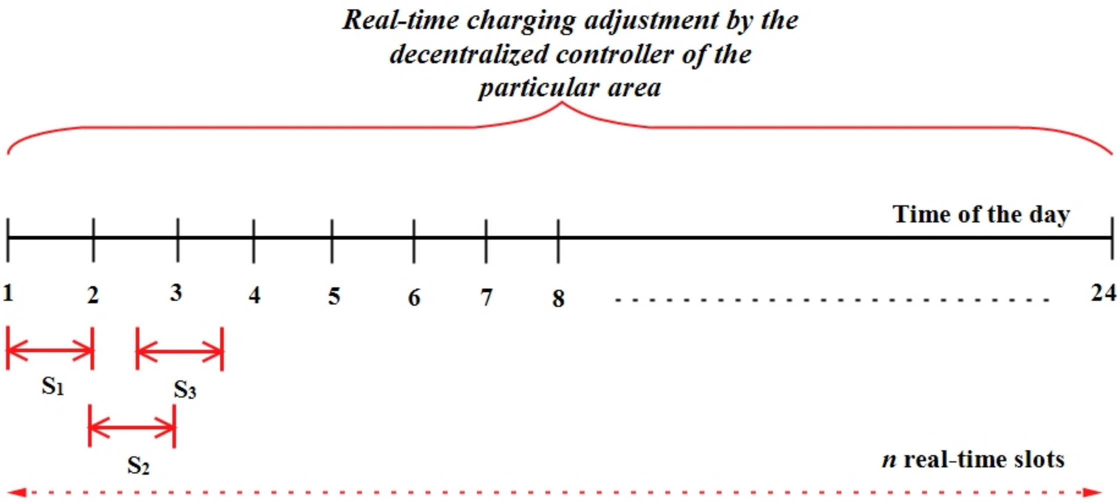


Figure 5.2: Slot allocation for EV charging.

time slot. By averaging the base loads from intervals with similar weather circumstances in recent days, the base load for each period is calculated. Further, the restrictions outlined in section II (A) ensure that the total charging power demanded by all EVs using the slot does not exceed the power capacity that is readily available. This multi-objective problem's objective is to reduce charging costs while meeting the aforementioned restrictions. By taking into account the current ongoing slot for EV charging, the cost function can be recast as follows:

$$C = \sum_{i \in O} \int_{t_i}^{t_i+T_d} (c_i(t)p(i,t) - r_c(i,t)p(i,t)dt \tag{5.11}$$

The modified cost component composed of two parts: the charging cost from the grid and the discharging reward to the grid in the current time slot. The optimization problem considers a set of ongoing EVs in the current window, denoted by O. For each EV_i, in the slot, the optimization problem defines the start time t_i and the charging duration T_d, along with the charging rate $c_i(t)$ at any given time t. The price of electricity from the grid at time t is denoted by $p(i,t)$, and the reward for discharging electricity from EV_i to the grid at time t is denoted by $r_c(i,t)$.

$$\sum P_{ev}i(t) - \sum P_{ev}i(t-\delta_t) <= \delta_t * P_S^{max} \tag{5.12}$$

$$\sum_{i \in O} p_i(t) + p_b(t) \leq P_{max}(t), \forall t \in S \tag{5.13}$$

$$\sum_{i \in O} \int_{t_i}^{t_i+T_c} p_i(t)dt \leq e_i(t), \forall t \in S, i \in O \tag{5.14}$$

$$\sum_{i \in O} e_i(t_c) = E_i^{target}, \forall i \in O \tag{5.15}$$

$$p_i(t) \in [P_i^{min}, P_i^{max}], \forall t \in S, i \in O \tag{5.16}$$

By utilizing a real-time charge adjustment mechanism, power usage is effectively managed, and the risk of exceeding the available capacity is minimized. It works by limiting the charging rate of each electric vehicle based on the available power capacity within the current time slot as mention in Eq. (5.12). Here, δ_t is the time interval of the slot and P_S^{max} is the maximum power capacity of the current slot. To additionally guarantee that the total load remains below the maximum permissible load, the following Eq. (5.13) is applied. Here, O represents the set of ongoing EVs in the current slot, $p_i(t)$ represents the charging power of EV i at time t, $p_b(t)$ represents the base load in the current slot, $P_{max}(t)$ is the maximum allowable load at time t, and S represents the time slot.

The system also includes initial and final energy constraints to ensure that the charging of EVs is done in a controlled manner as mentioned in Eq. (5.14) and Eq. (5.15). Further, $e_i(t)$ denotes the energy level of EV i, and t_c represents the completion time of the charging period of EV i. The final energy constraint guarantees that each EV achieves a predefined level by the end of the charging period. Finally, lower and upper bounds of charging power are established using the Eq. (5.16). This ensures that the charging power of each EV remains within a specified range. The decision variables are the power demand from EVs (P_{ev}), the power discharge from EVs to the grid (P_{v2g}), and the state-of-charge of the EV battery (SOC). The objective is to reduce the total cost of power (C) and the overall cost of the EVs in the present ongoing EV set during the current slot.

Algorithm 1 Proposed scheduling algorithm for decentralized EV dispatching

1: **Input:** O, t_i, T_d, p, r_c, P_{v2g}^{max}, P_{ev}^{max}, P_{sr}^{max}, SOC_{min}, SOC_{max}, δt, P_S^{max}, and P_{max}.

2: **Output:** c_i, P_g, P_{sr}, P_{ev}, and P_{v2g}

3: **Procedure**

Initialize $c_i(t) = 0$ for all t

Perform this process for every time interval 't' within the daily time slots.

1. *Solve the optimization problem:*

$$\min_{ci(t)} \quad \sum_{i \in O} \int_{t_i}^{t_i+T_d} (c_i(t)p(i,t) - r_c(i,t)p(i,t)dt$$

subject to

Power demand

$P(t)$ = $\sum P_{ev}^i(t)$ + $P_g(t)$ + $P_{sr}(t)$ - $P_{v2g}(t)$ - $P_l(t)$

and other constraints such as net metering, V2G, renewable energy integration and SOC constraint

1.1 *Add initial and final energy constraint to ensure the charging in controlled manner*

$$\sum_{i \in O} \int_{t_i}^{t_i+T_c} p_i(t)dt \leq e_i(t), \forall t \in S, i \in O$$

1.2 *Add lower and upper bound of charging power*

$$p_i(t) \in [P_i^{min}, P_i^{max}], \forall t \in S, i \in O$$

2. Update $c_i(t)$ for all $i \in O$ using the optimization problem

4: Continue charging the ongoing EVs according to the updated charging rates until the end of their charging period.

5: Repeat steps 1 to 4 for each time slot.

6: Output the optimal charging rates $c_i(t)$ and other parameters mentioned in Step 2

5.3 Results and Discussion

Extensive simulations using CVX were conducted to assess the proposed scheduling method for charging and discharging. The main objective is to investigate an electric load of microgrid during a 24-hour period starting at midnight. Actual load data from a Californian microgrid on July 20, 2020, was scaled down to reduce the size of the dataset and approximate the base load for each period. The electric vehicles considered in the study were equipped with 15 kWh batteries and a range of up to 150 kilometers. All EVs had identical battery requirements, mandating that the battery energy must be 90% of its maximum capacity at the closing of the charging session. Meanwhile, the modelling of arrival times, charging periods, and initial energy levels of the EVs is outlined as follows. The number of EVs was typically set to 350. The arrival times of the EVs were uniformly distributed throughout the day, with less than 10% of vehicles arriving at any given hour. The charging times range from 4 to 12 hours evenly, making for an average charge time of 8 hours. The initial energy levels of the EVs were evenly distributed between 0 and 80% of the battery capacity.

By considering data from multiple weekdays, variations caused by irregular events or specific day-to-day patterns were effectively reduced, thereby ensuring a more consistent and reliable load data. As a result, it offers a more precise representation of the total energy demand. Furthermore, the base load data has been used to forecast the load using averaging approach. The calculated mean error between the base and predicted load is remarkably low, measuring only 0.015. The entire cost for a decentralized EV charging system is computed as 521.6$ depending on the real base load. Fig. 5.3 depicts the variation of both the base load and the forecasted load within each interval.

The decentralized nature of charging stations and the diverse preferences of EV users introduce variability to the charging load curve. This variability arises from factors such as individual charging preferences, charging duration, charging power levels, and the availability of charging stations. Consequently, the charging load shown in Fig. 5.4 demonstrates fluctuating charging and discharging patterns as different EVs connect and disconnect from the charging infrastructure. Further, the base load that persists throughout the day is influenced by the pres-

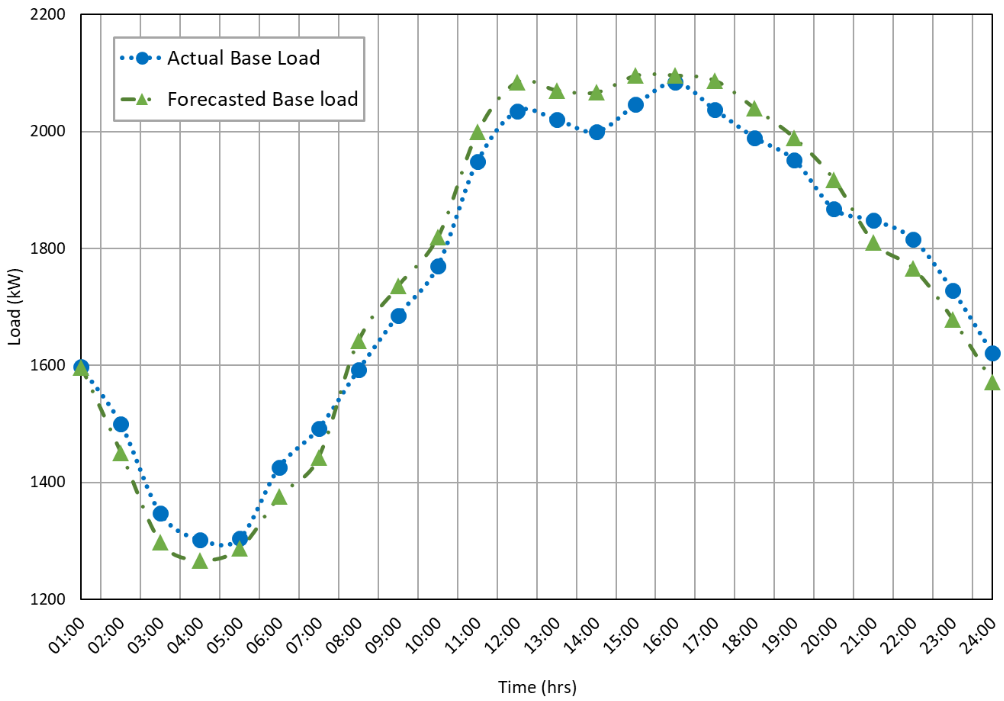


Figure 5.3: Comparison of actual base load and forecasted load.

ence of EV charging in a decentralized scheme as shown in Fig. 5.5. It is important to note that EV owners were charging their vehicles during off-peak times and discharging them during daytime peak times to lessen the load on the grid.

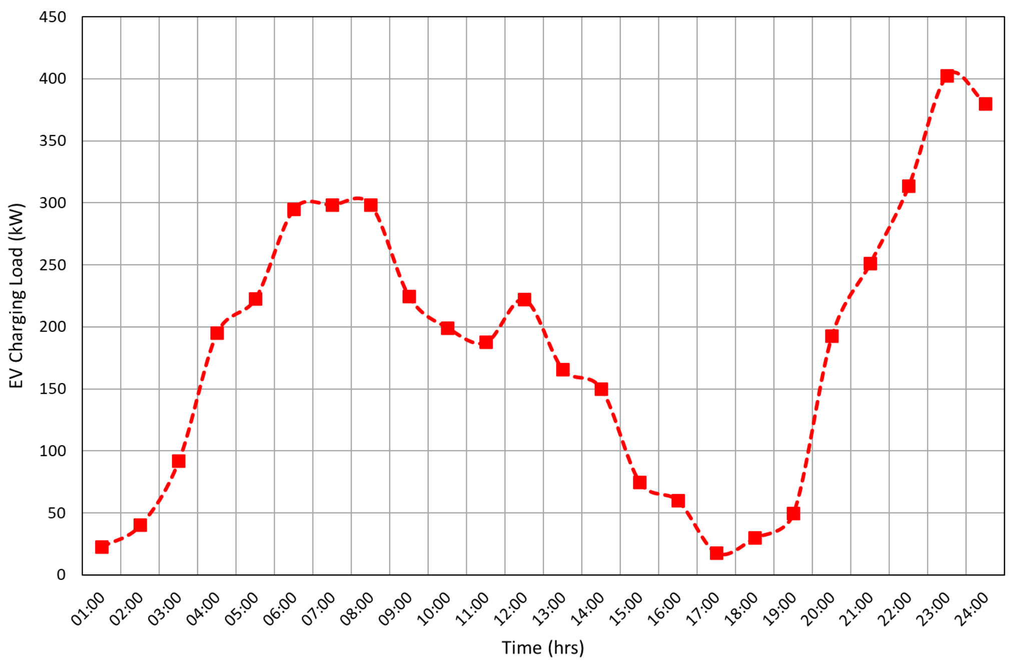


Figure 5.4: EV charging load.

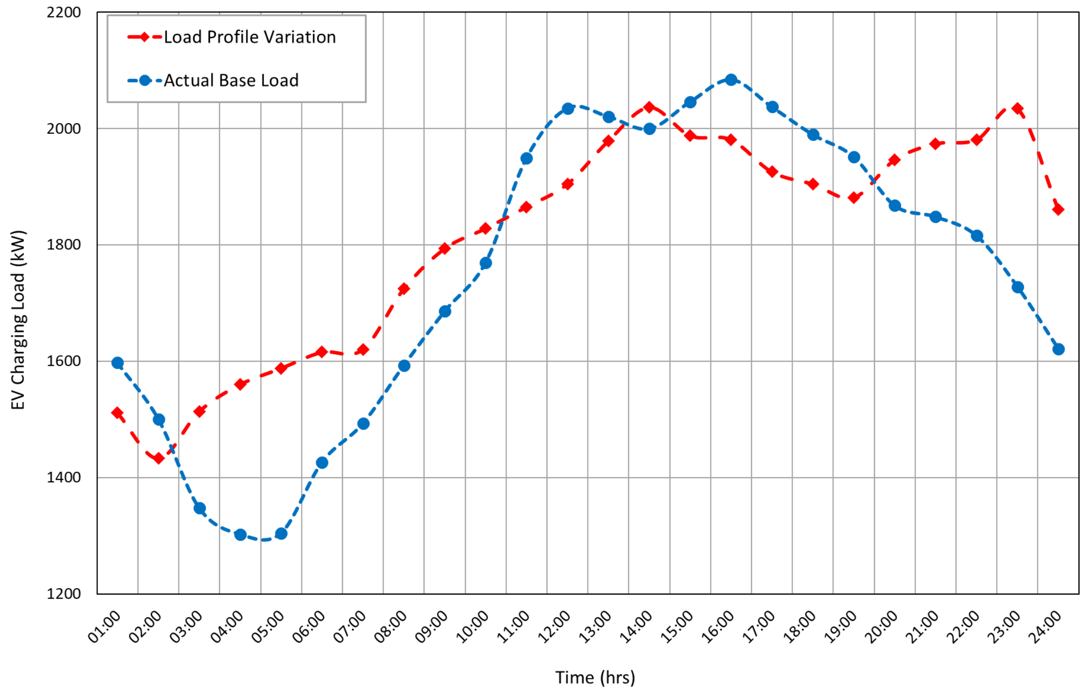


Figure 5.5: Impact of EV charging/discharging on actual load curve.

Moreover, the decentralized system intends to divide the charging load across a number of vehicles, easing the strain on the grid and maximizing the use of the current infrastructure. By allowing EVs to communicate with each other and make decisions collectively, the proposed scheme maximizes the efficiency and minimizes costs for EV charging. The cost is typically highest when there is only one EV per charging station, as seen in Fig. 5.6. This can be attributed to several factors. Firstly, the charging infrastructure, such as charging stations and associated equipment, has fixed costs that are spread across the number of EVs in the group. In the presence of a single EV, the entire cost responsibility falls on the individual user, resulting in elevated charging expenses. However, the price gradually drops as the average group size increases. The fixed costs of infrastructure and maintenance are split across a larger number of users when there are more EVs in the group. As a result, the individual cost per EV decreases, making charging more affordable for each individual.

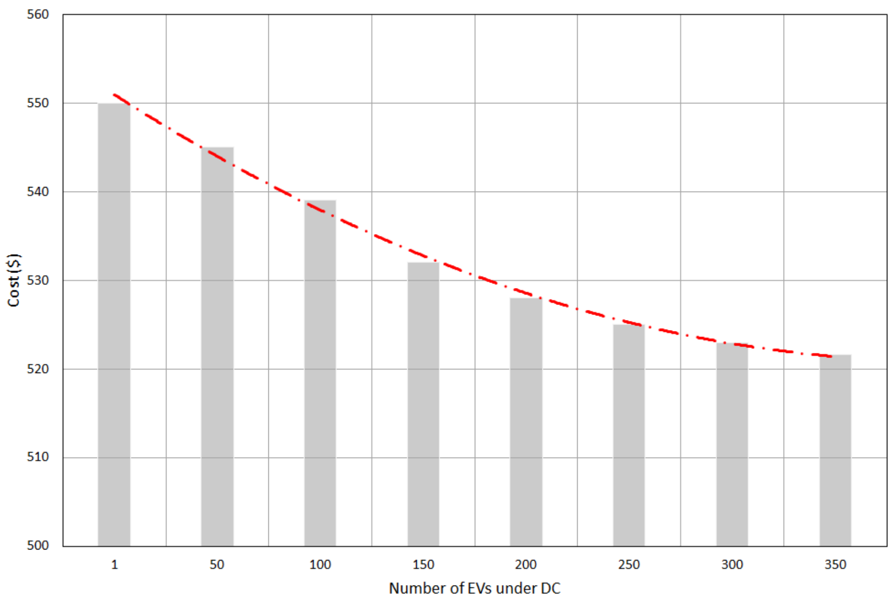


Figure 5.6: Total cost variation per decentralized controller with number of EVs.

Nevertheless, it is crucial to consider both the total number of EVs and the average group size to comprehend their impact on charging costs. As the total number of EVs increases, the cost per EV rises, even with a larger average group size. This occurs when the demand for charging infrastructure surpasses the economies of scale achieved by higher group sizes. In addition, Fig. 5.8 shows how the collective charging needs of the increasing number of EVs impact the base load curve, consequently altering the overall electricity consumption pattern in the decentralized scheme.

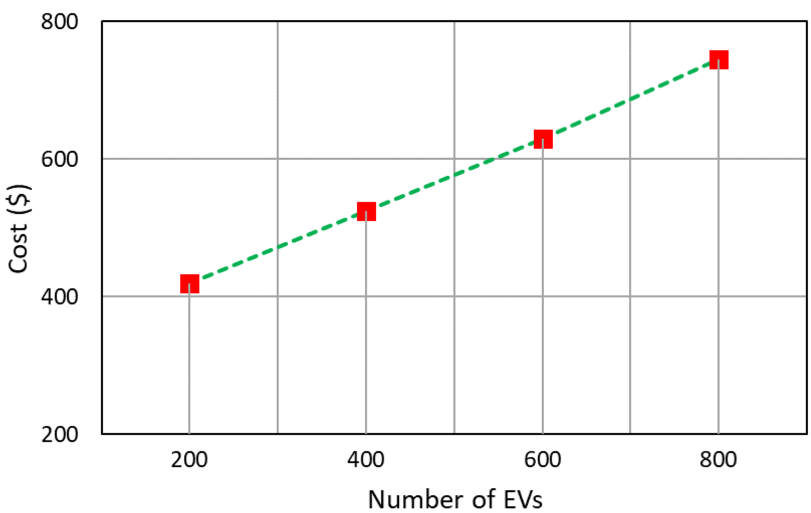


Figure 5.7: Total cost variation with total number of EVs.

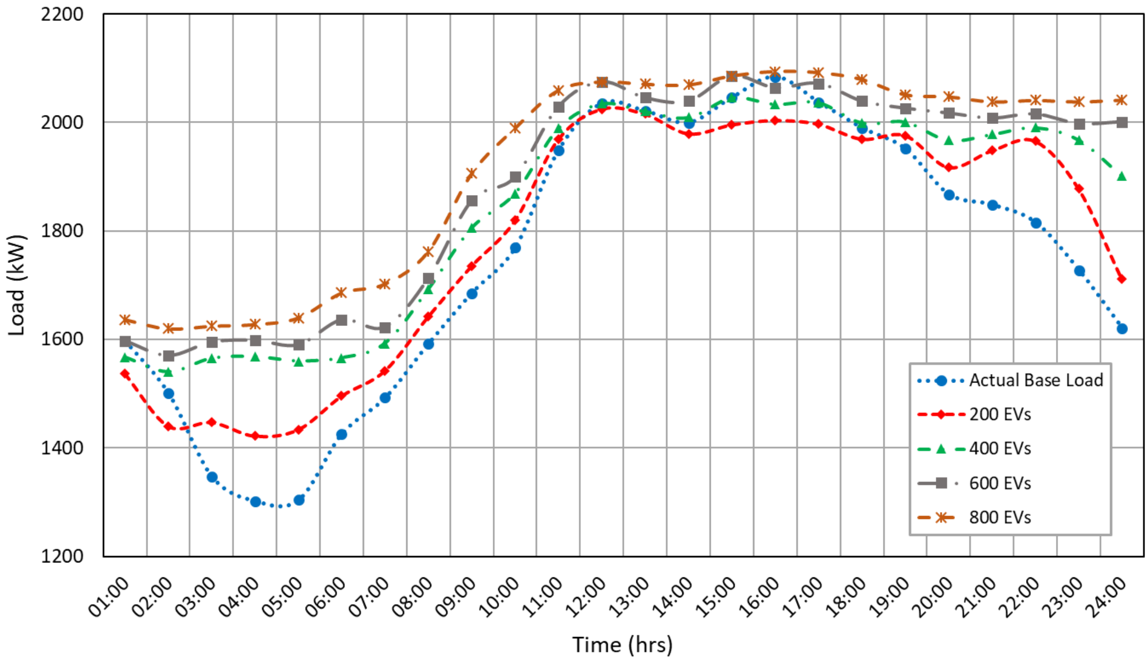


Figure 5.8: Load curve shift analysis with different number of EVs.

The inclusion of more EVs results in a noticeable shift in the base load curve. During peak charging periods, the curve displays higher peaks and an elevated baseline, signifying increased energy consumption. Nonetheless, incorporating renewable generation or V2G technology can help alleviate the impact of this heightened demand by supplying surplus electricity back to the grid.

The implementation of a decentralized EV charging system offers several compelling advantages. A key benefit is achieved through effective load balancing by grouping EVs based on their locations, each managed by a decentralized controller. Further, the approach ensures a more equitable distribution of charging requirements, thereby reducing the likelihood of localized grid congestion. Additionally, the decentralized strategy optimizes resource allocation by leverage real-time data and predicted loads to create efficient charging schedules. As the total number of EVs increases, overall expenses decreases due to the spreading of shared infrastructure costs among a larger user base. Moreover, the system demonstrates flexibility in deciding when to charge and discharge, allowing prioritization based on individual EV battery levels and power grid conditions. The integration of sustainable energy sources, such as solar panels, contributes to the development of an environmentally friendly energy system. Finally, the simulation results illustrates how strategically organizing EV activities in a decentralized manner effectively mitigates peak loads on the grid, thereby enhancing overall grid stability.

5.4 Conclusion

With the increasing number of EVs on the road, comprehending the effects of their charging and discharging patterns is imperative for upholding a stable and efficient power grid. Therefore, the research investigates the scheduling pattern of EVs in a decentralized charging systems. The proposed method involves a decentralized controller designated to groups of EVs based on their locations. The controller optimizes the charging schedule for each EV, considering various objectives and constraints. Further, the scheduling algorithm divides the time horizon into fixed-length EV charging intervals to accommodate both anticipated and unanticipated EV charging demand. The results highlight the variation introduced to the charging load curve as a result of the system's decentralization. The cost analysis reveals that the decentralized system optimally distributes the charging burden across EVs, thereby reducing charging costs as more EVs share infrastructure. To maintain cost-effectiveness, the total number of EVs must be balanced with the average group size. Furthermore, with the growing EV population, the cumulative demand for charging starts to exert an impact on the overarching electricity consumption pattern. By supplying excess electricity to the grid, renewable generation and V2G technologies play a vital role in mitigating this impact. The future scope of work in this field holds promising avenues for further research and development. It includes the focus on investigating cutting-edge algorithms & optimization methods and executing practical pilot projects to improve the effectiveness, scalability, and usability of decentralized EV dispatching systems.

Chapter 6

LOAD FORECASTING FOR CHARGING OPTIMIZATION

6.1 Introduction

The shift towards electric mobility represents a promising global strategy for de carbonizing the transport sector. Numerous nations are supporting the Global EV30@30 initiative, aiming to achieve a minimum of 30% new vehicle sales by 2030 [161]. The integration of electric vehicles into the power grid requires careful management of the energy demand from the charging of these vehicles [44]. Load prediction is a key technology that helps to predict the future energy demand from EVs, allowing for the efficient management of the power grid. Further, during vehicle charging, it consumes power from the grid, potentially causing a spike in energy demand. However, if many EVs charge simultaneously, this can result in strain on the grid and even lead to blackouts and brownouts [162]. Predicting the charging demand of EV fleets, can have important implications for grid planning and operation, as it is necessary for infrastructure planning and investment decisions.

Once utilities have accurate load forecasts, they can adjust their energy supply to meet the predicted demand, potentially reducing the need to rely on expensive and environmentally unfriendly peaker plants to meet peak demand. Additionally, load forecasting can help utilities better manage their energy storage systems, ensuring that they have enough energy stored to meet the demand during peak periods. Moreover, load prediction can be based on various factors such as historical charging data, weather patterns, and expected driving patterns [137,163]. Machine learning (ML) algorithms such as neural networks, support vector machines (SVM), k-nearest neighbor (KNN) and decision trees, are employed for data analysis and forecasting future demand. However, machine learning algorithms has its own drawbacks in terms of accessibility and problem-solving ability. On the other contrary, deep learning algorithms, such as LSTM, GRU [164–166] can be used to improve load prediction by modeling the complex relationships between these factors and the energy demand from EVs.

Further, as EV charging demand is influenced by many factors that can change rapidly, such as weather conditions, traffic patterns, and public events. Deep learning models possess the capacity to adapt and learn from new data continuously, enabling them to provide accurate predictions, even when confronted with evolving conditions [167]. Moreover, traditional deep learning models uses fixed architectures and treat all input features equally. Therefore, in this research, attention-based model is used that can dynamically weight the importance of different features, allowing them to focus on the most relevant information and ignore irrelevant information. For example, an attention-based model might place more weight on weather conditions, charging station locations, or the time of day, depending on which factors are most important in a given context. In addition, attention-based mechanisms are designed to handle long-term dependencies more effectively. Lastly, for V2G to be implemented effectively in future, accurate predictions of EV charging and discharging behavior are essential.

6.1.1 Motivation

Prediction of EV charging demand is critical to ensure the stability of the power grid, as well as to minimize energy waste and reduce costs. Nonetheless, predicting charging loads poses a formidable challenge owing to the complex and dynamic characteristics of charging pattern. Traditional load prediction methods, such as time-series analysis are limited in their ability to capture the complex relationships between various factors that influence EV charging loads, such as weather, energy prices, and vehicle charging patterns. To address these limitations, recent research has explored the use of deep learning methods, such as recurrent neural networks (RNNs), for EV charging load prediction. However, the performance of RNNs can vary depending on the type of RNN model used. Long short-term memory (LSTM) and gated recurrent unit (GRU) algorithms are two popular types of RNN framework that have shown promising results in various applications. In this research, the potential of attention-based LSTM and other artificial intelligence (AI) algorithms has been investigated for load prediction. The proposed technique is evaluated on a real-world ACN dataset, demonstrating its potential for practical application in the field of EV charging management.

6.1.2 Contribution

The primary contribution of this research are as follows:

1. The proposed attention-based deep learning model outperforms traditional models in predicting EV charging load with improved accuracy and lower MSE error values.

2. The novel application of attention mechanisms within the framework of deep learning allows the model to selectively concentrate on relevant features and more efficiently capture long-term dependencies in the data.

3. The study demonstrates the potential of attention-based deep learning mechanisms in advancing the field of energy forecasting, providing a valuable contribution to the development of more accurate and efficient energy management systems.

6.2 Data Preparation and Analysis

6.2.1 Dataset

The quality of the dataset determines the success of a successful predictive AI model. This section discusses the most often used datasets for analysing EV charging behaviour. Dataport [168] serves as the repository for residential water and energy data gathered through Pecan Street's water and power research. While this dataset is publicly accessible for research endeavours, its scope is restricted to home EV charging usage. In contrast, ACN Data is one of the most recently made public datasets on EV charging, encompassing more than 30,000 charging sessions recorded at three non-residential charging facilities in California (Caltech, JPL, and Office 1) [169]. In this research, user behavior prediction specifically for enterprise charging has been emphasized based on Caltech site data as it has the highest number of electric vehicle supply equipment (EVSE) as compared to other sites. Thus, ACN dataset from April 2018 to February 2019 which consists of 16699 rows and 13 columns has been used to train and evaluate all our models. Further user details, including their anticipated departure time and energy consumption requirements, are obtained by scanning a QR code through a mobile app. If a user doesn't access the mobile app during a given session, default values will be created for these fields.

6.2.2 Data Preprocessing

Data preprocessing is a set of techniques that aim to improve the quality, accuracy, and usefulness of data by addressing issues such as missing values, outliers, and inconsistent data formats [170]. The success of data analysis and modelling hinges significantly on the quality of the input data, with data preprocessing serving as a pivotal role in ensuring that the data is appropriately prepared for these tasks. The issues occurred in the ACN dataset has been addressed below with the necessary preprocessing steps.

Missing values treatment

Missing data points can arise due to a variety of reasons such as data corruption, data entry errors, or data unavailability. In the case of the ACN EV charging dataset, data had missing values for three columns: *doneChargingtime, userID and user Inputs*. The individual percentage of missing values is shown in Table 6.1 below:

Table 6.1: Missing columns and their percentage.

Missing value columns	Missing values (in %)
doneChargingTime	0.0479071%
userID	77.7292%
userInputs	77.7292%

It is quite evident that *doneChargingTime* has very few null values hence the missing values in the specified column has been imputed with the mode of *doneChargingTime*. Further, *userID* and *userInputs* has high percentage (around 78%) of null values, so it has not been possible to remove such a high number of rows. From the data dictionary, it is observes that this field is populated with the users who claimed sessions using mobile app of EV charging. Therefore, a separate data sheet has been created including the rows having same type of information.

Outliers detection

Identifying and managing outliers constitutes a crucial phase in data preprocessing as they can exert a substantial influence on the analysis and interpretation of the data. Some of the outliers has been detected but later they have been ruled out as the average battery capacity of an EV is around 40kWh, but some EVs now have up to a 100 kWh capacity.

Derived columns

Derived columns, also known as calculated columns, are additional columns that are created during the data preparation stage. In order to do the analysis around peak hours and charging time, few derived columns have been made as shown in Table 6.2.

Table 6.2: Derived columns and their description

ConnectionTime derived columns	connectionTime_Year connectionTime_Month connectionTime_Day connectionTime_Weekday connectionTime_Hr connectionTime_Yr_Month
Charging duration on different gradients	charging_time_seconds charging_time_minutes charging_time_hrs

Normalization of data

The scale of the data measurement bar significantly influences both the training outcome and the model's output since this experiment relies on recurrent neural network models. Hence, standardising the data is a prerequisite for removing the data dimension's impact on the outcome. Normalization, or scaling all data to 0-1, is often referred to as maximum and minimum normalisation, and is defined as.

$$Y = \frac{X - X_{MIN}}{X_{MAX} - X_{MIN}} \tag{6.1}$$

6.2.3 Analysis of the data

To gain insights into the charging patterns of EV users, an exploratory data analysis (EDA) on an ACN dataset of charging sessions at public charging stations has been conducted. The Python's Matplotlib and Seaborn libraries has been utilised to create visualizations that helped us understand the data distribution. Moreover, univariate analysis is performed to explore the characteristics of individual variables such as connection time, kWh delivered, charging time and location.

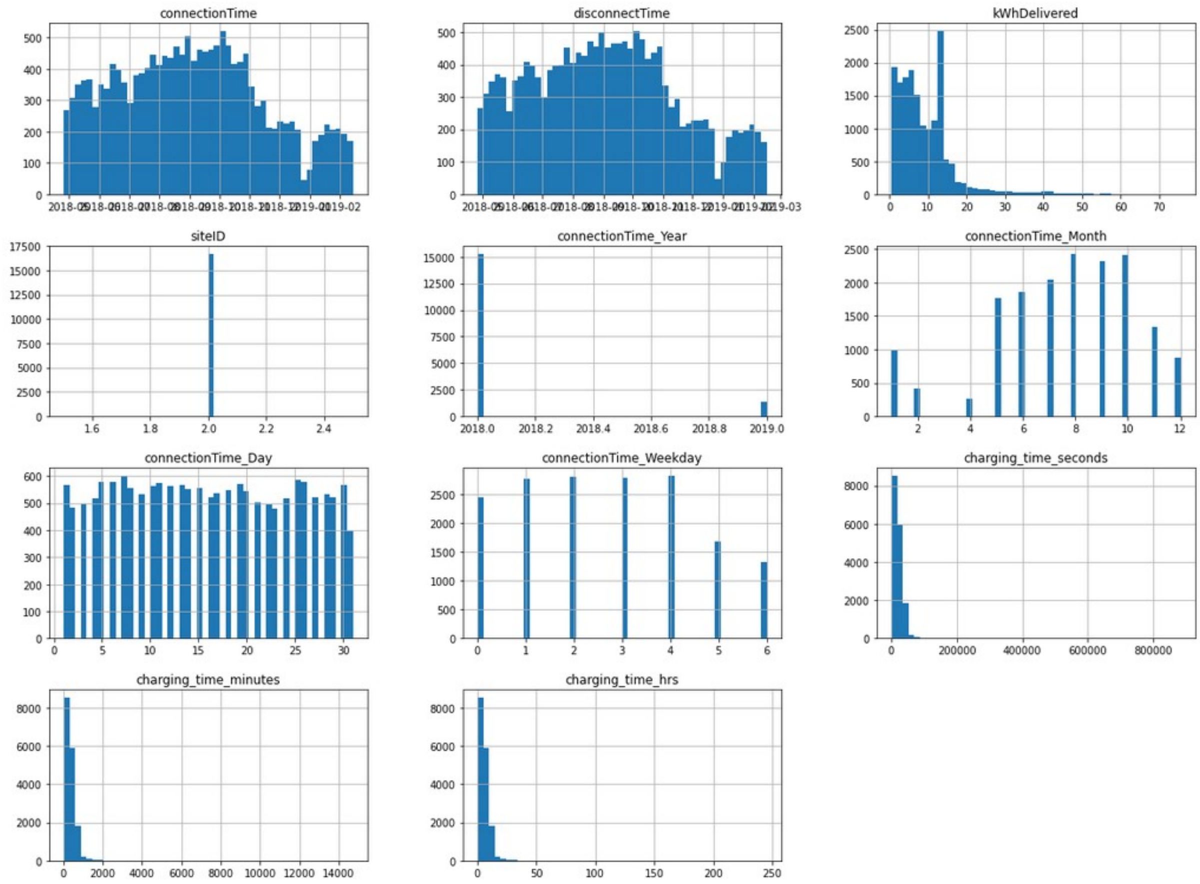
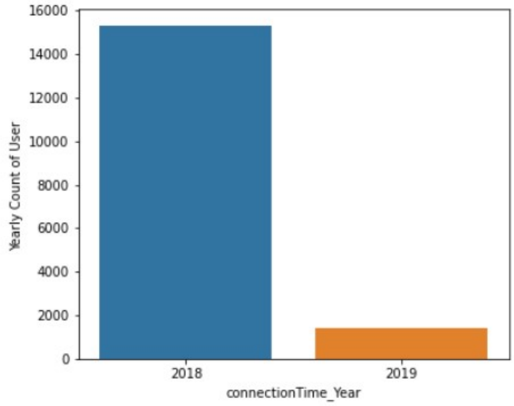
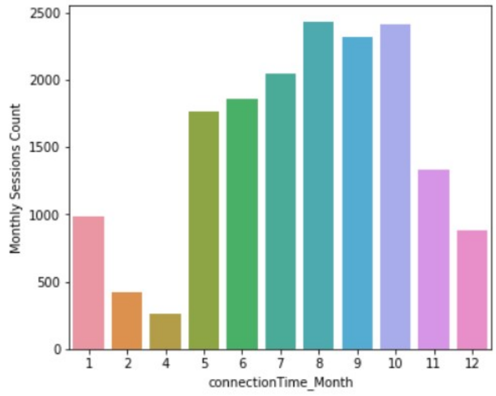


Figure 6.1: Distribution of ACN dataset

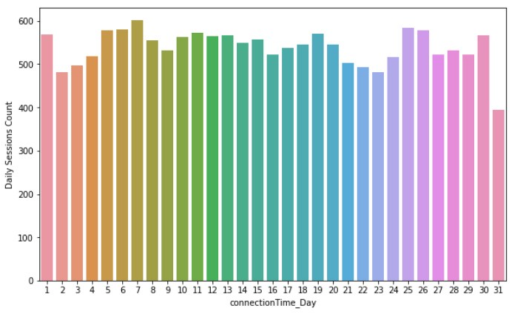
Fig. 6.1 illustrates the distribution of numerous variables within the ACN dataset. Multiple variables such as connectionTime, chargingTime, disconnectTime, location, and power delivered are observed to be distributed normally. Furthermore, it also implies that majority of the charging stations offers charging within the range of 0-20kW, leading to a left-skewed distribution of the power delivery data.



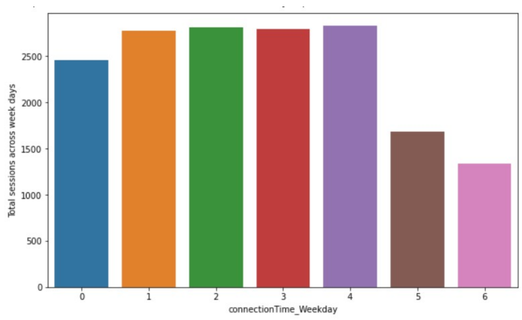
(a) Distribution of EV sessions across years.



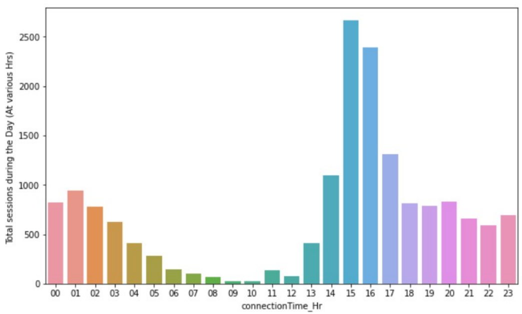
(b) EV sessions across months.



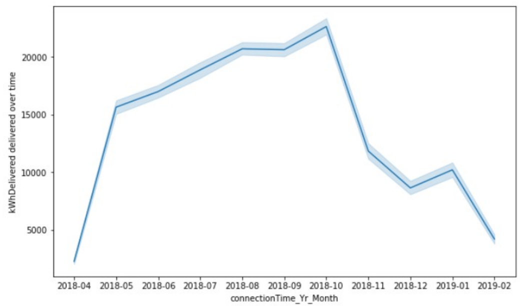
(c) Distribution of EV sessions across days.



(d) Distribution of EV sessions across weekdays.



(e) Peak hour distribution.



(f) Power delivered over time.

Figure 6.2: Segmented analysis of the dataset.

Following that, segmented analysis has been conducted to explore the relationships between different variables. As shown in Fig. 6.2, the data has been segmented based on various factors such as time of day, day of week, location, charging sessions across years, months, days, and peak hours. Since the dataset contains two months of data in 2019, it has fewer sessions, as illustrated in Fig. 6.2 (a). In 2018, the months of August, September, and November had the highest number of EV sessions, with the subsequent decline in the sessions after November. It is due to the fact that these months (December-March) fall within the winter season, it makes sense that there would be fewer sessions overall during this time as illustrated in Fig. 6.2 (b). Further, numbers 0 and 6 in Fig.6. 2 (d) represent sunday and monday, respectively. It was found that session counts were lower on weekends and higher during the week.

On the other hand, peak distribution plot in Fig. 6.2 (e) shows that afternoons, specifically between 3-5pm tend to be the busiest hours of the day. Moreover, Fig. 6.2 (f) demonstrates a rising trend in kWh delivered that is established through session distribution, while it sharply decreases in winter. Furthermore, it is important to highlight that V2G technology can help alleviate the effects of peak demand by providing additional power to the grid during these times. Through V2G technology, electric vehicles can store surplus energy during off-peak hours when demand is lower and subsequently release this stored energy back to the grid during peak hours when demand surges. This mechanism serves to alleviate the grid's stress, enhancing both its reliability and stability.

6.3 Modelling Description

6.3.1 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of recurrent RNN designed to address the issue of disappearing gradients encountered in conventional RNNs. In a standard RNN, the gradient of the loss function concerning the weights tends to diminish as it propagates through time, hindering the learning of long-term dependencies in sequential data [171]. This challenge is solved by LSTM, which introduces a specific mechanism known as a memory cell, which allows the network to selectively remember or forget information from prior time steps [172]. Fig. 6.3 depicts the basic framework of LSTM model.

Let x_t, h_t, and c_t be the input, output, and cell state vector at time t. The LSTM updates the cell state and output using the following equations:

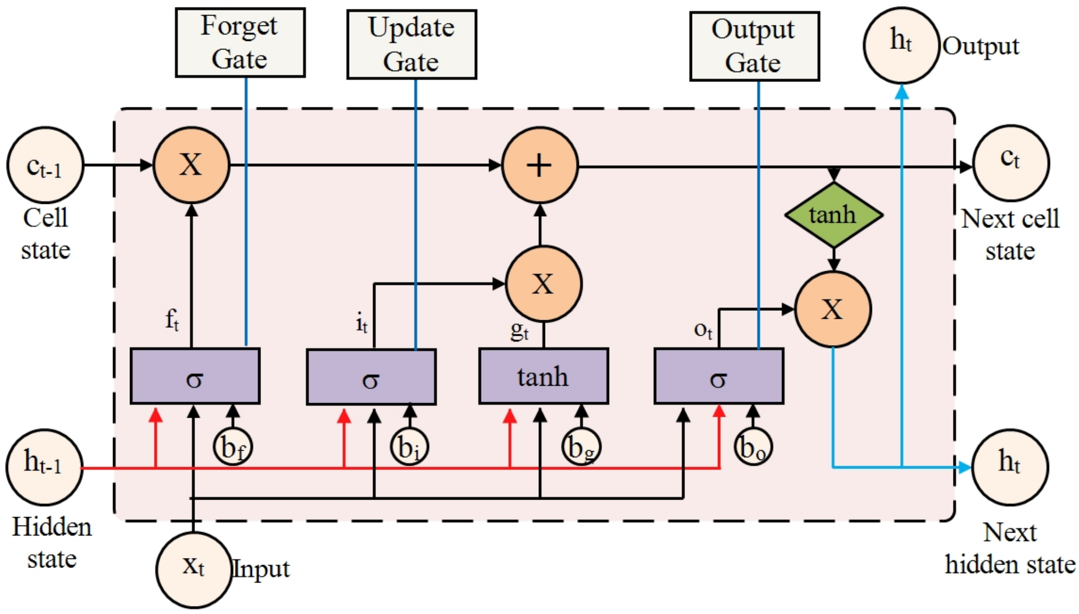


Figure 6.3: Basic LSTM architecture

$$i_t = \sigma(W_i[x_t, h_{t-1}] + b_i) \tag{6.2}$$

$$f_t = \sigma(W_f[x_t, h_{t-1}] + b_f) \tag{6.3}$$

$$o_t = \sigma(W_o[x_t, h_{t-1}] + b_o) \tag{6.4}$$

$$g_t = tanh(W_g[x_t, h_{t-1}] + b_g) \tag{6.5}$$

$$c_t = f_t * c_{t-1} + i_t * g_t \tag{6.6}$$

$$h_t = o_t * tanh(c_t) \tag{6.7}$$

where σ is the sigmoid function, and W_i, W_f, W_o, W_g, b_i, b_f, b_o, & b_g are the learnable weight matrices and biases.

The input gate i_t regulates the incorporation of information from the current input into the cell state c_t. It is calculated as a sigmoid function applied to the concatenation of the current input x_t and the preceding output h_{t-1}. In contrast, forget gate, f_t, decides which information from the prior cell state c_{t-1} should be retained. The output gate, o_t, determines which information should be output at the current time step. Moreover, the input gate output, i_t, is merged with the candidate cell state update, referred to as g_t. This update is calculated as a hyperbolic tangent function applied to the concatenation of the current input x_t and the previous output h_{t-1}. Meanwhile, the forget gate output, f_t, serves to selectively discard information from the preceding cell state c_{t-1}. Consequently, the updated cell state c_t is computed as a combination of the forget gate output f_t, the input gate output i_t and the candidate cell state update g_t. Subsequently, the output gate output o_t is then used to determine which information from the updated cell state c_t is to be emitted at the present time step. The final output h_t is calculated as a combination of the output gate output o_t and the hyperbolic tangent of the updated cell state c_t.

6.3.2 Gated Recurrent Units (GRUs)

Long Short-Term Memory (LSTM) networks and gated recurrent units (GRUs) are analogous, but GRUs have fewer parameters. GRUs are created to address the vanishing gradient issue in regular RNNs, which can make it challenging to train models on extended data sequences, similar to how LSTMs do [173]. The main principle of GRUs is to selectively update the hidden state of the RNN using gating mechanisms at each time step as opposed to adding or multiplying the input by a predetermined weight matrix as in a conventional RNN. In this way, the vanishing gradient problem is avoided and GRUs are able to learn long-term relationships in the input sequence. Fig. 6.4 below illustrates the fundamental organisation of the GRU algorithm:

At every time step, denoted as ”t”, a GRU calculates an updated hidden state h_t using the following equations:

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{6.8}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{6.9}$$

$$h'_t = tanh(W_h x_t + U_h(r_t * h_{t-1}) + b_h) \tag{6.10}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * h'_t \tag{6.11}$$

Here, x_t represents the input vector at time t, h_t stands for the hidden state vector at time t,

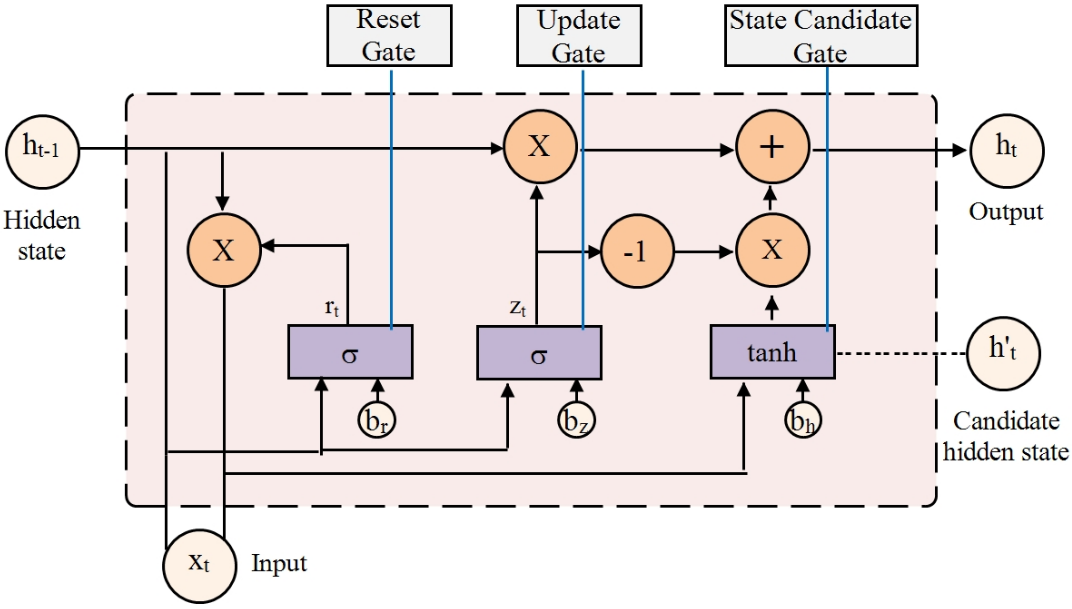


Figure 6.4: Basic GRU architecture

h'_t denotes the candidate hidden state vector, z_t signifies an updated gate vector, r_t represents a reset gate vector, and σ corresponds to the sigmoid activation function. The update gate vector z_t regulates the extent to which the candidate hidden state h'_t is utilized for updating the previous hidden state h_{t-1}, whereas the reset gate vector r_t manages the degree to which the previous hidden state h_{t-1} contributes to the computation the candidate hidden state h'_t.

The computation of the candidate hidden state h'_t involves applying a hyperbolic tangent activation function to a linear combination of the current input x_t and the previous hidden state h_{t-1}, further modulated by the reset gate r_t. This allows the model to selectively ”reset” or ”retain” information from the prior time step. Subsequently, the updated hidden state h_t is derived as a weighted average of the previous hidden state h_{t-1} and the candidate hidden state h'_t-the weighting being determined by the update gate vector z_t. A with LSTMs, GRUs can also be stacked to create deeper architectures, which can enhance performance.

6.3.3 Attention Mechanism

In an LSTM network incorporating attention, the attention mechanism is typically employed on the output of the LSTM cell at each time step, as illustrated in Figure 6.5. Specifically, a weighted sum of the LSTM outputs is computed, with the weights determined by an attention mechanism [174, 175].

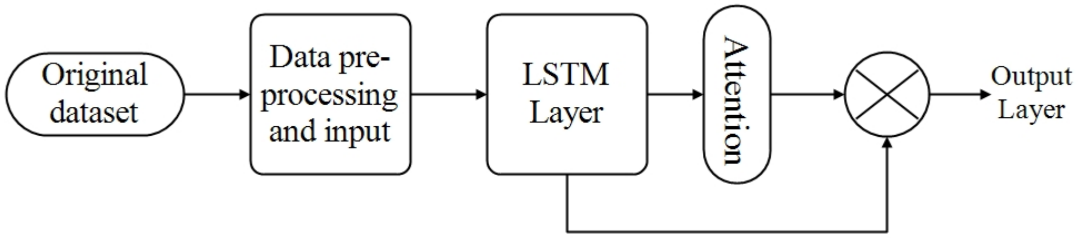


Figure 6.5: Attention-based architecture.

Initially, the LSTM output at each time step "t" is computed as follows:

$$h_t = LSTM(x_t, h_[t-1]) \tag{6.12}$$

Next, the attention scores α_t for each LSTM output at time step t are computed using a learned alignment model:

$$\alpha_t = softmax(W_a * tanh(W_q * h_t + W_p * h_s) \tag{6.13}$$

where W_a, W_q, and W_p are learned weight matrices, h_s is the context vector computed from previous attention weights, and tanh is the hyperbolic tangent function. The context vector is then obtained by computing a weighted sum of the LSTM outputs using the attention scores:

$$c_t = \sum(\alpha_t * h_t) \tag{6.14}$$

Lastly, the context vector is combined with the LSTM output at time step "t" and processed through a fully connected layer to yield the final output y_t:

$$y_t = softmax(W_y * [c_s; h_t]) \tag{6.15}$$

where W_y represents a weight matrix that is learned during training, $[c_s;\ h_t]$ signifies the concatenation of the context vector and the LSTM output at time step "t", and "softmax" refers to the softmax function.

6.3.4 Evaluation Metrics

Depending on the type of problem being solved and the characteristics of the data, various evaluation measures, including accuracy, precision, recall, and F1 score, can be utilised [176]. Nonetheless, for regression problems, the mean squared error (MSE) is a commonly employed metric that quantifies the average squared disparity between the predicted values and the true values. MSE serves as a valuable indicator for evaluating the overall accuracy of a regression model, with reduced MSE values indicative of superior performance. In this research, MSE is utilized as an evaluation metrics and is defined as follows:

$$MSE = (\frac{1}{n}) * \sum((y_i - y_i')^2) \tag{6.16}$$

Here, "n" represents the total number of observations in the dataset, y_i corresponds to the actual value of the target variable for the i_{th} observation, and y_i' denoted the predicted value of the target variable for the same i_{th} observation.

6.4 Results and Discussion

The preprocessing employed in this study played a vital role in preparing the data for deep learning. Various techniques were applied to clean and transform the data, encompassing tasks such as eliminating missing values, standardizing feature scales, and reducing the dimensionality of the ACN data. The correlation matrix to visualize the relationship between the variables is shown in Fig. 6.6 below. It is observed that there is a strong correlation between kWhRequested,kWhDelivered and milesRequested which is understandable that users are provided with the requested kWh that is required. In addition, one-hot encoding was another critical step that has been used in preparing the data for the attention-based-LSTM and other deep learning models. It enabled us to convert the categorical information in the data into the numerical format. By doing so, the deep learning models were able to better understand the relationships between the input variables and the target variable.

	index	kWhDelivered	siteID	connectionTime_Year	connectionTime_Month	connectionTime_Day	connectionTime_Weekday	charging_time_seconds	charging_time_minutes	charging_time_hrs	WhPerMile	kWhRequested	milesRequested	minutesAvailable
index	1.000000	-0.216717	nan	0.555841	-0.330615	-0.008257	0.088469	-0.058475	-0.058475	-0.058475	0.098451	-0.152503	-0.175480	-0.136477
kWhDelivered	-0.216717	1.000000	nan	-0.080900	0.022074	0.055291	0.043232	0.340577	0.340577	0.340577	-0.084693	0.714732	0.726954	0.472105
siteID	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
connectionTime_Year	0.555841	-0.080900	nan	1.000000	-0.965980	-0.037577	0.026633	-0.028955	-0.028955	-0.028955	0.058934	-0.028907	-0.036117	-0.051044
connectionTime_Month	-0.330615	0.022074	nan	-0.965980	1.000000	-0.017395	-0.003383	0.013725	0.013725	0.013725	-0.033968	-0.015245	-0.014018	0.013844
connectionTime_Day	-0.008257	0.055291	nan	-0.037577	-0.017395	1.000000	-0.018138	0.011724	0.011724	0.011724	-0.051684	0.059809	0.063458	0.032206
connectionTime_Weekday	0.088469	0.043232	nan	0.026633	-0.003383	-0.018138	1.000000	-0.041501	-0.041501	-0.041501	0.031120	0.081125	0.079316	-0.079982
charging_time_seconds	-0.058475	0.340577	nan	-0.028955	0.013725	0.011724	-0.041501	1.000000	1.000000	1.000000	0.019451	0.180426	0.155396	0.396738
charging_time_minutes	-0.058475	0.340577	nan	-0.028955	0.013725	0.011724	-0.041501	1.000000	1.000000	1.000000	0.019451	0.180426	0.155396	0.396738
charging_time_hrs	-0.058475	0.340577	nan	-0.028955	0.013725	0.011724	-0.041501	1.000000	1.000000	1.000000	0.019451	0.180426	0.155396	0.396738
WhPerMile	0.098451	-0.084693	nan	0.058934	-0.033968	-0.051684	0.031120	0.019451	0.019451	0.019451	1.000000	0.145444	-0.249743	-0.041277
kWhRequested	-0.152503	0.714732	nan	-0.028907	-0.015245	0.059809	0.081125	0.180426	0.180426	0.180426	0.145444	1.000000	0.869107	0.369486
milesRequested	-0.175480	0.726954	nan	-0.036117	-0.014018	0.063458	0.079316	0.155396	0.155396	0.155396	-0.249743	0.869107	1.000000	0.355515
minutesAvailable	-0.136477	0.472105	nan	-0.051044	0.013844	0.032206	-0.079982	0.396738	0.396738	0.396738	-0.041277	0.369486	0.355515	1.000000
paymentRequired	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan

Figure 6.6: Correlation matrix of the variables in the ACN dataset.

The complete range of trainable variables in each of the models is calculated and shown in Table 6.3. This suggests that the attention-based-LSTM model added additional parameters that are used to compute attention weights for each input sequence element. The final output of the model is a weighted sum of the LSTM outputs, which is calculated using these weights. But it's crucial to remember that adding more trainable parameters also raises the chance of overfitting the data.

Table 6.3: Number of trainable parameters.

Deep learning model	Total trainable parameters
Attention-based LSTM	171,301
Traditional LSTM	129,101

Further, to optimize both the models grid search algorithm is employed to determine the best combination of hyper-parameters for each model. It searches over a predefined set of hyper-parameters such as batch size, epochs, units and learning rate to find the best combination that maximizes the performance metric. The Table 6.4 below shows the results obtained from grid search algorithm.

In this research, the models were trained using different numbers of epochs and evaluated using the mean squared error (MSE) as the performance metric. It was found that after 10 epochs, the values of loss and MSE remained constant or showed a negligible change. Based

Table 6.4: Parameters obtained from gridsearch algorithm

Parameters	Attention-based LSTM	Traditional LSTM
Size of the Batch	16	32
Learning rate	0.001	0.1
Units	100	100

on the final outputs, it can be observed that the attention-based LSTM model performed well on the ACN dataset. Nonetheless, it is notable that the validation loss initially exceeded the training loss, as depicted in Figure 6.7. This phenomenon is common in deep learning models and can be attributed to the model's challenge in generalizing effectively to unseen data during the early stages of training.

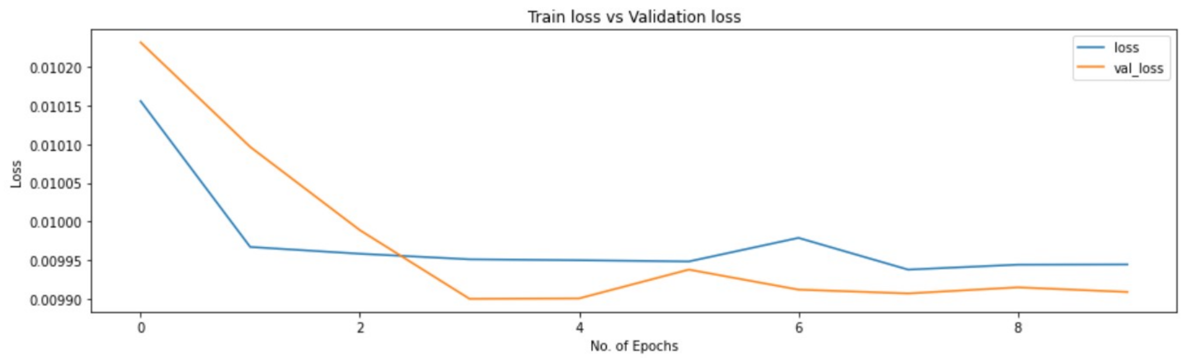


Figure 6.7: Training and validation loss for the Attention-based LSTM model

Furthermore, with an increasing number of epochs, both the training and validation losses decreased, indicating that the model had successfully grasped the inherent data patterns and demonstrated the ability to generalize effectively to novel data. In terms of the MSE value, both models achieved low values, with the attention-based LSTM model achieving an MSE of 0.0099 and the simple LSTM model of 0.015 which is better than the MSE mentioned in [77]. This indicates that attention-based LSTM model is more accurate in making predictions on the given ACN dataset. For this reason, the model has been planned to generate the predictions and evaluate its performance on the test data. The result obtained is shown in Fig. 6.8.

A similar actual and predicted curve indicates that the attention model has effectively captured the temporal dependencies and patterns in the data using its attention mechanism. This is consistent with the known ability of the attention models to capture long-term dependencies more efficiently than traditional recurrent neural networks. It also indicates that model has

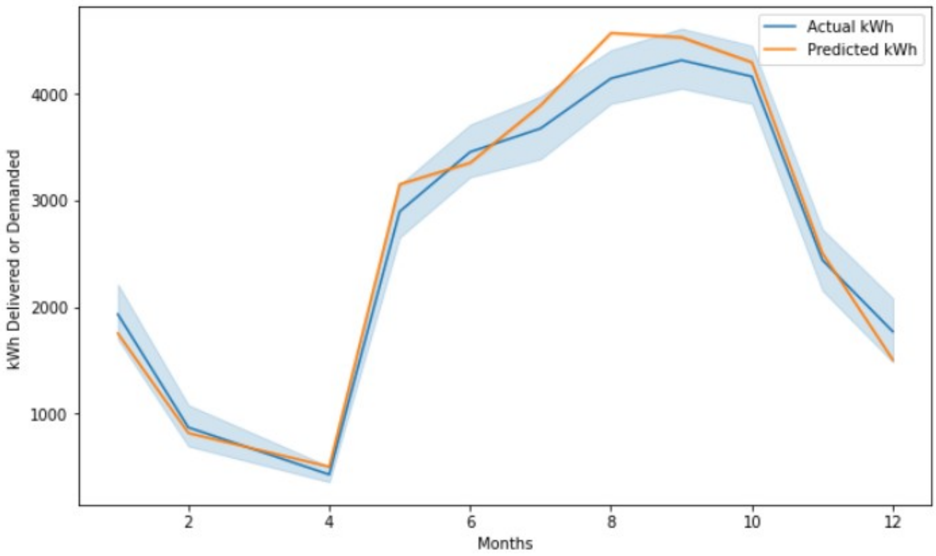


Figure 6.8: Actual versus predicted curve

learned the relevant features and patterns in the input data, and can accurately predict the output variable.

Table 6.5: Accuracy obtained by all the algorithms

Algorithms	Accuracy
Attention-based LSTM	98.2
LSTM	96.4
GRU	90.2
KNN	77.9
CNN	70.1
MLP	69.9

In addition, the deep learning models are compared with the state-of-the-art machine learning algorithms such as k-nearest neighbor (KNN), convolutional neural network and multi layer perceptron (MLP). The accuracies of the different algorithms are mentioned in Table 6.5. It can be observed that the performance accuracy of KNN, MLP and CNN are not satisfactory. Since GRU, is a variant of LSTM which works well but not as compared to LSTM. The proposed attention-based model for EV charging prediction achieves a higher accuracy compared to existing research works in the [177, 178]. Specifically, the model achieves an accuracy of 98.2%, which is higher than the state-of-the-art models in this domain.

6.5 Conclusion

Deep Learning techniques offers a valuable avenue for enhancing the accuracy of energy demand forecasting, a critical component of efficient energy management. Based on the insights derived from the study, it can be concluded that the integration of deep learning techniques, including LSTM and GRU, along with effective attention-mechanism, can significantly improve energy management for public EV charging infrastructure. Additionally, this research underscores the pivotal role of data preprocessing in ensuring the accuracy of algorithms for energy management. By cleaning and transforming data to remove noise and outliers, the quality of the data used in deep learning framework can be improved. Further, the data analysis of the preprocessed data helps in identifying the peak demand periods, leading to the efficient use of renewable energy sources and reducing overall energy costs. The attainment of low Mean Squared Error (MSE) values and high accuracy in this study attests to the precision of the employed models, which can contribute to cost reduction and mitigate grid impact. In the future, the research in the domain of energy management for public EV charging infrastructure could explore alternative deep Learning techniques, integrating other data sources, developing predictive maintenance systems, and implementing real-world systems and testing.

Chapter 7

CONCLUSION AND FUTURE WORK SCOPE

In this chapter, a detailed summary is presented of the work carried out in this thesis to address the challenges addresses in previous sections. Additionally, the chapter highlights the main contributions made and suggests potential areas for improvement that could enhance the results in future research.

7.1 Conclusion

The fundamental purpose of this research was to develop a V2G-enabled smart DC net metering system that adhered to international standards such as IEC 61000/60255/60252. The proposed net meter featured bi-directional power transmission via RS545 and Wi-fi along with real-time data communication through software implementation. In addition, the research in Chapter 3 addressed the challenges associated with AC side metering. Through rigorous testing and validation, the findings confirmed that the DC net meter complied with standard requirements with voltage and current percentage errors of less than 1%. Furthermore, the research study also highlighted the potential of the proposed meter to be expanded with the implementation of dynamic pricing scheme, including time-of use, real-time pricing, critical peak pricing and peak time rebates.

Likewise, Chapter 4 underscored the significance of dynamic pricing in alleviating the burden on the power industry and curbing greenhouse gas emissions, following the advent of electric vehicles. The research delves into the role of dynamic pricing in effectively coordinating the charging and discharging of electric vehicles, all without the need for network expansion. Through the formulation of a multi-objective problem that integrates time-of-use (TOU), critical peak pricing (CPP), and peak time rebate (PTR) components within a tariff structure, the study aims at lowering costs. Moreover, the research proposed a TOU-enabled DC net metering strategy for EV charging systems, which could be advantageous to both customers and utilities. Using the TOU-enabled DC net metering regulation, consumers can only pay for the energy that is legitimately supplied to their EVs.

The introduction of electric vehicles has significantly altered the energy landscape, particularly the demand for electricity. The study in Chapter 5 highlighted the significance of comprehending the impact of charging patterns on electricity consumption and total costs. It highlighted the dynamic relationship between EV adoption, fluctuations in the base load curve, and the implementation of net metering in a decentralized system. In Chapter 6, the integration of deep learning techniques, specifically LSTM and GRU, was investigated in order to increase the precision of energy demand forecasting for efficient energy management in public EV charging infrastructure. The research concluded that by incorporating effective data preprocessing and analysis, deep learning techniques significantly enhanced energy management. Data preprocessing played a crucial role in removing noise and outliers, ensuring high-quality input data for the deep learning models. The study demonstrated the accuracy of the models in reducing energy costs and minimizing the impact on the grid, with low mean squared error (MSE) values.

In summary, the primary objective of this research was to conceptualize and create a DC net meter tailored for vehicle-to-grid technology, enriched with time-of-use functionality. The outcomes affirm that the net meter has been thoughtfully designed for precise real-time measurement and stands poised for potential commercial application. As a result, this research significantly contributes to the advancement of various domains, including electric vehicle charging infrastructure, net metering strategies, energy demand forecasting, and the utilization of deep learning techniques.

7.2 Future scope of work

The work presented in this thesis paves the way for future advancements in the fields of EV charging infrastructure, net metering strategies, energy demand forecasting, and deep learning techniques. Further, to enhance the scope and impact of the thesis, the following future areas of research are proposed:

1. To examine the recent developments in battery technology and their possible integration with the V2G system. It will be helpful in order to assess the benefits of energy storage systems for managing EV charging demands, balancing the grid and providing backup electricity during emergencies.

2. To explore the implementation of Vehicle-to-Home (V2H) and Vehicle-to-Building (V2B) technologies to use EVs to power homes and buildings during peak demand periods.

3. To address cybersecurity concerns associated with V2G systems and implement robust security measures to protect against potential cyber threats. Additionally, to ensure data privacy for EV owners and grid operators while enabling seamless communication between vehicles and the grid.

4. To investigate on a larger scale the scalability of the proposed V2G technology and decentralized EV charging systems. The study will include an economic analysis to determine the financial viability of implementing these systems in real-world scenarios.

5. To study existing policies and regulations related to V2G technology and propose necessary amendments or new frameworks to facilitate its widespread adoption.

6. Conduct demonstrations of the proposed DC net metering system, V2G technology, and decentralized EV charging stations in the actual world. The goal is to collect data from pilot programs in order to validate the effectiveness as well as advantages of the developed solutions.

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