



# Energy Management Scheme for Electric Vehicle Charging Station

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**Abstract:** There are major problems associated with EV charging management system. These problems are associated with primary control like load current sharing, balance of power supply, voltage control, power quality and service reliability. The objective of the current research is to develop a control algorithm for EV charging systems. The proposed control algorithm comprises a centralized controller and a local controller, which ensures 2-layer control. By controlling the local source (PV system) and the ESS, the algorithm aims to mitigate power fluctuations in the grid that might otherwise occur due to changes in solar irradiance, cloud cover, or variations in energy consumption by the connected EVs. The energy management system should prioritize using solar energy generated by the PV system to charge electric vehicles whenever possible. By maximizing solar energy utilization, the charging station can reduce dependency on grid electricity and decrease carbon emissions.

**Index Terms – EV's, Energy management**

## I. INTRODUCTION

Transportation is an essential aspect of modern life, as it enables the efficient movement of people and goods. However, the conventional internal combustion engine, which has long served as the primary means of propulsion, is becoming outdated. Conventional petrol and diesel-powered vehicles are associated with significant environmental pollution, while electric vehicles (EVs) are rapidly emerging as a cleaner alternative. Electric vehicles (EVs) are environmentally superior to conventional cars as they operate solely on electricity, resulting in zero emissions of pollutants. Electric cars offer significantly reduced operating expenses when compared to their petrol or diesel counterparts. Electric vehicles (EVs) differ from conventional vehicles that rely on solid fuels such as petrol or diesel. Instead, EVs utilise electricity as an energy source to charge their batteries. Electric vehicles offer a more cost-effective alternative to petrol or diesel cars due to their superior efficiency and reduced power consumption. The utilisation of electric vehicles powered by renewable energy sources has the potential to yield significant environmental benefits [1]. The utilisation of sustainable energy sources, such as solar panels, installed in residential settings, can further reduce the cost of power when employed for charging purposes. Electric vehicles (EVs) are an environmentally friendly transportation option due to their lack of emissions. By choosing to drive an electric car, individuals can effectively reduce their carbon footprint. By sourcing renewable energy for your home, you can mitigate the environmental impact associated with refuelling your vehicle.

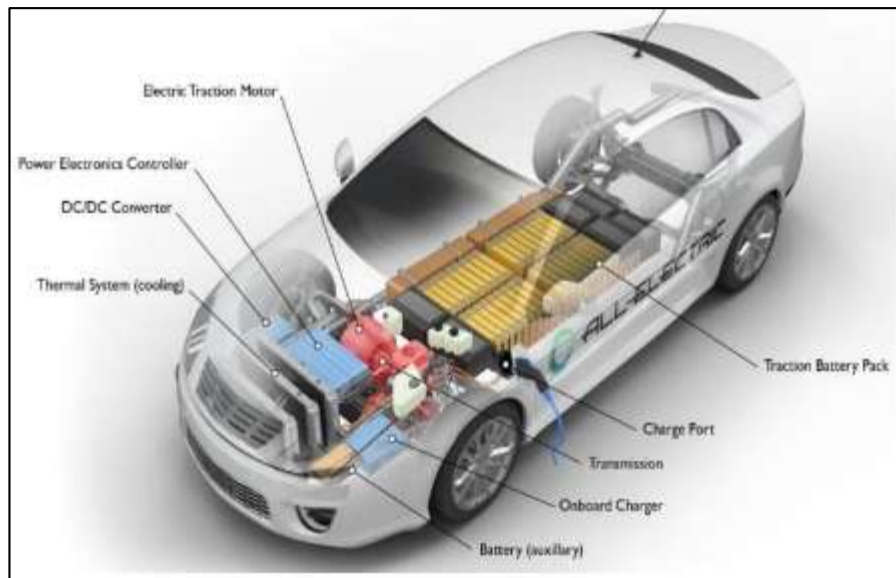


Figure 1: EV vehicle [2]

## II. LITERATURE REVIEW

Yang et al. [3] The feasibility of implementing demand-side management strategies for the purpose of charging electric vehicles (EVs) on the electrical grid has been made possible through the utilization of a charging capacity model, which was developed. The objective of the study outlined in reference was to establish a connection between the modelling of electric vehicle (EV) charging demand profiles and the potential impact of widespread charging on the electrical power grid. The analysis of the electric vehicle charging load profile and its impact on traffic flow was conducted by researchers utilizing ant colony algorithms. This approach allowed for the identification of crucial factors within the charging process that influence the overall traffic dynamics. This method involved the assessment of the duration of a specific electric vehicle charging process, the charging power profile associated with it, and the designated start time. The authors in reference presented a compelling argument in favour of the augmentation of electric vehicle (EV) charging infrastructure. They asserted that the identification of key attributes and primary factors influencing the power grid was facilitated through the utilization of the charging traffic flow concept, which relied on the AC algorithm.

Tangrand et al. [4] conducted a study to investigate the feasibility of the Flex-ChEV as a means to analyze EV travel patterns, EV charging energy consumption, and the possibility of charging station overcrowding. Studies have demonstrated that the prevalence of electric vehicle (EV) congestion at charging stations will have a notable impact on the distribution network of the power grid, further contributing to the already substantial base loads on the energy system. In order to address this issue, the researchers in conducted an investigation into the correlation between the energy requirements of plug-in electric vehicles (EVs) and their traffic patterns, which directly impacts the frequency of EV recharging. The findings of the simulation experiment suggest that ant colony optimisation has the potential to enhance the design of electric vehicle (EV) charging stations by effectively assessing their load-bearing capacities.

Habib et al. [5] The objective of the research conducted was to identify strategies for mitigating the economic, environmental, and environmental impacts related to the grid-based charging of electric vehicles. The accomplishment of these three objectives was facilitated through the implementation of the ABC optimization technique. The findings of the study indicated that the ABC technique exhibited superior performance compared to particle swarm optimization (PSO) in the context of managing the charging and discharging of electric vehicles on a large scale.

Ali et al. [6] employed the ABC method as a means to address voltage oscillations in grid distribution networks within their study. This study considered the intermittent electricity supply from photovoltaic (PV) panels and the voltage fluctuations caused by plug-in hybrid electric vehicles (PHEVs) in the power system. The optimization of the reactive power injected by the photovoltaic (PV) inverter and the charging and discharging power of the electric vehicle (EV) was conducted using the ABC algorithm as outlined in reference.

Alvarez et al. [7] employed an enhanced ABC algorithm in order to effectively address the challenges associated with the integration of electric vehicle (EV) charging infrastructure into the existing power grid. One of the objectives achieved in the study was the optimization of the charging station's utilization to its fullest capacity. In this particular scenario, the ABC algorithm was integrated with local search algorithms in order to mitigate the adverse effects of unregulated charging on the distribution grid and optimize the economic utilization of electric vehicle (EV) charging stations.

Shivappriya et al. [8] A potential approach for mitigating the consequences of unrestricted and widespread electric vehicle charging is to optimize fuel efficiency, as demonstrated in the research. The researchers asserted their ability to enhance the efficiency of electric vehicle (EV) fuel consumption, specifically in parallel hybrid EVs, by employing a modified ABC technique and sequential quadratic programming (SQP) to simultaneously reduce CO<sub>2</sub> emissions. This discovery demonstrates that the overall charge of the battery is minimally impacted by the implementation of this method. This study was motivated by the need to address the limitations

of the Sequential Quadratic Programming (SQP) algorithm in minimizing fuel consumption of electric vehicles (EVs) and identifying a global minimum.

Falabretti et al. [9] In order to mitigate potential adverse impacts on the power grid caused by large-scale electric vehicle (EV) charging, researchers have developed a hybridized ABC (Artificial Bee Colony) algorithm to effectively determine the optimal power allocation required for accommodating the demands of extensive EV car sharing initiatives. The proposed approach entails the involvement of a central planner who is responsible for selecting an appropriate sharing scheme for electric cars (EVs) and subsequently regulating the initial charging time for each EV, taking into account the power limit allocated to each individual vehicle. In a computational experiment, a total of 3200 electric vehicles (EVs) were employed to evaluate the efficacy of the hybridized ABC algorithm in rectifying potential grid mismatch arising from EV charging.

Liu et al. [10] In order to mitigate the energy consumption associated with the integration of a significant number of electric vehicles (EVs) into the power grid, scholars have investigated the route optimization challenge pertaining to EVs, specifically in relation to the battery State of Charge (SoC). The battery SoC serves as a predictive measure to estimate the energy consumption of EVs. A novel hybrid genetic algorithm (GA) has been developed for the purpose of addressing the route optimization problem. The present study involved a computational approach that combined simulated annealing and genetic algorithms (GA) in order to evaluate and analyze the obtained outcomes. The study revealed that the implementation of the hybrid genetic algorithm yielded superior results and provided a more accurate approximation.

Zeng et al. [11] A multi-objective evolutionary system was employed, utilizing electric vehicle trip data. The objective of their research was to enhance the electric vehicle (EV) charging infrastructure with the aim of reducing fluctuations in demand and minimizing grid energy expenses.

Efthymiou et al. [12] conducted a study on the demand for electric vehicle charging and the necessity of widespread deployment of EV chargers. In order to promote the widespread adoption of electric vehicles (EVs) and effectively reduce carbon emissions, a proposal has been put forth to strategically deploy charging stations throughout various European towns. The placement of the charging stations was resolved through the utilization of a Genetic Algorithm (GA).

### III. OBJECTIVES

There are major problems associated with EV charging management system. These problems are associated with primary control like load current sharing, balance of power supply, voltage control, power quality and service reliability. The objective of the current research is to develop a control algorithm for EV charging systems. The proposed control algorithm comprises a centralized controller and a local controller, which ensures 2-layer control.

1. Power Fluctuation Mitigation: By controlling the local source (PV system) and the ESS, the algorithm aims to mitigate power fluctuations in the grid that might otherwise occur due to changes in solar irradiance, cloud cover, or variations in energy consumption by the connected EVs.
2. Maximize Solar Energy Utilization: The energy management system should prioritize using solar energy generated by the PV system to charge electric vehicles whenever possible. By maximizing solar energy utilization, the charging station can reduce dependency on grid electricity and decrease carbon emissions.
3. Developing a two-layer control scheme: The centralised controller and the local controller are the two primary parts of the energy management system. The local controller's reference values are created by the centralised controller. On the other hand, depending on the reference signals supplied by the centralised controller, the local controller is in charge of managing the power output of the local source (such as a PV system) and the Energy Storage System (ESS)

### IV. METHODOLOGY

The integration of solar power with the charging of electric vehicles plays a crucial role in substantially reducing our reliance on fossil fuels. Electric cars require renewable sources of energy for fuel due to the wide range of electricity types available. Due to the increasing demand for electric vehicles, it is likely that solar charging stations will be installed at residences equipped with solar energy systems in the future. To facilitate this endeavor, it is imperative to reassess the procedure employed for refilling vehicles and allow for the organic progression of our energy infrastructure. The numerical expression for the value of PV is as follows:

The “voltage–current characteristic equation of a solar cell is provided

$$I_{ph} = [I_{sc} + K_i(T - 298)] \times I_r / 1000$$

Here,  $I_{ph}$ : photo-current (A);  $I_{sc}$ : short circuit current (A);  $K_i$ : short-circuit current of cell at 25 °C and 1000 W/m<sup>2</sup>; T: operating temperature (K);  $I_r$ : solar irradiation (W/m<sup>2</sup>).

Module reverse saturation current  $I_{rs}$ :

$$I_{rs} = I_{sc} / [\exp(qV_{oc} / N_s k n T) - 1]$$

Here,  $q$ : electron charge,  $= 1.6 \times 10^{-19} \text{C}$ ;  $V_{oc}$ : open circuit voltage (V);  $N_s$ : number of cells connected in series;  $n$ : the identity factor of the diode;  $k$ : Boltzmann's constant,  $= 1.3805 \times 10^{-23} \text{J/K}$ .

The module saturation current  $I_0$  varies with the cell temperature, which is given by

$$I_0 = I_{rs} [T/T_r]^3 \exp\left[\frac{q \times E_{g0}}{nk} (1/T - 1/T_r)\right]$$

Here,  $T_r$ : nominal temperature  $= 298.15 \text{K}$ ;  $E_{g0}$ : band gap energy of the semiconductor,  $= 1.1 \text{eV}$ ; The current output of PV module is:

$$I = N_p \times I_{ph} - N_p \times I_0 \times \left[ \exp\left(\frac{V/NS + I \times R_s / NPn \times V_t}{n \times V_t}\right) - 1 \right] - I_{sh}$$

With

$$V_t = k \times T$$

and

$$I_{sh} = \frac{V \times NP / NS + I \times R_s}{R_{sh}}$$

Here:  $N_p$ : number of PV modules connected in parallel;  $R_s$ : series resistance ( $\Omega$ );  $R_{sh}$ : shunt resistance ( $\Omega$ );  $V_t$ : diode thermal voltage (V) [8]

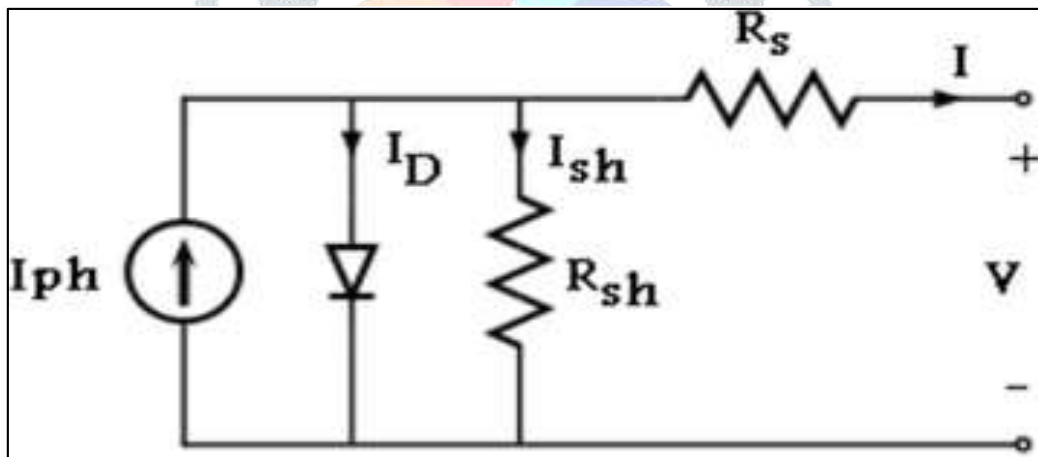


Fig 2: PV circuit

### EV Battery

Lithium-ion batteries are currently utilised in a wide range of portable consumer products, such as mobile phones and laptops, due to their higher energy density when compared to other forms of electrical energy storage. The reason for this is that these batteries are commonly utilised in consumer electronics. Furthermore, these devices exhibit exceptional performance even under elevated temperatures, boasting a remarkable power-to-weight ratio, superior energy efficiency, and minimal self-discharge. While it is technically possible to recycle most of the components found in lithium-ion batteries, the industry remains concerned about the cost associated with material recovery. The Lithium-Ion Battery Recycling Prize is an initiative provided by the United States Department of Energy (DOE) to promote the advancement of inventive methods for the gathering, categorization, storage, and transportation of utilised and discarded lithium-ion batteries with the objective of recycling and recovering materials. While the chemistry of lithium-ion batteries may vary from that of consumer device batteries, they are widely employed in plug-in hybrid electric vehicles (PHEVs) and electric vehicles (EVs) currently in use. Ongoing research and development efforts are

currently focused on reducing the cost, increasing the lifespan, and addressing safety concerns related to overheating of these items.

### DC-DC Converter

A direct current (DC) to direct current (DC) converter performs the function indicated by its name. Different integrated circuits (ICs) and other electronic components have varying voltage requirements. Therefore, it is crucial to ensure that each component's specific voltage needs are met accordingly. The Buck Converter is characterized by an output voltage that is lower than the input voltage, which distinguishes it from the Boost Converter.

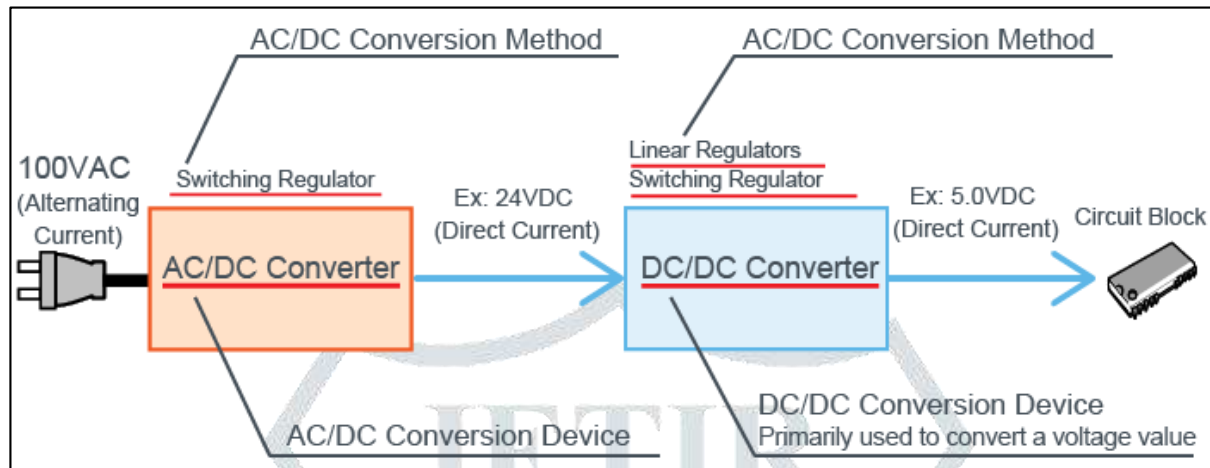


Fig. 3: block diagram of ac to dc and dc to dc conversion

The proposed control algorithm is based on two-layer control

- Centralized controller
- Local controller

The power grid serves as the primary provider of electrical energy, while the objective of the control programme is to maintain a consistent power supply. The proposed approach mitigates the likelihood of fluctuations in the electric grid's power supply. The local controller regulates the output of both the local source and the energy storage system (ESS) in the proposed control strategy. The central authority governs the power distribution network, with the local controller receiving real-time standardized data from the central authority. The local controller effectively regulates the power output of the local source and energy storage system (ESS) by manipulating the interface converters, guided by reference signals received from the central controller. The proposed control methodology involves the localization of electric vehicle charging stations in close proximity to their intended usage locations.

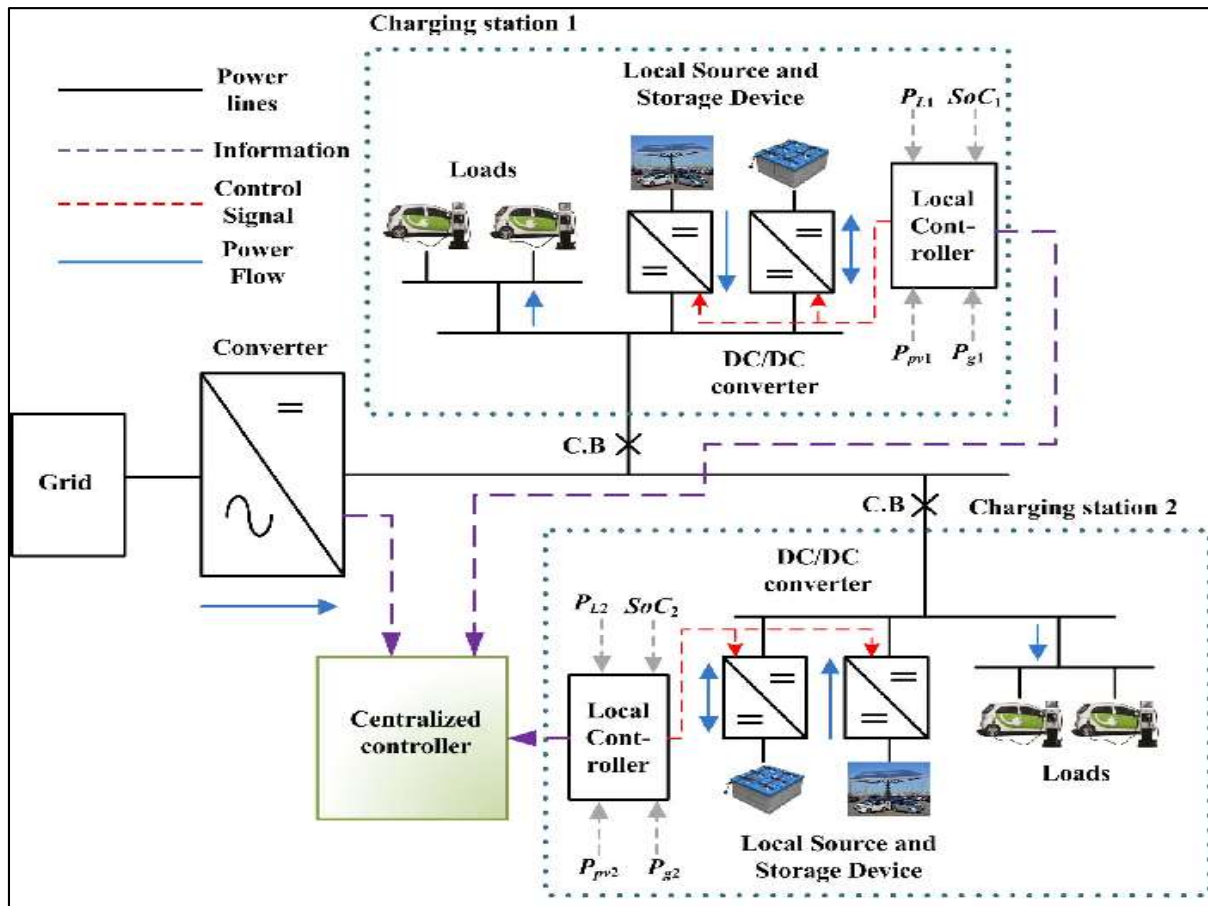


Fig 4: system of energy management

The charging station (PL1 and PL2) relies on both the primary energy source and local sources (source1 and ESS1) to meet its energy requirements.

$$PL1 = P_{g1} + P_{s1} + P_{ess1}$$

$$PL2 = P_{g2} + P_{s2} + P_{ess2}$$

PL1 and PL2 demonstrate the power requirements of the local loads. The variables PS1 and PESS1 represent the power generated by local source 1 and energy storage system 1, respectively, at charging station 1. Similarly, the variables PS2 and PESS2 represent the power generated by local source 2 and energy storage system 2, respectively, at charging station 2. The magnitude of electrical power generated by the electric grid (Pg) is indicated by.

$$P_g = P_{g1} + P_{g2}$$

The primary controller transmits reference signals to the local controller based on various power scenarios observed at the local load demand. The transmission of data from the local controller to the central controller triggers the updating of reference values for the interfaced converters at charging stations under the occurrence of specific events.

$$PL1 < P_{g1} + P_{s1}$$

$$\Delta P = (P_{g1} + P_{s1}) - PL1$$

$$I = \Delta P / V_{dc}$$

$$I_c \leq I_{cmax}$$

where, the charge current (Ic) serves as a reference for the manager of the adjacent charging station. Voltage direct current (V<sub>dc</sub>) refers to the amount of energy expended in the process of transporting objects. Currently, the ESS is operating in charge mode. The updated charging current reference number is transmitted to the local processor. To ensure optimal charging, it is advisable to utilise a charging current (Ic) that is below the maximum charging current (I<sub>cmax</sub>). As the Energy Storage System (ESS) undergoes charging, its State of Charge (SoC) increases. The maximum state of charge (SoC<sub>max</sub>), which represents the upper limit of the state of charge that can be achieved during the charging process of an energy storage system (ESS), is commonly believed to be 90%. A reserve of 10% is allocated to account for potential fluctuations in power demand, ensuring the stability of the electric grid's power supply in the event of insufficient demand. As a result of this, the ESS is perceived as an inconvenience. The identical reference signals are employed in instances where there is a decrease in local load demand or an increase in local source power. The comparative assessment of the reference current's actual worth is juxtaposed with the provided numerical value, thereby facilitating the computation of a novel error.

$$I_c - I_{act} = \Delta I$$

The error value feeds to PI controller have proportional gain as  $K_{pc}$  and integral gain as  $K_{ic}$  given in. The PI controller output  $d$  is used to produce PWM pulses is expressed as,

$$d = K_{pc} \Delta I + K_{ic} \int \Delta I dt$$

In an alternative power scenario, the Energy Storage System (ESS) is employed as a power source to meet the energy demands of the local community. The central processing unit (CPU) is responsible for providing the electrical current required for the discharge process.

$$P_{L1} > P_{g1} + P_{S1}$$

$$\Delta P = P_{L1} - (P_{g1} + P_{S1})$$

$$I = \Delta P / V_{dc}$$

$$I_d \leq I_{d_{max}}$$

The new reference point is defined as the value of  $I_{d_{max}}$ , which represents the maximum discharge current for the Energy Storage System (ESS). Meanwhile,  $I_d$  is the designated reference value for the ESS discharge current. When there is a decrease or increase in either the local power source or the local load demand, a similar outcome occurs.

$$I_{s1ref} = P_{S1} / V_{dc\_ref}$$

$$\Delta I = I_{s1ref} - I_{act}$$

$$d_{s1} = K_{ps} \Delta I_{s1} + K_{is1} \int \Delta I_{s1}$$

The calculation of the reference value for source 1 is performed, and subsequently, the proportional gain ( $K_{ps1}$ ) and integral gain ( $K_{is1}$ ), along with the error signal, are transmitted to the PI controller in accordance with the reference value. The PI processor's output is utilized to generate pulse width modulation (PWM) signals for the converter. The reference value, denoted as  $I_{s1ref}$ , represents the newly established benchmark. On the other hand,  $I_{act}$  refers to the actual numerical value obtained from the source at the present moment. In the event that the circuit breaker (CB) is in an open state and the utility grid is absent, each charging station disengages from both the utility grid and from one another.

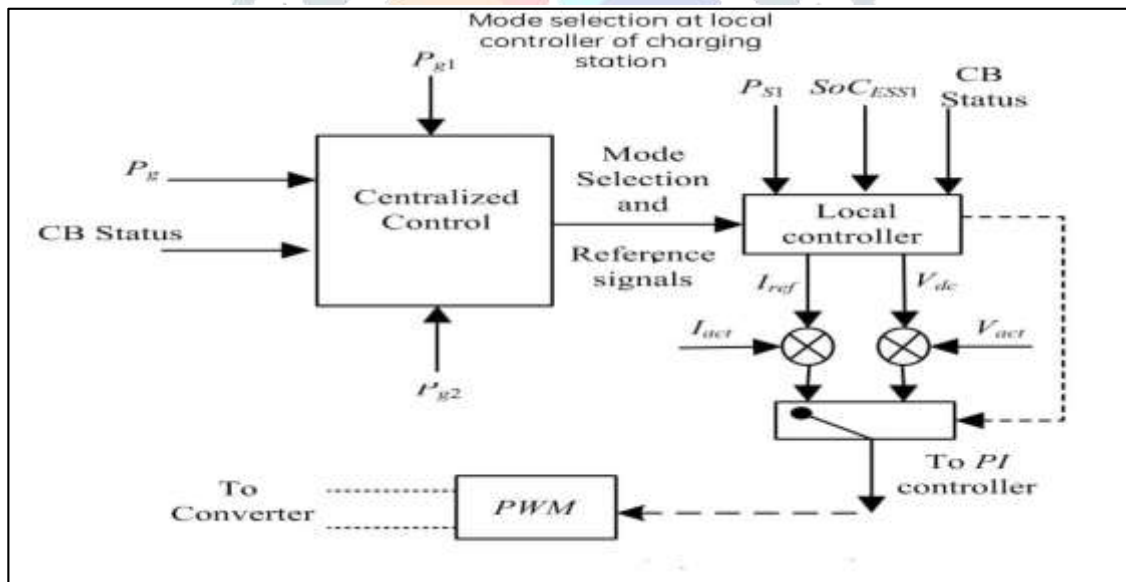


Fig 5. Mode selection at local controller of charging station

In the present scenario, the local energy storage system (ESS) operates in a mode of current control, whereas the source located at the charging station operates in a mode of voltage control in order to maintain a stable voltage level. In this particular scenario, the entirety of the system's voltage control is managed solely by the local processor. After achieving stable voltage regulation, the primary power source transitions into a state known as "current control mode" in the energy storage system (ESS). Modifications in the primary catalyst.

$$\Delta V = V_{dc} - V_{act}$$

$$d_g = K_{pg} \Delta V + K_{ig} \int \Delta V dt$$

The primary operational mode utilised is known as "voltage-controlled mode" in the context of the main source. The responsibility for maintaining the  $V_{dc}$  voltage of the system lies with the source. The voltage is maintained at a constant level throughout the entire process. The proportional gain,  $K_{pg}$ , and the integral gain,  $K_{ig}$ , are represented by the variable  $V_{act}$ , which corresponds to

the actual voltage. The Coulomb counting method is utilised in the calculation of both the State of Charge (SoC) for ESS1 and ESS2.

### V. RESULTS AND DISCUSSION

The simulation of a photovoltaic (PV) panel was conducted using MATLAB-Simulink. The module consists of a series connection of 36 solar cells. The short circuit current of each cell is measured to be 7.98 A, while the open circuit voltage is recorded as 36.72 V. The solar array comprises multiple interconnected units. The voltage at maximum power ( $V_{mp}$ ) is measured at 30.3 volts, while the current is recorded at 7.26 amperes. Consequently, the power output at maximum capacity is determined to be 219.98 watts. Figure 5.1 illustrates the variation in energy as it transitions from 700 to 1200 W/m<sup>2</sup>. The demonstration of the solar cell module's MPP behaviour is evident through the I-V and P-V curves generated.

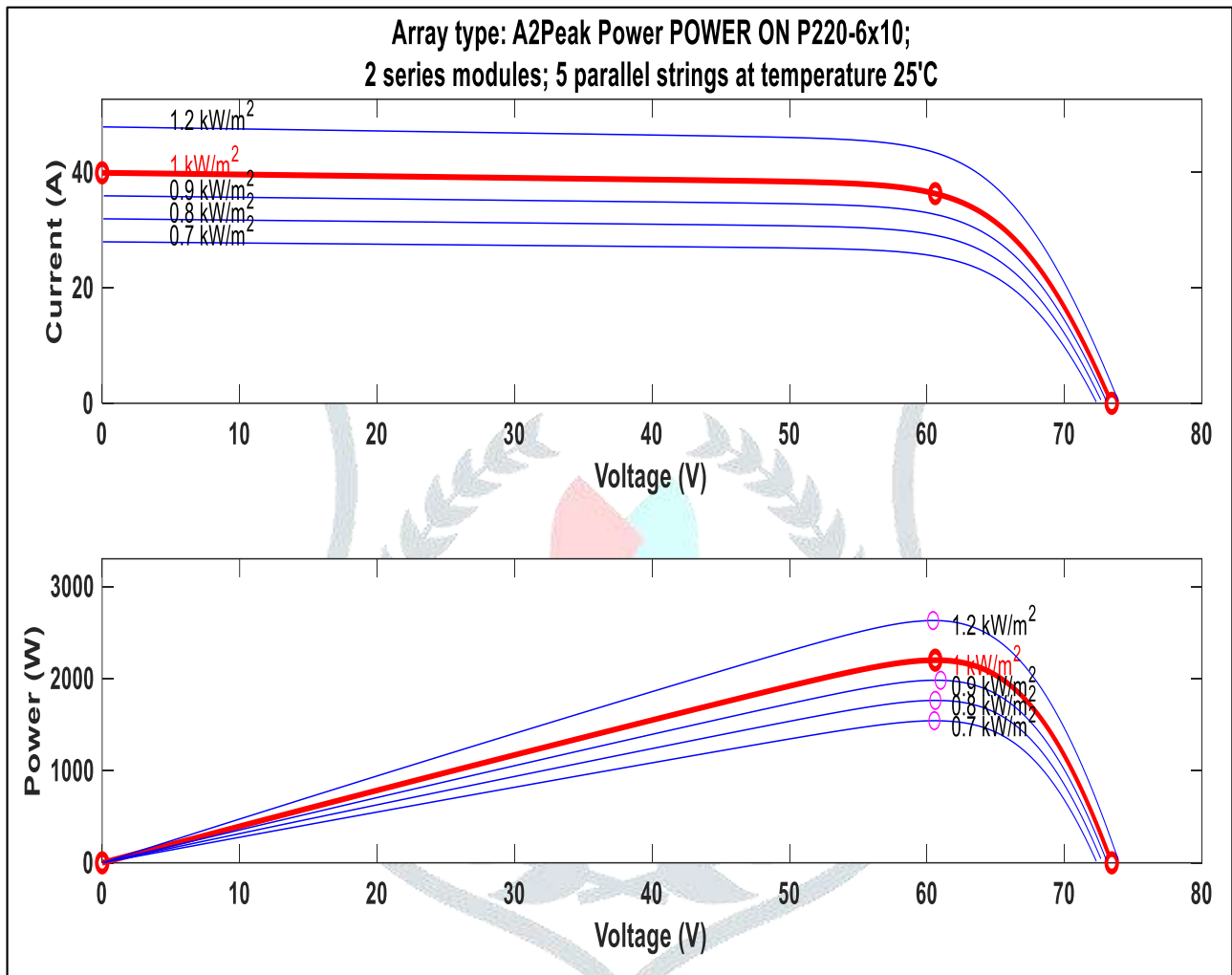


Figure 6: V-I and P-V curves of a photovoltaic (PV) module at different solar irradiation levels

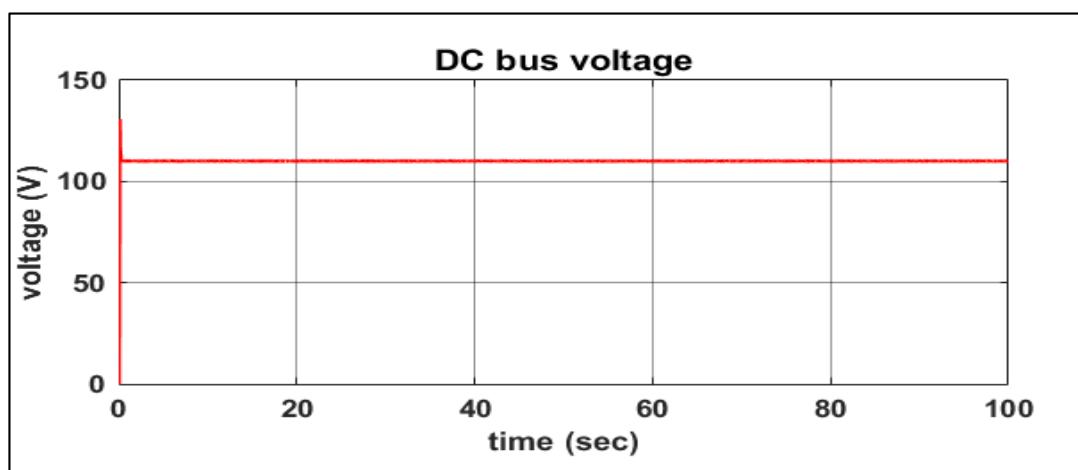


Figure 7: DC bus voltage



The DC voltage time graph is shown in figure 7. As its evident from the figure, the DC bus voltage observed is constant throughout the operations. This is attained due to grid supply. The 230v AC supply is converted in to DC supply using controlled rectifier. In the subsequent step, using DC to DC converter, the voltage is stepped down to 110V which is shown as red curve in figure 5.2 above.

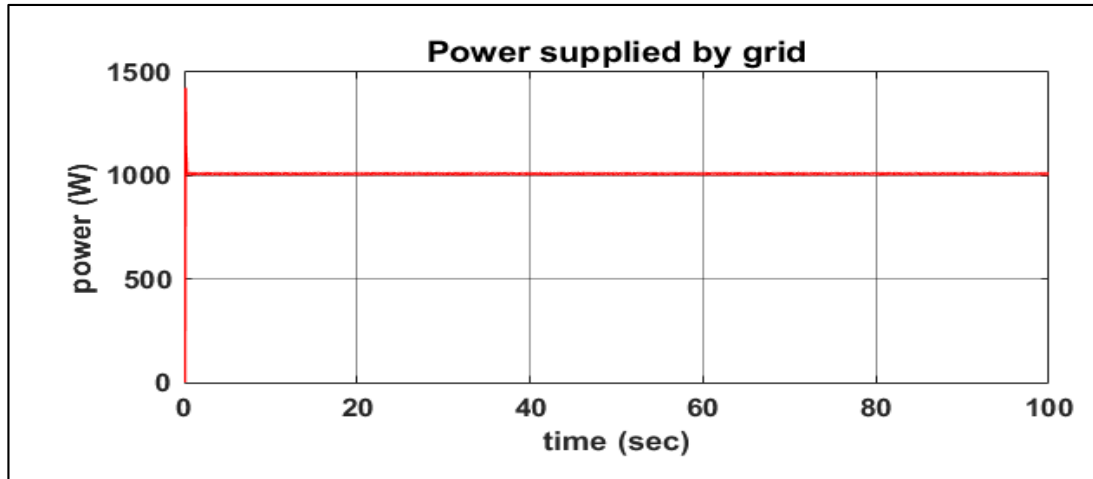


Figure 8: Power supplied by the grid

From the analysis conducted it was observed that grid power unaffected due to any variation in applied loads (EV charging) as its evident in figure 8. The graph represents constant power is maintained in the grid with magnitude of 1000W.

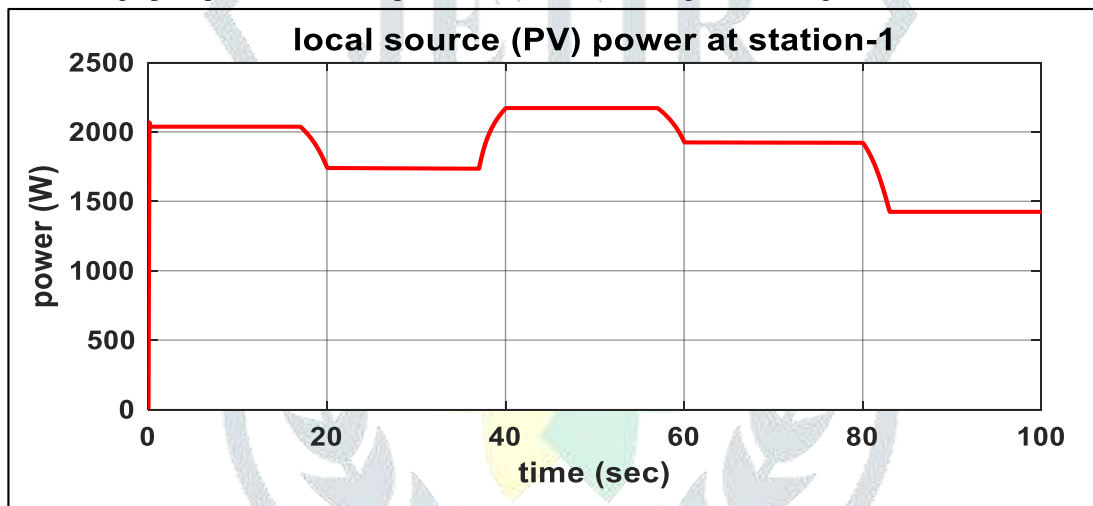


Figure 9: Load profile at station 1

For the simulation the variation of solar radiation is incorporated in the system. Due to variation in solar irradiation the non-uniform/inconsistent power is generated as its evident from figure 9 above. The maximum power considered is 2200W at temperature of 25°C and 1200W/m<sup>2</sup> solar irradiation. The range of solar irradiation considered in the simulation is 700W/m<sup>2</sup> to 1200W/m<sup>2</sup>.

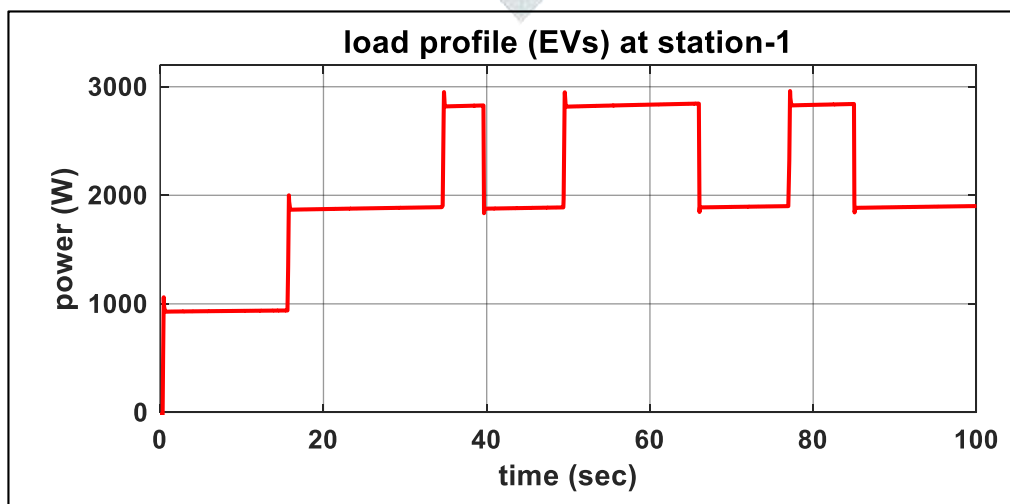


Figure 10: Power consumption w.r.t. time at charging station 1

The figure 10 above represents the power consumption in charging station 1. The charging station comprises of 5 vehicles wherein the power consumption by each vehicle is 1000W. It has been observed that at certain time intervals the power

consumption is high and is lower on other time intervals due to simultaneous charging of multiple vehicles. The maximum power consumption of 2900W is obtained for 3 different time intervals.

## VI. CONCLUSION

Using the MATLAB Simulink software a control algorithm for EV charging system is developed. The developed control algorithm comprised of centralized controller and local controller which ensured 2-layer control. The developed algorithm enabled to reduce the power fluctuation on the utility grid.

1. From the analysis conducted it was observed that grid power unaffected due to any variation in applied loads (EV charging). A constant power is maintained in the grid with magnitude of 1000W.
2. Due to variation in solar irradiation the non-uniform/inconsistent power is generated at station 1. The maximum power considered is 2200W at temperature of 25<sup>0</sup>C and 1200W/m<sup>2</sup> solar irradiation. The range of solar irradiation considered in the simulation is 700W/m<sup>2</sup> to 1200W/m<sup>2</sup>.
3. Due to variation in solar irradiation the non-uniform/inconsistent power is generated at station 2. The maximum power considered is 3300W at temperature of 25<sup>0</sup>C and 1200W/m<sup>2</sup> solar irradiation. The range of solar irradiation considered in the simulation is 1800W/m<sup>2</sup> to 3300W/m<sup>2</sup>.
4. At station 2, the power consumption of each vehicle is different which ranges of 1000W to 1500W. It has been observed that at certain time intervals the power consumption is high and is lower on other time intervals due to simultaneous charging of multiple vehicles. The maximum power consumption of 3200W.
5. The terminal voltage of PV varies with respect to time which is attributed to different magnitudes of solar irradiation at different time intervals. The incident solar irradiation varies from 700W/m<sup>2</sup> to 1200W/m<sup>2</sup> during the operation. The base value considered for solar irradiation is 1000 W/m<sup>2</sup> which represents 100%. Using this as reference, the voltage is evaluated at different time intervals. The maximum voltage obtained at 120% of solar irradiation i.e. time duration ranging from 40secs to 60secs.

## REFERENCES

- [1]. <https://www.amrit.niti.gov.in/benefits-of-electric-vehicles>
- [2] I Avinash V. Shrivastav, Sajidhussain S. Khan, "Electric Vehicle Charging Station" 2020 JETIR April 2020, Volume 7, Issue 4
- [3] Yang, S.; Wu, M.; Yao, X.; Jiang, J. Load Modeling and Identification Based on Ant Colony Algorithms for EV Charging Stations. *IEEE Trans. Power Syst.* **2015**, *30*, 1997–2003. [CrossRef]
- [4] Tangrand, K.; Bremdal, B.A. Using Ant Colony Optimization to determine influx of EVs and Charging Station capacities. In Proceedings of the 2016 IEEE International Energy Conference (ENERGYCON), Leuven, Belgium, 4–8 April 2016; pp. 1–6. [CrossRef]
- [5] Habib, H.; Subramaniam, U.; Waqar, A.; Farhan, B.; Kotb, K.; Wang, S. Energy Cost Optimization of Hybrid Renewables Based V2G Microgrid Considering Multi Objective Function by Using Artificial Bee Colony Optimization. *IEEE Access* **2020**, *8*, 62076–62093. [CrossRef]
- [6] Ali, A.; Raisz, D.; Mahmoud, K. Mitigation of voltage fluctuation in distribution system connected with PV and PHEVs using artificial bee colony algorithm. In Proceedings of the 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 25–26 April 2018; pp. 144–148. [CrossRef]
- [7] Álvarez, J.G.; González, M.; Vela, C.R.; Varela, R. Electric Vehicle Charging Scheduling by an Enhanced Artificial Bee Colony Algorithm. *Energies* **2018**, *11*, 2752. [CrossRef]
- [8] Shivappriya, S.; Karthikeyan, S.; Prabu, S.; De Prado, R.P.; Parameshchhari, B. A Modified ABC-SQP-Based Combined Approach for the Optimization of a Parallel Hybrid Electric Vehicle. *Energies* **2020**, *13*, 4529. [CrossRef]
- [9] Falabretti, D.; Gulotta, F. A Nature-Inspired Algorithm to Enable the E-Mobility Participation in the Ancillary Service Market. *Energies* **2022**, *15*, 3023. [CrossRef]
- [10] Liu, Q.; Xu, P.; Wu, Y.; Shen, T. A hybrid genetic algorithm for the electric vehicle routing problem with time windows. *Control. Theory Technol.* **2022**, *20*, 279–286. [CrossRef]
- [11] Zeng, L.; Krallmann, T.; Fiege, A.; Stess, M.; Graen, T.; Nolting, M. Optimization of future charging infrastructure for commercial electric vehicles using a multi-objective genetic algorithm and real travel data. *Evol. Syst.* **2019**, *11*, 241–254. [CrossRef]
- [12] Efthymiou, D.; Chrysostomou, K.; Morfoulaki, M.; Aifantopoulou, G. Electric Vehicles Charging Infrastructure location: A Genetic Algorithm Approach. *Eur. Transp. Res. Rev.* **2017**, *9*, 27. [CrossRef]