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Technical Report TA User Project

EVACC

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Abbreviations

AI	Artificial Intelligence
DG	Distributed Generation
ECT	End of Charge Times
EV	Electric Vehicle
GHG	Green-house gas
HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
LMS	Least Mean Squared
ML	Machine Learning
MLP	Multi-Layer Perceptron
NN	Neural Network
PEV	Plug-in Electric Vehicle
POC	Point of charging
RTDS	Real Time Digital Simulator
SOC	State-of-charge

Executive Summary

Despite many advantages, wide-spread integration of electric vehicles (EVs) in the power system is challenging. Large-scale uncontrolled EV charging load may lead to under-voltage violations, higher power losses, overloading of transformers and transmission lines. In this project, a machine learning-based communication-free EV charge control strategy is developed to mitigate the issues caused by uncontrolled EV charging. Furthermore, fairness is ensured among the EVs available at different locations in the power distribution system. To do so, a nodal voltage and the voltage-to-load sensitivity, are measured at each load node, which are fed to the EV charge controller. The output of the charge controller is the charging rate of an EV. In fact, an upstream node is generally less sensitive to changes in the load as it is closer to the feeding point. In order to validate the robustness of the proposed controller, light and heavy loading conditions are considered which mimics the daily, monthly, yearly, and seasonal load variations. Results prove that the proposed controller effectively improves the voltage profiles while ensuring fairness among the EVs connected at various charging points in the system.

1 General Information of the User Project

USER PROJECT INFORMATION	
User Project Acronym	EVACC
User Project Title	An Autonomous Charge Controller for EVs Using Online Sensitivity Estimation
Main scientific/technical field	Autonomous charge controller, distribution power system, electric vehicles, machine learning
Keywords	Distribution power system, electric vehicles, voltage-to-load sensitivity
Host Research Infrastructures	MultiPower Laboratory - VTT Technical Research Centre of Finland Ltd
Starting date for the access	08-01-2020

2 Research Motivation

Fossil fuel depletion and rising concerns on the global climate shift motivate both governments and the public to shift towards sustainability. Worldwide energy consumption trends are focusing on adopting environmentally friendly renewable resources [1]. Auto industries are also urged by fuel price volatility and gowning public interest in renewable fuel-powered transportation to invest in sustainable fuel-based vehicles [2]. Consequently, for internal combustion engines (ICE) the shift from fossil fuels is addressed urgently through the introduction of electric vehicles (EVs). ICE-based cars are replaced by plug-in electric vehicles (PEVs) and Hybrid electric vehicles (HEVs). The European Commission had set an emission standard of 95g CO_2 by 2020, and the US government set new fuel economy standards for 2025 that sets average fuel economy for passenger vehicles and light-duty trucks to be 4.3L/100 km [3]–[5].

EVs provide numerous green services to the society through the reduction in greenhouse gas (GHG) emissions, reducing a state's dependence on foreign oil imports, and grid support during peak hours of energy consumption [3]–[6]. These fast-paced set targets can only partially be achieved by making conventional vehicles energy efficient. Fully electrification of the transport sector is the key agent that will realize the emission targets. The expected EV penetration rate for the United States is 62% by 2050 [7]. About 40% of the world's electric cars are is in China, as the fleet of electric cars on the rose above one million in 2017, while the US and EU accounted for a quarter of the total EV fleet. Interestingly, Norway has an EV stock of 6.4% which is by far the world's highest. The EV market share in Norway has still the highest market penetration, and they have the world's largest plug-in segment market around 49.1% in 2018. The highest amount of EV charging stations is in Amsterdam [8].

While EVs offer greater benefits to the society they may pose significant operational problems to the distribution systems if their charging is uncontrolled [9]. Line congestions, low voltage sags, transformer overloads, and price volatility are more prominent for large-scale EV integrations in the distribution systems [10]. Improvising charge control strategies for EVs can mitigate the cons that succeed in the EV integration in the power grids.

Distribution systems serve as the load centres and they may become the epicentre for cascading failures. Uncontrolled EV charging if remains in status-quo, increasing EV penetration in the future will overload the distribution systems. Although EVs offer several advantages over ICE, peak charging demands may rise considerably. Current EV market penetration is small so they have a minimal effect on the power systems. However, a surge in demand peaks will be visible when a significant rise in their market share is adopted soon. To address the uncontrolled charging of EVs and issues of under-voltages, higher losses, phase unbalance, and demand peaks, we propose an autonomous charge controller, that addresses the problems associated with the EV charging.

2.1 Objectives

This EVACC project presents a new Artificial Intelligence (AI)-based autonomous EV charge controller. Online local measurement is performed for calculating sensitivity, i.e., changes in voltage to the changes in load at a node. And local voltage measurements along with sensitivity are the controller inputs. Pre-system deployment the controller is trained with a machine learning (ML) approach using shallow deep multi-layer fully connected neural networks. This relieves the system of depending on the communication infrastructure and makes fairness easy to implement. The ML-inclusion adds robustness in the system regarding possible system changes in loading conditions and system re-configurations.
Therefore, the specific contributions of this article are as follows:

- An approach is proposed for estimating, in real-time, the sensitivity of point-of-charging (POC) voltage to load power changes using local measurements only in the real-time digital simulator (RTDS).

- A new ML-based communication-free EV charge control strategy is implemented that is dependent on the local nodal voltage and sensitivity measurements.

2.2 Scope

EV charge control strategies are differentiated into centralized, decentralized, and autonomous control strategies. In the centralized charge controllers, the EV owners submit their charging requests to the central EV aggregator that determines optimum charging rates for the connected EVs. EVs are deployed for procuring ancillary services in [11]–[13] through their charging rates exploitation.

Authors demonstrated in [14] that EV charging rates can be controlled through centralized controllers. Many works manifest that a centralized strategy can be harnessed for power distribution systems loss reduction, extending to transformer service life, fattening feeder profile and minimizing voltage excursions from nominal values [15]–[18]. However, the centralized EV charge controllers require substantial communication network topology for two-way communication.

The decentralized EV charge controllers are embedded with smart charging control functionalities, i.e., upon receiving a charging input signal from the system operator it performs local optimization for determining the charging rate [19]–[26]. A smart controller may sometimes manage a group of EVs in a residential area of EV parking lots. Authors in [19] consider charging strategies for apartments. The non-cooperative game approach is employed in [20],[21] for EV charge management. For ensuring valley filling EV charging schedules are determined [23]. In this method, the EV charging and power flow are decomposed and solved through a nested approach. However, each EV can solve its local charging rate optimization problem [24]. In order to manage EV charging rate for multi-apartment/multi-customer EVs and satisfy secondary LV transformer loading constraints mixed-integer linear programming has been derived [26].

Autonomous strategies do not rely on communication structure for curtailing EV load and setting charge schedules. However, fairness becomes challenging during application as it is a specific strategy depends on how the controller ensures fairness among the wide varied nodes. Thus, this kind of controllers are more adaptive and self-sustaining in systems that do not incorporate enough networked communication or computation tenacity. The EV charge controller takes the local measurements at point-of-charging (POC) and decides on an optimal charging rate in an efficient manner. Many researchers develop and discuss disparate autonomous strategies [27]–[35]. A bi-directional frequency dependent EV charge controller is presented in [27], which utilizes EV for offering frequency regulation service. However, this frequency responsive charger does not address voltage excursions around nominal ANSI standard voltage values, i.e., 1 ±5% p.u. Since all distribution system nodes have the same system frequency, fairness regarding charging times among EVs is adequately ensured. Peak demand hours are avoided by developing a rule-based charge controller that uses customer house load profiles for determining EV charge schedules [28]. The system's conditions are not considered by the rule-based charge controller.

Some voltage-based charge controllers are also discussed in [29]–[32]. For example, a proportional EV charge controller's output is proportional to POC voltage and reference voltage difference. In [29], it is demonstrated that proportional voltage-based charge controllers result in smooth load profiles, reduction in power losses, and improved voltages. However, they do not address the fairness among the EVs available at different nodes. In opposite to the frequency-based control methods, these voltage-based control techniques require special tuning for incorporating fairness since voltage is a local entity signal while frequency is a global signal. Another voltage-based controller is discussed in [30] that uses different reference voltages for fairness application. The downstream nodes have lower voltage references than the nodes at the upstream. Each POC reference voltage is derived from the average historical voltage profile. Fairness is ensured in addition to improved voltages. But, this type of controller becomes prone to reconfigurations in the system which are more frequent in the routine power system's operation. Authors in [31] implemented an EV charge controller by considering all system nodes balanced for reducing simulation time, disregarding the true behavior of power distribution systems. Another voltage-based controller is presented in [32] that sets EV charging rates depending on local voltages and battery state-of-charge (SOC). This controller is a non-linear controller which also satisfies EV owners' choice of end of charge times (ECT) preference. The voltage-based non-linear charger addresses fairness among the EVs but by being very conservative as it restrains EVs from charging at full rate even when there is room for fast charging.

Authors in [33], proposes a charging approach that relies on local node voltages and a predetermined voltage sensitivity to the load variations at the POC to decide on the EV charging rate. However, due to possible system reconfigurations and demand variations, the predetermined voltage sensitivities will continuously change which may result in unfair charging. On the other hand, authors in [34] have introduced the concept of online sensitivity measurement which has been used along with the nodal voltage to determine the charging rates. Although this method is robust, however, the charging rates can be increased further since there is room available for fast charging. Additionally, since it's an evolving business for the auto sector some researchers have considered applying artificial intelligence (AI) for optimizing EV loads and other residential demands [35],[36].

3 State-of-the-Art

Recently, worldwide Artificial Intelligence (AI) and Machine learning (ML) are at the forefront of many leading applications. From self-driving to heavy industrial complexes, much of these utilize the universal nature of these innovative algorithms that easily regenerate complex patterns within the ginormous data that these applications generate. Since power systems generate a huge amount of data, they will define the emerging smart grid field in which data will drive most of the grid operations. From renewable distributed generation (DG) to 5G applications, every second a large data is generated which defines the system status and the succeeding decisions from grid operators or system optimization tools that keep the system in stable operation. Haphazard and opportunistic EV charging will become problematic for power systems as they do not consider distribution system status.

In this research work, the ML approach is being used on the extensive data generated by the RTDS in the VTT MultiPower lab. Voltage and online sensitivity estimation in RTDS at the nodes of our test system serve as the learning parameters for the MLP network to decide on EV charging rates. Coming up with optimum layers and learning algorithms is an important step in determining the same charging rate for all the EVs available at upstream and downstream nodes of the distribution system. As to keep customers satisfied and distribution system relieved of voltage mitigations fairness is necessary. The neural network (NN)-based learning approach achieves that through training on the generated dataset.

4 Executed Tests and Experiments

The following tests are executed in our project "EVACC":

1) Online sensitivity estimation at the nodes in the system. Sensitivity estimated from an online method in RTDS coincides with sensitivities calculated from the direct diagonal entries in DIgSILENT PowerFactory 2019.
2) Voltage profile for light loading and heavy loadings in the distribution system are obtained and used together with sensitivities in training NNs.
3) A Multi-Layer perceptron network is used to derive the charging reduction factors for voltage violation elimination.
4) Training and testing of the neural networks.

4.1 Test Plan

The main idea of the proposed EV charge control scheme, controller layout shown in Fig. 1, is to curtail EV charging rate at load nodes based on their local voltage and sensitivity at POC. This aims at mitigating voltage violations. It also helps suppress the system peak load during excessively high loading conditions and reduces power losses. The reduction will be time-varying since the load variation at nodes results in voltage variation. At each instant of time, a new set point for the EV charge controller must be determined based on the network condition. Ensuring fairness without communication is a key idea in its implementation at the distribution level. Individual nodal voltages are different at upstream and downstream nodes. The downstream node voltages are more prone to undervoltage violations, while upstream nodes have improved voltage profiles. If the charge controller decides on the amount of EV demand reduction based on the nodal voltage at POC only, fairness will not be ensured. In fact, the loads connected to the downstream nodes will undesirably contribute more as compared to those connected upstream. To ensure fairness, the voltage sensitivity due to load variations is also incorporated. Note that POCs with higher voltage magnitudes tend to have lowered sensitivities than POCs with lower voltages. Hence, the charging factor, for each node, is a function of the node voltage and sensitivity.

To identify the EV charge controller structure, a neural network training-inspired approach is used. In the Multi-Layer Perceptron (MLP) neural networks, a back-propagation algorithm is employed using the Least mean squared (LMS) method. The procedure is repeated for multiple loading conditions. Different loading conditions will result in different voltage profiles. Based on the power flow results of each condition, the percent charging variation that needs to be applied at each node is determined so that acceptable voltage profiles are obtained. To enforce fair contribution from all the EVs, the same EV charging rate must be applied to all loads at any given set of system conditions. A fully connected MLP neural network is trained with the data, to obtain the weights at the input, output, and the biases. In this neural network approach, the inputs are the nodal voltages and their corresponding voltage-to-load sensitivities, and the desired output is the percent charge reduction. In this work, the sigmoid activation function given in (1) is employed in each neuron in all the layers of the network except at the output node which is linear as given by (2). Fig. 2 illustrates the MLP NN used for training. NNs are non-linear statistical models that are used to represent or envelop the complex behaviour of natural or engineered processes. They are a fully connected group of nodes and layers. We are employing them to train for EV charging factors determination using online sensitivity and voltage measurements. NN includes input nodes, output nodes, and several hidden layers.

$$\varphi(\mathrm{v}) = \tanh(V) \tag{1}$$

where

$$\mathrm{V} = \sum_{i=0}^{m} (W_i \times v_i \; + \; W_s \times \delta_i + b_i) \tag{2}$$

W_i is the input weight vector for the Voltages and W_s is the input weight vector for sensitivities, and b is input bias.

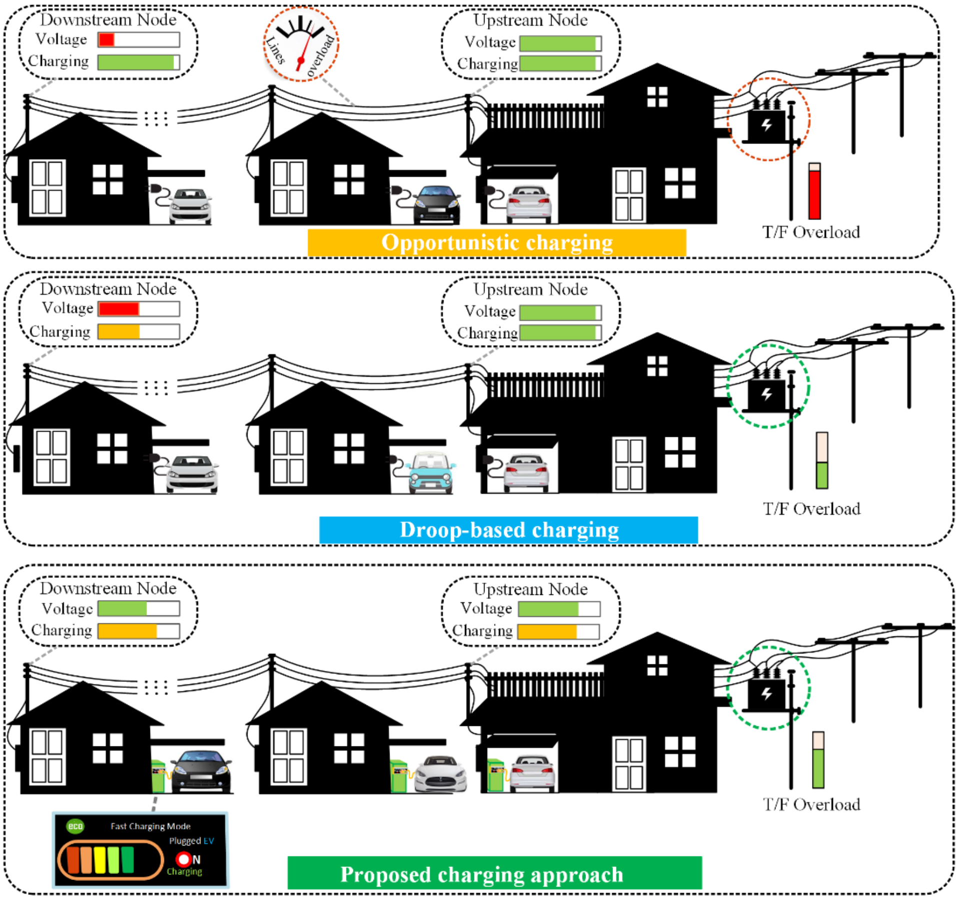

Figure 1: Overview of EV charge control structure.

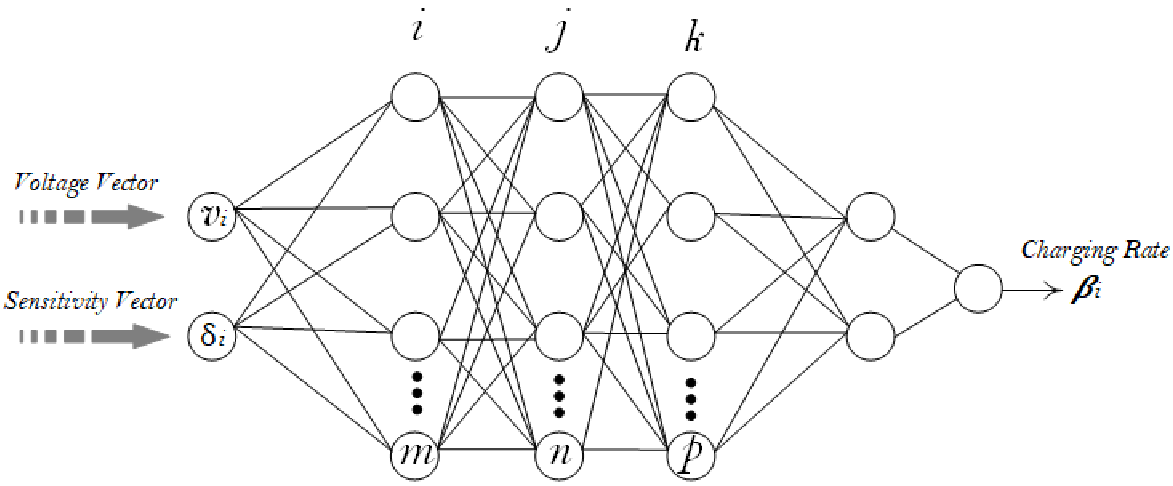

Figure 2: Fully connected multi-layer neural network.

4.2 Standards, Procedures, and Methodology

Standards

American National Standards Institute (ANSI) standards [37] are followed for keeping the voltage profile in the recommended allowable range. As per ANSI standards, the residential low voltage (LV) must be maintained within ± 5% of the nominal voltage.

Procedures

A residential test system is used for carrying out the simulation in DIgSILENT PowerFactory 2019, a power systems simulation software. There are seven nodes in the distribution system among them six are load nodes. Voltage and sensitivity factors are calculated for the system nodes online in the RSCAD simulation platform of the RTDS. Voltage-to-load sensitivity δ_i at i_{th} node is calculated using (3). The voltage and sensitivity measured data is used for neural network training.

$$\delta_i(t) = \frac{v_i(t+\Delta t) - v_i(t)}{p_i(t+\Delta t) - p_i(t)} \tag{3}$$

Methodology

The voltage and sensitivity vectors are utilized as input nodes for the NN training. The EV charging set points during various system conditions, i.e., during light and heavy loadings are determined by running simulations and analysing system conditions. Data analytics play its role here as the correct curtailment factors will effectively relieve the system voltage stresses, line and transformer overloading, and fairness issue in the system. Through various hit and trial sessions, final reductions factors are settled upon which are later used as the required output of the NNs. Training is performed using various ML approaches. By treating the charging as a classification problem and setting various classes for the different charging rates. And then training with Linear classification methods.

4.3 Test Set-up

The proposed EV charge controller is implemented on an EV-rich test distribution system, shown in Fig. 3. There are six load nodes where Node-2 is an upstream node and a Node-5 is a downstream node. The secondary distribution system operates at 220 V line-to-line voltage and the network parameters are provided in Table 1. It is considered that there are four houses at each load node, and three of them are assumed to own EVs, i.e. 75% EV penetration. Most of the EVs are considered as Nissan Leaf while few EVs are assumed to be Tesla to make the analysis more realistic. The data for Nissan Leaf and Tesla are provided in Tables 2 and 3, respectively. The load profiles at all the load nodes are shown in Fig. 4.

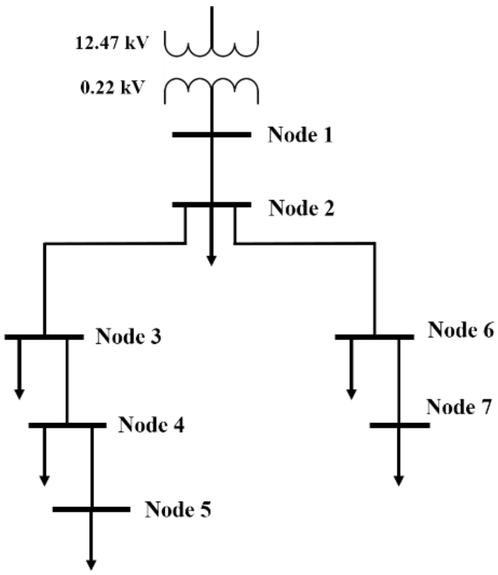

Figure 3: EV-rich test distribution system.

Table 1: Secondary Distribution System Parameters

Parameter	Value
Secondary conductor	350 Al, 4/0
No. of customers	4
EV penetration	75%
System frequency	60 Hz

Table 2: Specifications of Nissan Leaf [38]

Parameter	Value
Battery capacity	40 kWh
Maximum charging rate	6.6 kW
Initial battery SOC	30%
Maximum mileage	126 mi

Table 3: Specifications of Tesla Model S [39]

Parameter	Value
Battery capacity	75 kWh
Maximum charging rate	11.5 kW
Initial battery SOC	30%
Maximum mileage	348 mi

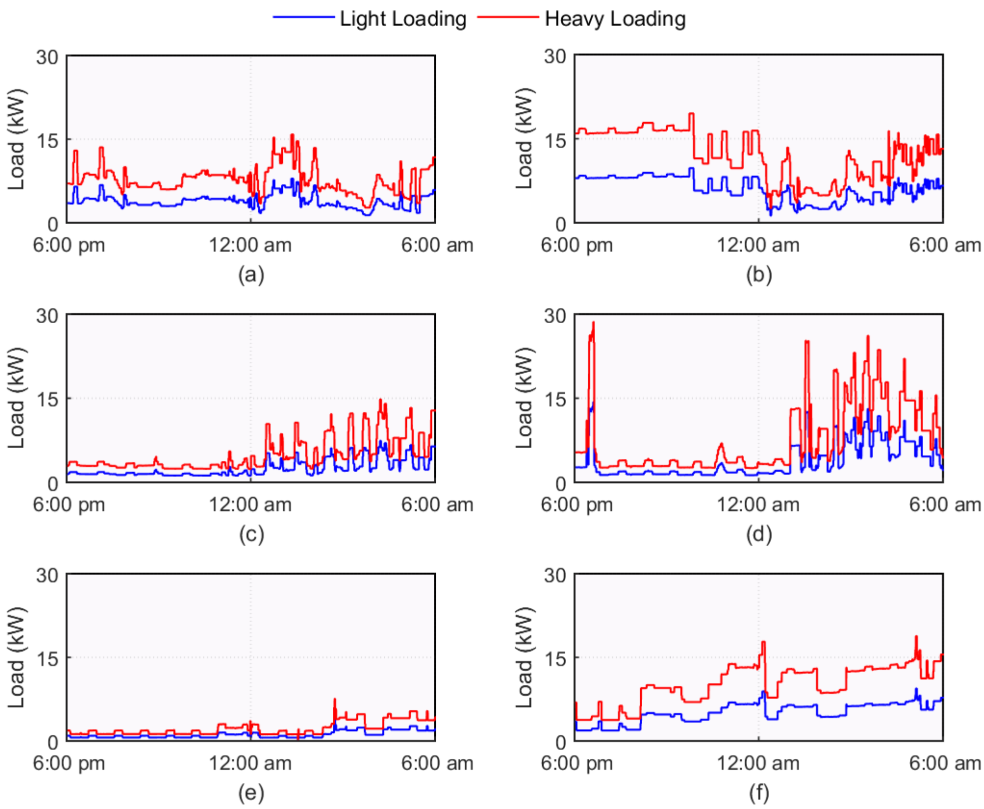

Figure 4: Non-EV load profile at (a) Node-2 (b) Node-3 (c) Node-4 (d) Node-5 (e) Node-6 (f) Node-7.

5 Results and Conclusions

The test system described in the previous section is used to assess and validate the proposed EV charge controller. In order to incorporate daily, monthly, and yearly load variations, different loading conditions are considered. Also, the performance of many EV charge controllers such as opportunistic, proportional, nonlinear, and voltage-and-sensitivity-based chargers are compared with the proposed EV charge controller. Note that two extreme nodes, i.e. Node-2 (upstream) and Node-5 (downstream), are selected since they can provide sufficient performance details.

5.1 Base Case (i.e., without EVs)

First of all, the system behaviour is studied when no EV is connected to the power distribution system. The voltage profiles for Node-2 and Node-5 for light and heavy loadings are shown in Figs. 5a and 5b, respectively. It can be seen that the voltage at Node-5 is always lower when compared to Node-2 since it is a downstream node.

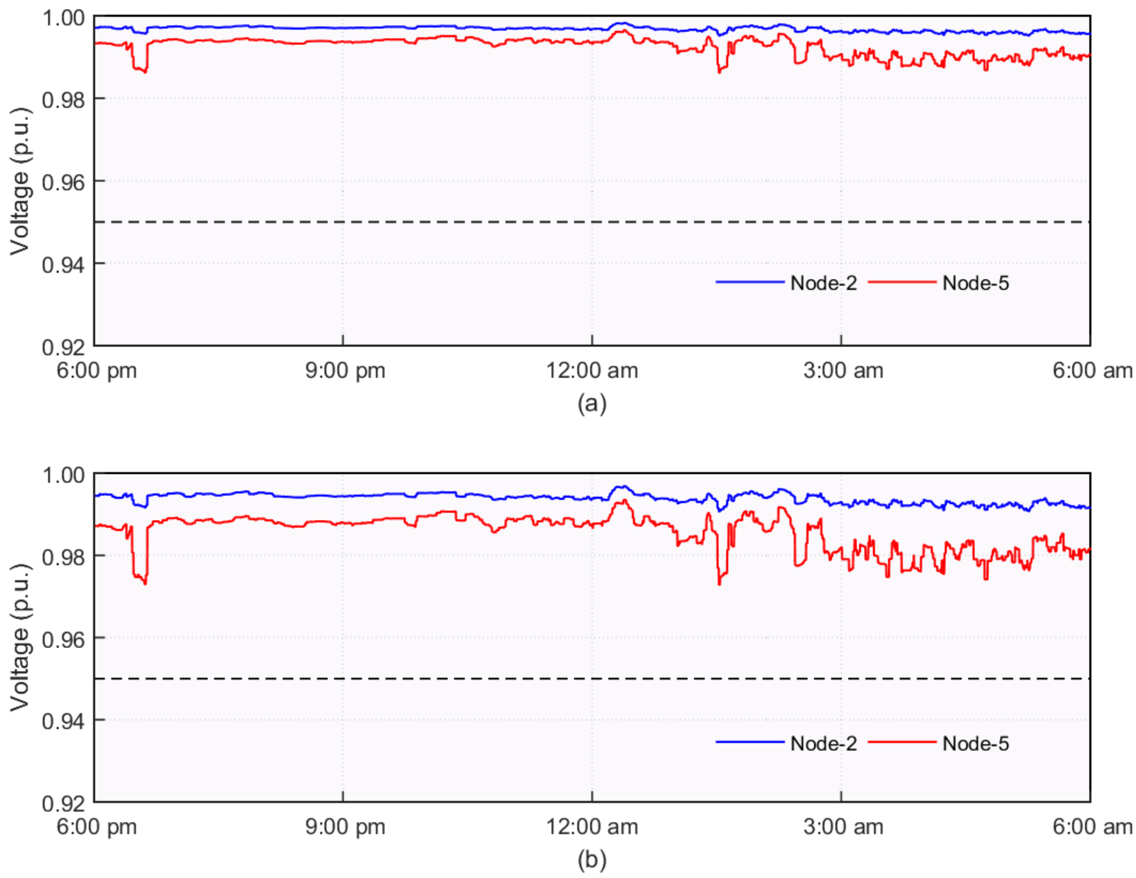

Figure 5: Base case voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

5.2 Opportunistic Charging

In an opportunistic charging strategy, EVs are charged at the maximum charging when connected to the system [32]. When all the EVs are being charged at a very high rate, the total load in the system increases significantly which may result in voltage violations and the line overloads. The charging time for Nissan Leaf and Tesla are provided in Table 4. The voltage profiles for Node-2 and Node-5 are illustrated in Figs. 6a and 6b for light and heavy loadings, respectively. It can be seen that the severe under-voltages occur at the downstream node during heavy loading. According to the ANSI C.84-2016 standard, the voltage must be within the range of 0.95 p.u. – 1.05 p.u. To mitigate under-voltage issues, the system load must be reduced, which means EVs should be charged at a slower rate especially during the events when the non-EV load is already high.

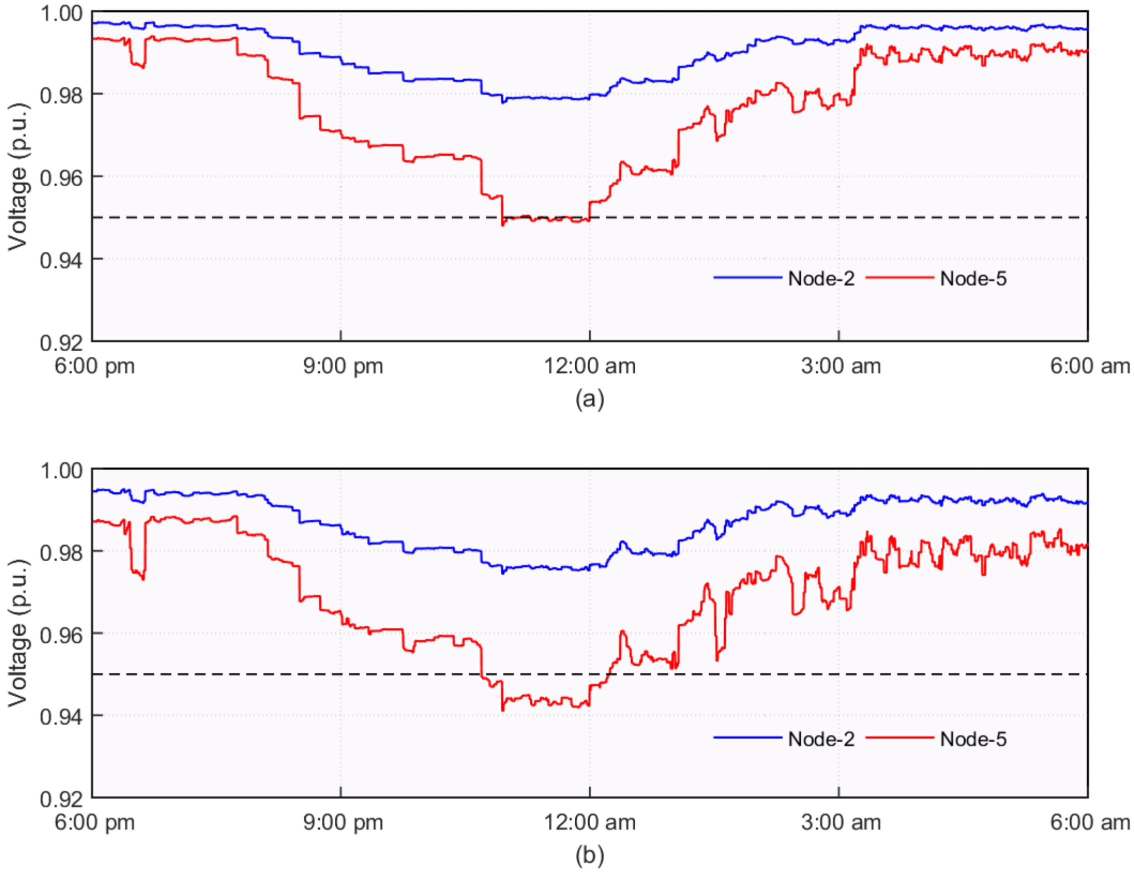

Figure 6: Opportunistic charging voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

Table 4: Minimum and maximum charging times for opportunistic charging

EV Type	Minimum charging time		Maximum charging time	
	Light loading	Heavy loading	Light loading	Heavy loading
Nissan Leaf	4.2417 hrs.	4.2417 hrs.	4.2417 hrs.	4.2417 hrs.
Tesla Model S	4.5639 hrs.	4.5639 hrs.	4.5639 hrs.	4.5639 hrs.

5.3 Proportional Voltage-Based Charging

As mentioned earlier that the system load must be reduced when the system voltage drops. Therefore, in proportional voltage-based charging, EVs are charged in proportion to the nodal voltages which assist in improving the voltage profiles. The relationship given in (4) is used to calculate the charging rate ($P_{k,j}$) for k_{th} EV of type j. The proportional controller gain k is set to 25 while v_r is considered 0.955 p.u.

$$P_{k,j}(t) = \begin{cases} k.(v_i(t) - v_r).\overline{P_j}, & v_i \geq v_r \\ 0 \quad , & v_i < v_r \end{cases} \tag{4}$$

where v_i is the nodal voltage of i_{th} node, v_r is the reference voltage, k is the proportional controller gain, and $\overline{\boldsymbol{P_j}}$ is the maximum charging rate of an EV of j_{th} type.
The voltage profiles at Node-2 and Node-5 are provided in Fig. 7. Note that the voltages are significantly improved as compared to opportunistic charging case however, the charging rates are unfairly

determined. EVs connected at upstream nodes are being charged faster since they are receiving good voltage profiles. In contrast, EVs available at downstream nodes are being charged at much lower rates, which tend them to take a very long time to get fully charged. The minimum and maximum charging times are tabulated in Table 5. It is evident that there is a large difference between the charging times of EVs available at different locations in the system. Some of the EVs are not even charged fully within the designated time. Hence, there is a need for an EV charge controller that can alleviate voltage violations, and ensure the fairness among the EVs available at various charging points in the power distribution system.

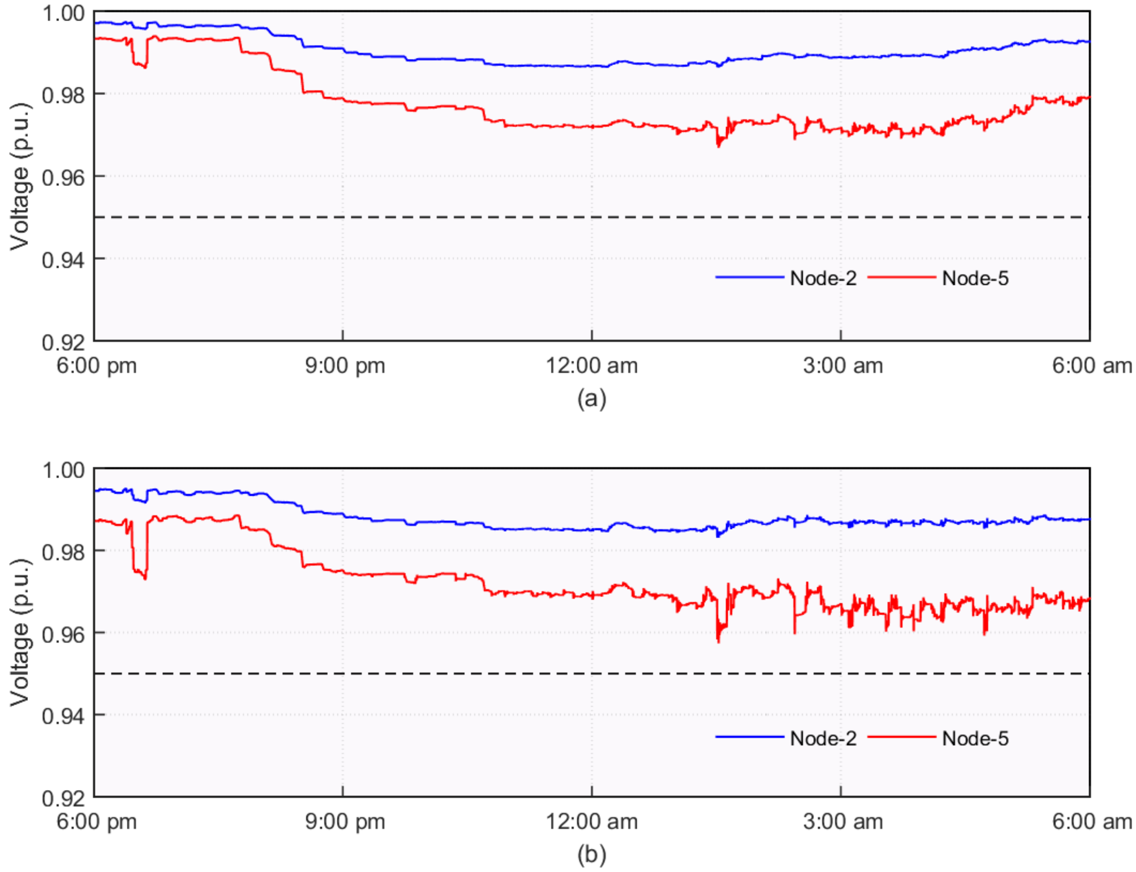

Figure 7: Proportional charging voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

Table 5: Minimum and maximum charging times for proportional charging

EV Type	Minimum charging time		Maximum charging time	
	Light loading	Heavy loading	Light loading	Heavy loading
Nissan Leaf	5.0778 hrs.	5.3722 hrs.	-	-
Tesla Model S	5.5472 hrs.	5.8528 hrs.	9.6056 hrs.	-

5.4 Voltage-Based Nonlinear Charging

A voltage-based nonlinear charge controller is presented in [32] that minimizes the voltage violations. Moreover, it ensures that all the EVs take almost the same time to be fully charged. The voltage profiles of Node-2 and Node-5 are shown in Figs. 8a and 8b for light and heavy loadings, respectively. The minimum and the maximum charging rates for both types of EVs are provided in Table 6. It can be observed that this controller improves the voltage profiles remarkably as compared to opportunistic charging (see Figs. 6 and 8) however, the conservative behaviour needs to be improved as it slows down the charging rate even when there is room for increasing the charging rate without impacting the system voltages, especially during light loading (see Tables 4 and 6).

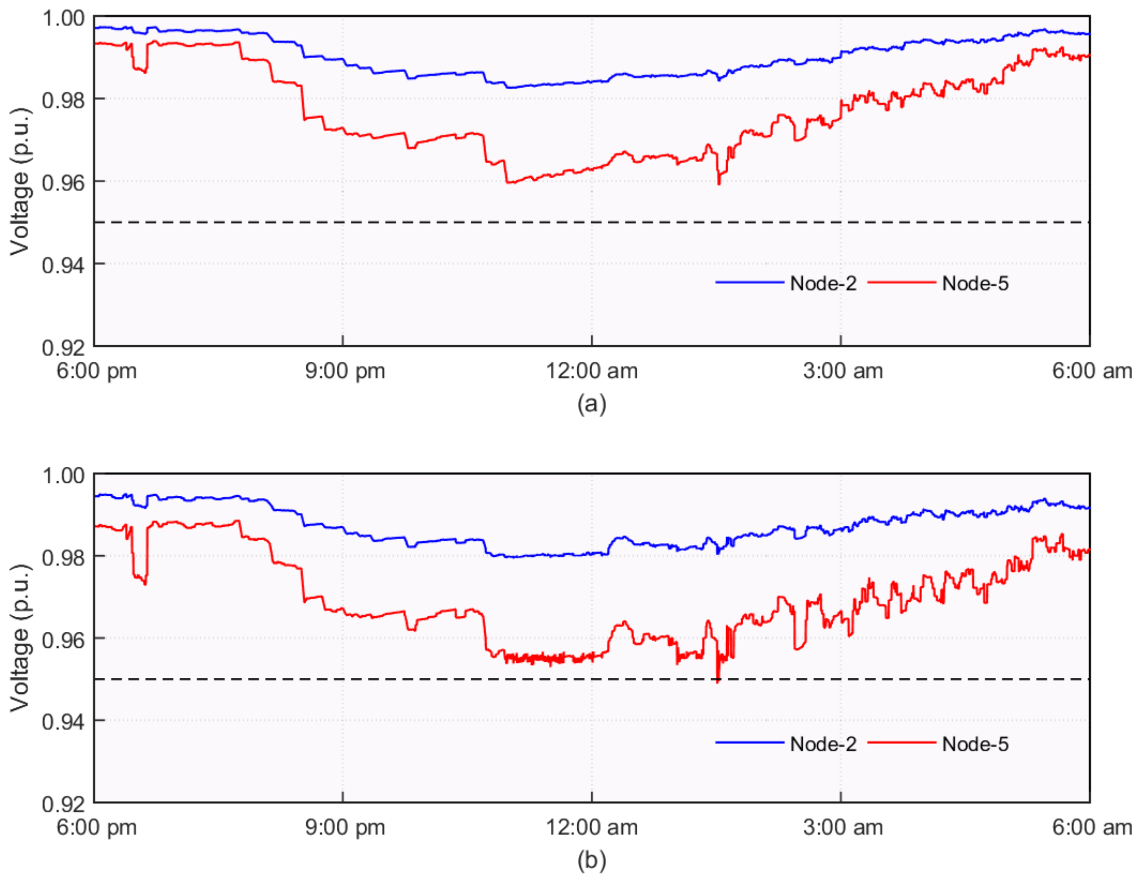

Figure 8: Nonlinear charging voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

Table 6: Minimum and maximum charging times for voltage-based nonlinear charging

EV Type	Minimum charging time		Maximum charging time	
	Light loading	Heavy loading	Light loading	Heavy loading
Nissan Leaf	5.9389 hrs.	5.9556 hrs.	6.0417 hrs.	6.2972 hrs.
Tesla Model S	6.3917 hrs.	6.4083 hrs.	6.4972 hrs.	6.7528 hrs.

5.5 Voltage-and-Sensitivity-Based Charging

In [34], a concept of voltage sensitivity is introduced to further enhance the fairness among the EVs available at different locations in the system. The upstream (or stronger) nodes are less sensitive to load changes when compared to the downstream (or weak) nodes as shown in Fig. 9. In other words, the same change in the load will have a higher voltage impact on the downstream node than on the upstream node. In fact, the node having a higher voltage is less sensitive to load variations or vice versa. Using this fact, this controller makes better use of system capacity by increasing the charging rates of EVs, whenever possible, without negatively impacting the voltage profiles. The voltage profiles at Node-2 and Node-5 during light and heavy loadings are shown in Figs. 10a and 10b, respectively. It can be seen that voltage profiles are slightly lower than that of the voltage-based nonlinear charging scheme (see Figs. 8 and 10). The minimum and the maximum charging times for EVs during the light and heavy loadings are tabulated in Table 7. This controller charges the EVs faster as compared to the voltage-based nonlinear charge controller. It can be seen that the EVs are not only charged faster but the time difference between the earliest and the latest EVs is also reduced (see Tables 6 and 7). Despite the fact that the EVs are charged faster with the voltage-and-sensitivity-based charger, there is still room available for further improvements.

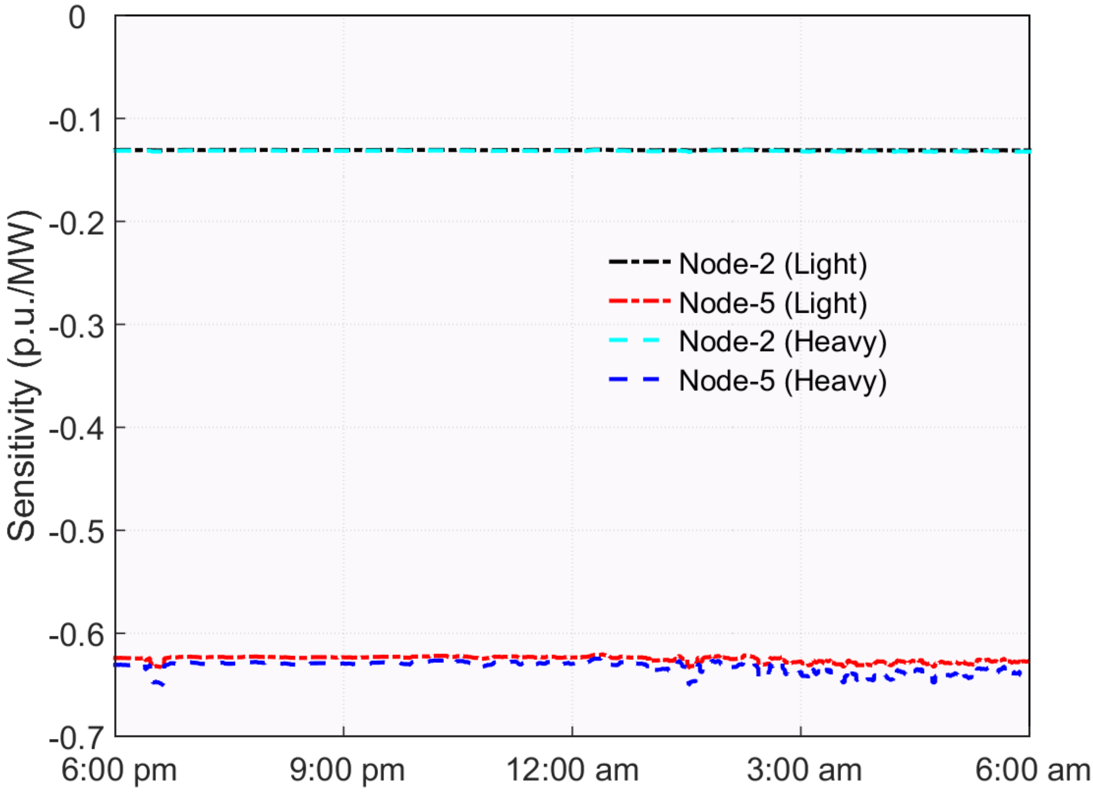

Figure 9: Voltage-sensitivity at Node-2 and Node-5 during light and heavy loading conditions.

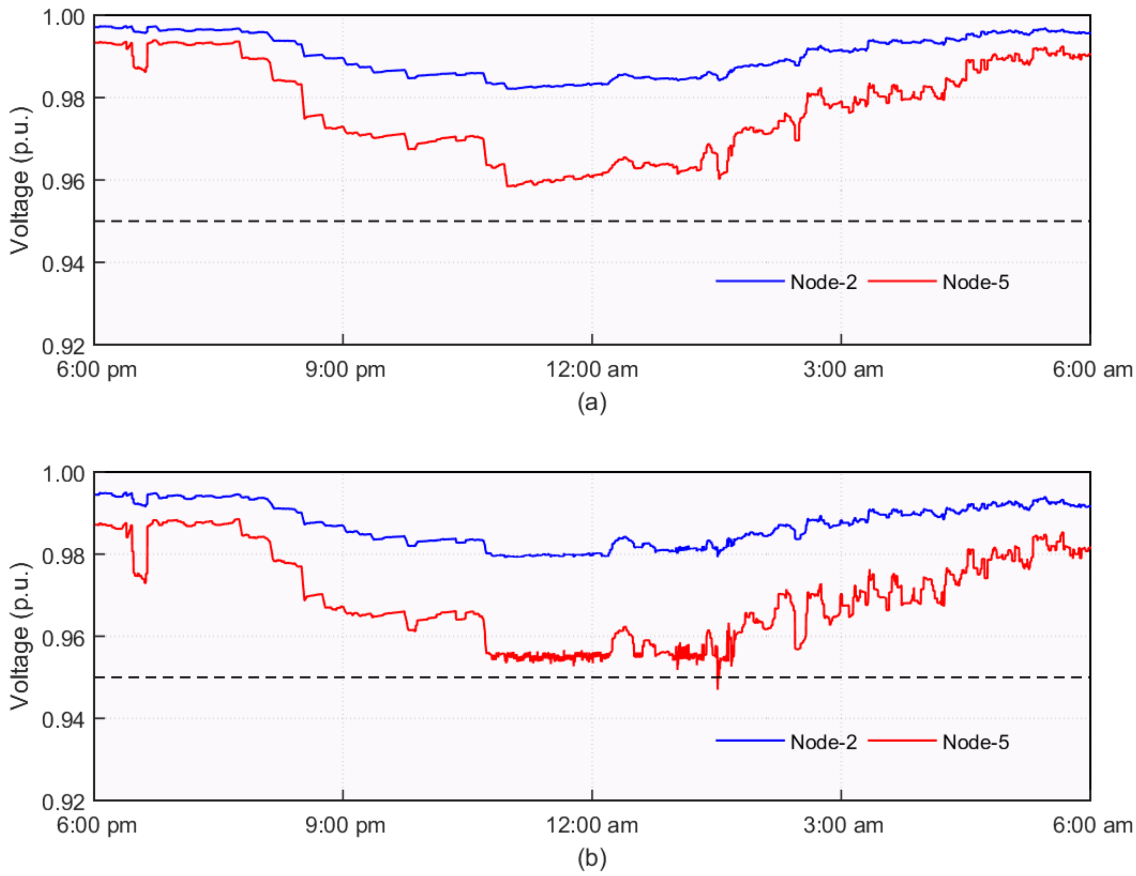

Figure 10: Voltage-and-sensitivity-based charging voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

Table 7: Minimum and maximum charging times for voltage-and-sensitivity-based charging

EV Type	Minimum charging time		Maximum charging time	
	Light loading	Heavy loading	Light loading	Heavy loading
Nissan Leaf	5.5500 hrs.	5.5611 hrs.	5.5778 hrs.	6.0889 hrs.
Tesla Model S	5.9861 hrs.	5.9917 hrs.	6.0028 hrs.	6.4833 hrs.

5.6 Proposed Charging

As stated earlier, opportunistic, proportional voltage-based, voltage-based nonlinear, and voltage-and-sensitivity-based controllers have some sort of limitations, such as power quality issues and/or unfair charging patterns. The artificial intelligence based proposed controller solves these issues. After obtaining all the measurement data, the controller is trained using NN shown in Fig. 11 with the data. The training performance is shown in Fig. 12. Several retraining, layers variation, and a number of neurons are performed as a hit and trial method since there is no single criterion regarding the best number of layers or the number of neurons in each layer. The testing performance is shown in Fig. 13, where the testing outputs from the trained network and target outputs from the analysis of the distribution system are plotted.

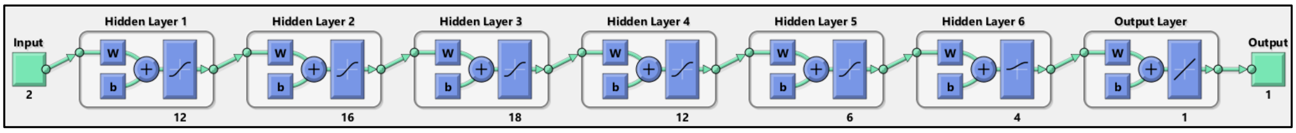

Figure 11: Layout showing number of neurons and layers in the NN.

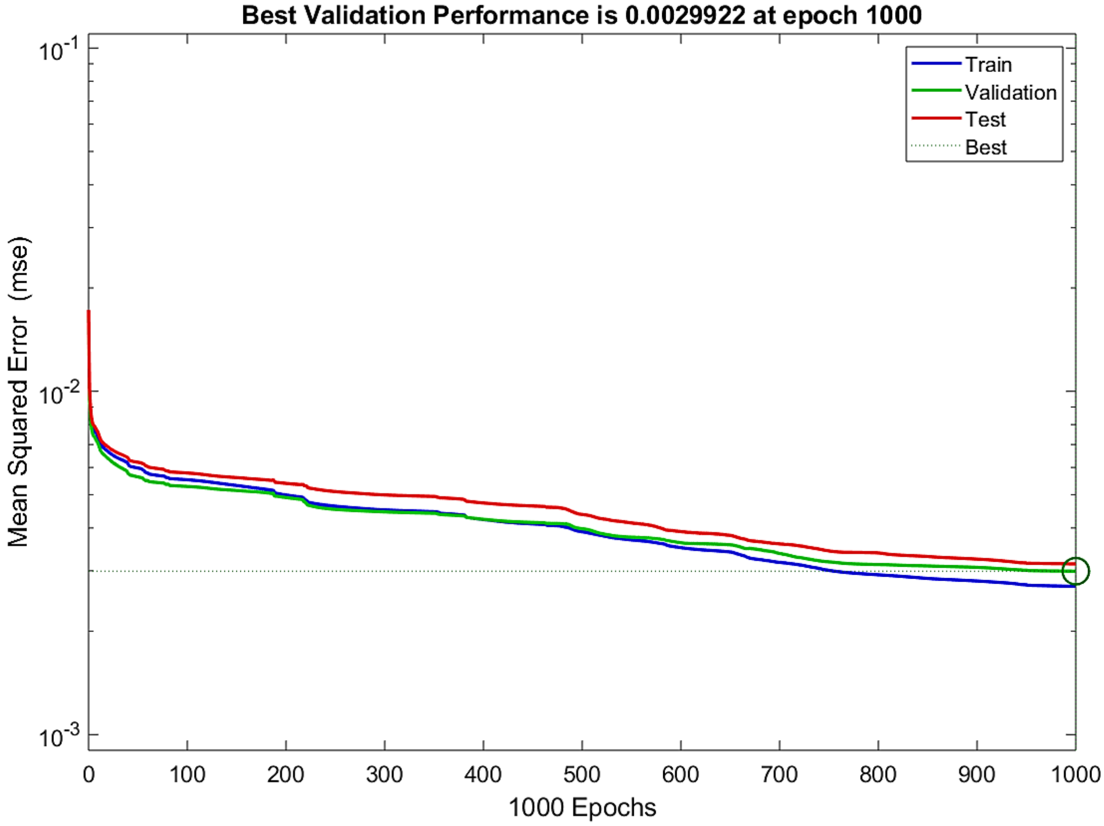

Figure 12: Performance of the trained NN.

Figure 13: Testing the performance of the trained multi-layer network.

The voltage profiles of Node-2 and Node-5 for light and heavy loadings are shown in Figs. 14a and 14b, respectively. It can be seen that the voltage is always well above the minimum allowable voltage limit as defined by the ANSI C.84-2016 standard. The minimum and the maximum charging times for the proposed controller are provided in Table 8. It can be noticed that all the EVs are charged much faster as compared to other techniques. For example, the minimum charging times for Nissan Leaf during light and heavy loadings have been considerably reduced to 4.2639 and 4.3139 hours, respectively. In contrast, the minimum charging times are 5.5500 and 5.5611 hours, and 5.9389 and 5.9556 hours during light and heavy loading conditions for voltage-and-sensitivity-based and voltage-based nonlinear charge controllers, respectively (see Tables 6 and 7). Similarly, the maximum charging times with the proposed controller have been significantly reduced to 4.8889 and 5.5667 hours for Nissan Leaf during light and heavy loading conditions, respectively. Similarly, there is a remarkable reduction in the charging time of Tesla during both the light and heavy loadings (see Table 5).

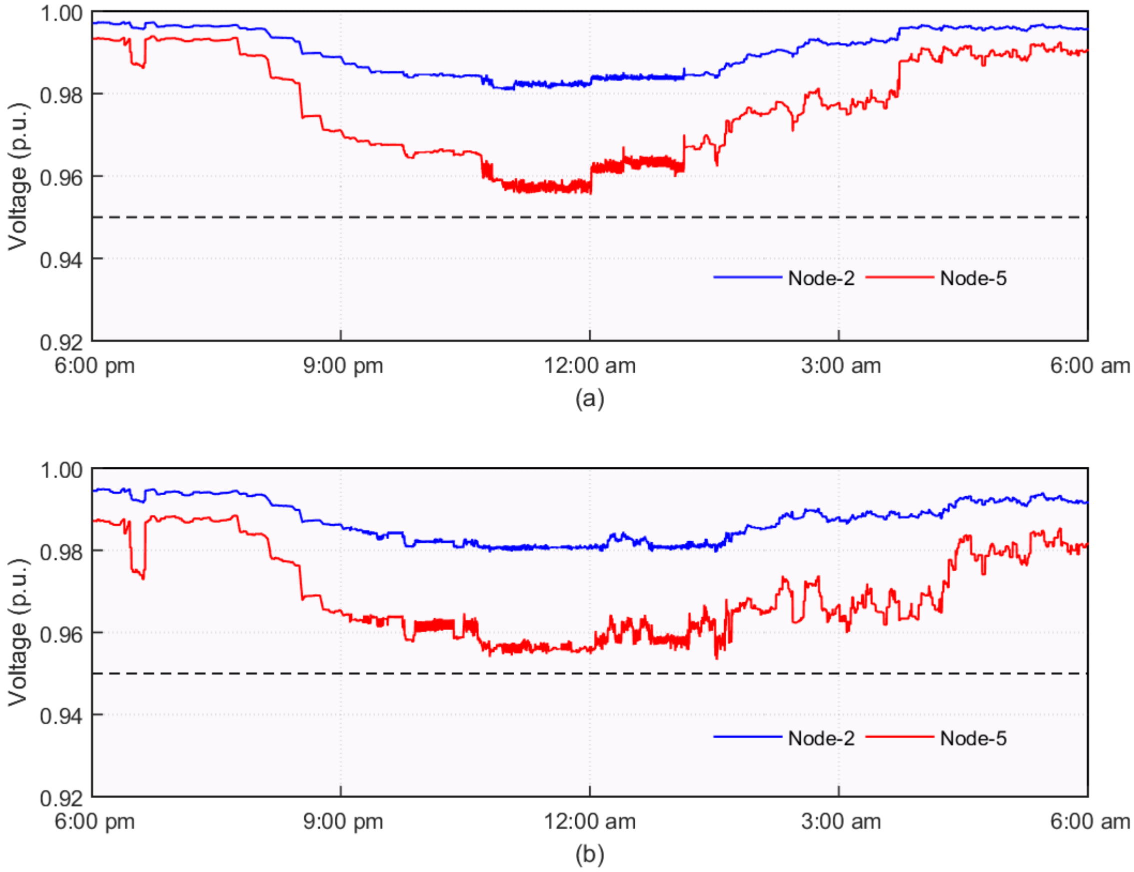

Figure 14: Proposed charging voltages at Node-2 and Node-5 during (a) light loading (b) heavy loading.

Table 8: Minimum and maximum charging times for proposed charging

EV Type	Minimum charging time		Maximum charging time	
	Light loading	Heavy loading	Light loading	Heavy loading
Nissan Leaf	4.2639 hrs.	4.3139 hrs.	4.8889 hrs.	5.5667 hrs.
Tesla Model S	4.6306 hrs.	4.6944 hrs.	5.1639 hrs.	5.7778 hrs.

Another noteworthy aspect of the proposed controller is fair charging among the EVs available at different locations in the system. To prove the effectiveness of the proposed charge controller, EVs which are plugged-in almost at the same time, irrespective of their locations in the system, are compared. In Figs. 15-19, various EVs are compared during light and heavy loading conditions when different charge controllers are utilized. It can be observed that EVs are not only charged faster but they are charged fairly. The average charging time of Nissan Leaf and Tesla for various charge control strategies during the light and heavy loading conditions are shown in Fig. 20. It can be noticed that EVs are charged quickly during the light loading when the proposed controller is utilized as the system can accommodate higher charging rates which proves the efficacy of the proposed controller.

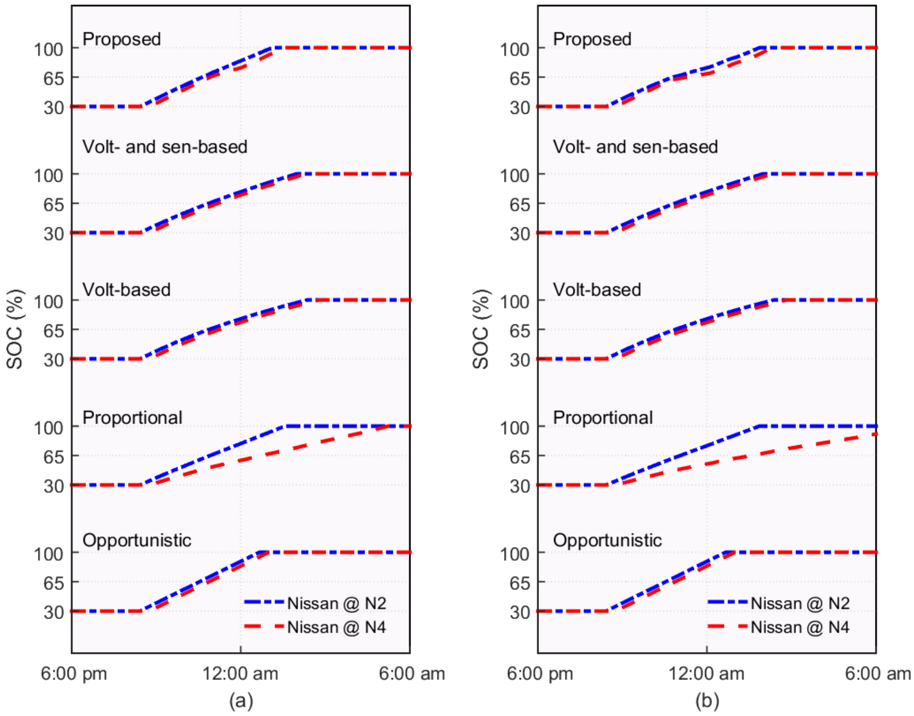

Figure 15: Comparison of Nissan Leafs available at Node-2 and Node-4 with different controllers during (a) light loading (b) heavy loading.

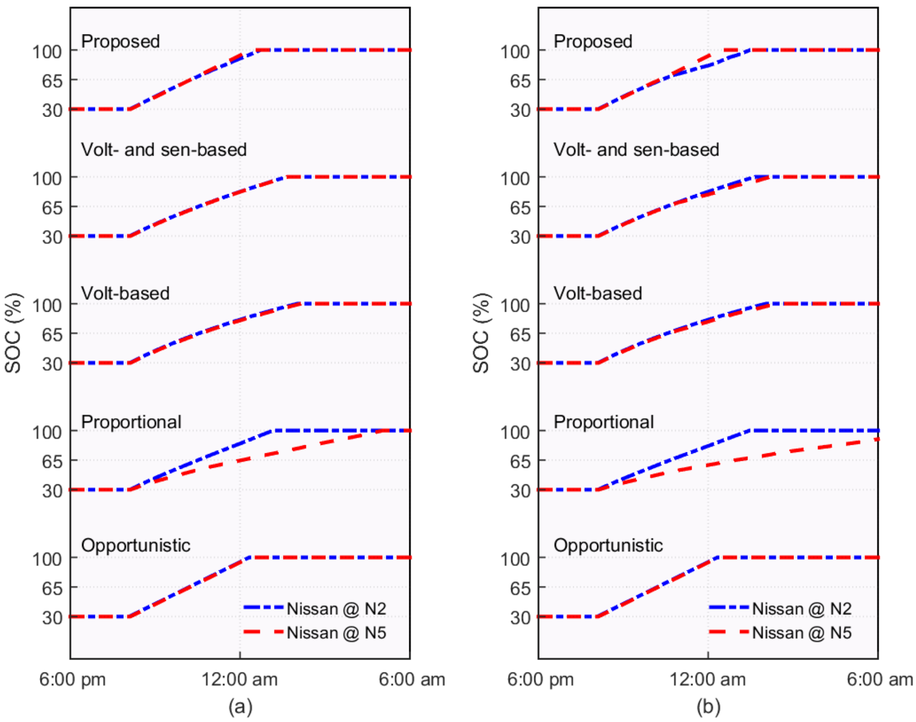

Figure 16: Comparison of Nissan Leafs available at Node-2 and Node-5 with different controllers during (a) light loading (b) heavy loading.

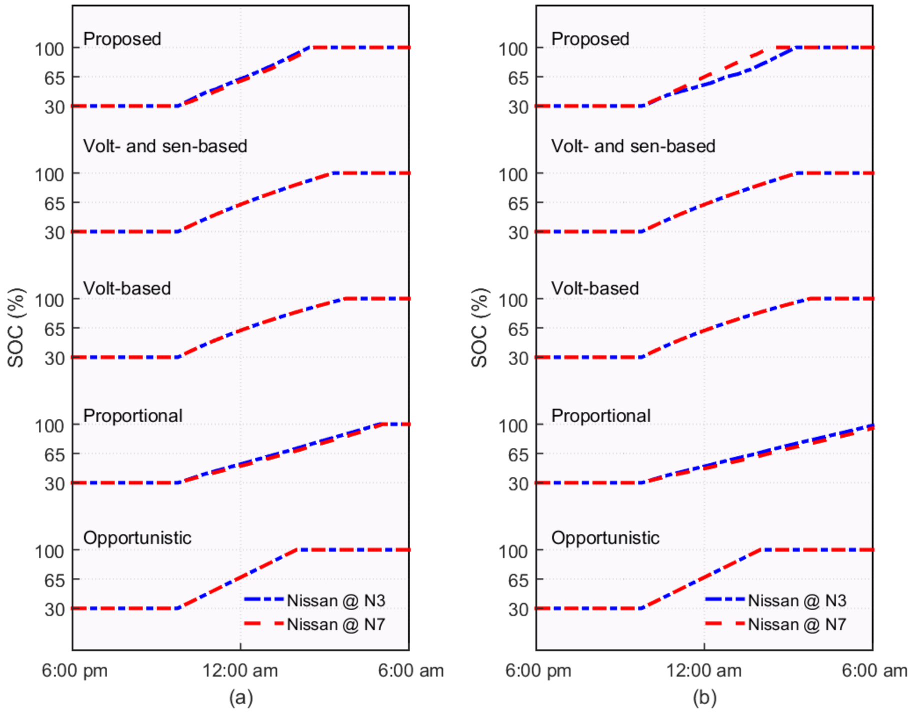

Figure 17: Comparison of Nissan Leafs available at Node-3 and Node-7 with different controllers during (a) light loading (b) heavy loading.

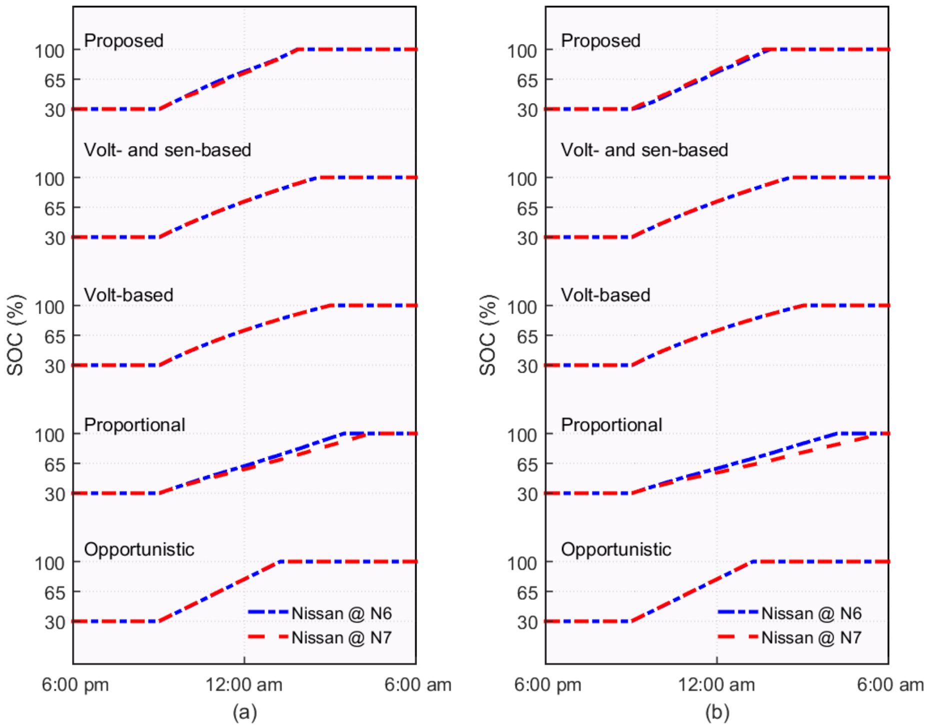

Figure 18: Comparison of Nissan Leafs available at Node-6 and Node-7 with different controllers during a) light loading (b) heavy loading.

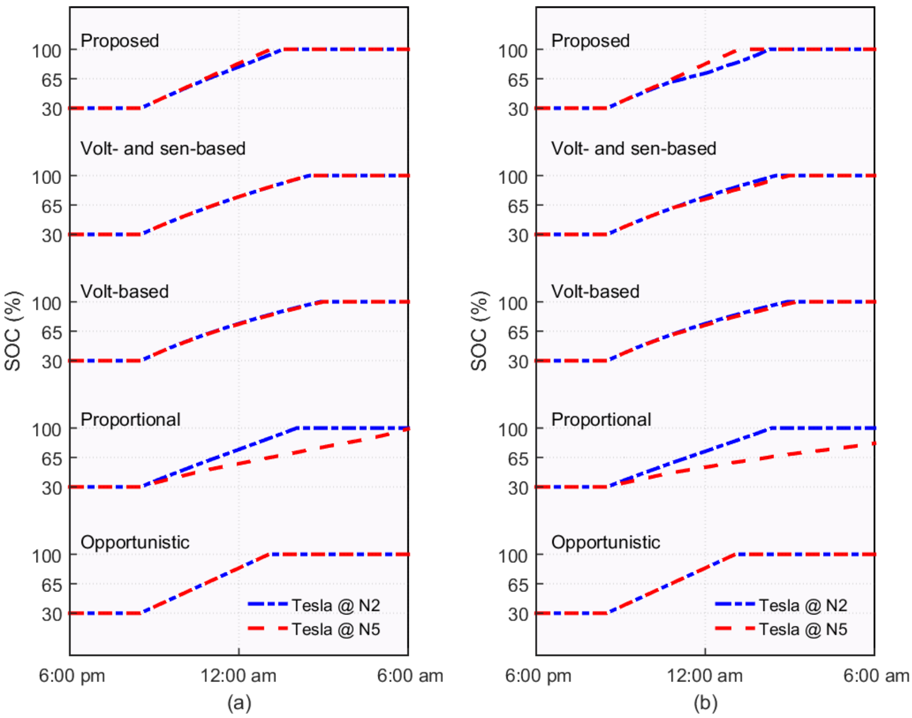

Figure 19: Comparison of Tesla available at Node-2 and Node-2 with different controllers during (a) light loading (b) heavy loading.

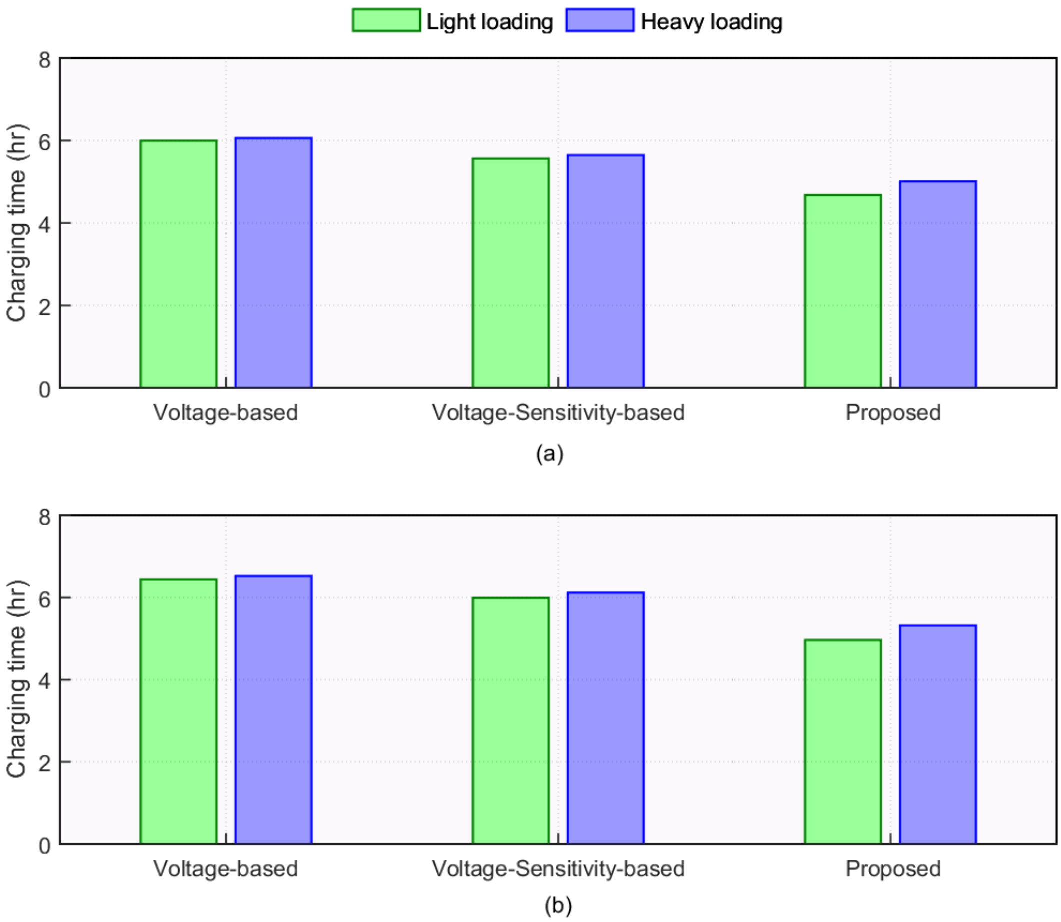

Figure 20: Comparison of the average charging time with different controllers for (a) Nissan Leaf (b) Tesla.

Open Issues and Suggestions for Improvements

Electric vehicles (EVs) are becoming ubiquitous all over the world especially in European countries. The large-scale adoption of EVs may pose many challenges such as line congestion, transformer overloading, under-voltages, and increased power losses. These issues can be mitigated if the charging rate of EVs is controlled. EV charging strategies are classified as centralized, decentralized, and autonomous schemes. In a centralized charging strategy, a well-established communication infrastructure must be available in the power system. Many countries still lack an extensive communication network which makes centralized strategies less practical. A decentralized charging strategy requires reduced communication infrastructure which seldom exists in most of the countries.

On the other hand, an autonomous charging strategy does not require any kind of communication infrastructure as it depends only on the local measurements such as voltage, voltage-to-load sensitivity, and frequency. The major challenge associated with the communication-free charging strategies is to ensure fairness among the EVs available at various charging points throughout the distribution system since there is no way of communication among them. Another major challenge is hunting, which is a state of turning on and off an EV when the voltage goes above and below a certain threshold.

The issue of fairness can be mitigated by implementing an artificial intelligence based EV charge controller. However, extensive data are required to train and implement a robust charge controller. Moreover, it needs to be continuously updated as the system may undergo expansion plans and continuous modifications such as system reconfiguration and renewables integration. It is also suggested that if the charge controller is based on the classification methods, the difference between the various classes must not be too big as it may result in sharp voltage spikes which are highly unacceptable. Moreover, the variations among the class must be smooth. Similarly, the problem of hunting can be avoided if EVs' charging rates are varied in smaller steps. Furthermore, if the EV is turned off because of under-voltage, it must not be turned on unless the voltage improves significantly.

6 Dissemination Planning

The plan is to publish one conference and one journal article from this work. The journal article will be submitted to one of the following well-reputed peer-reviewed journals:

1. IEEE Transactions on Industrial Informatics
2. Applied Energy
3. IEEE Access

It is also planned to submit a part of this work to one of the following conferences:

1. 10th IEEE PES Innovative Smart Grid Technologies (ISGT) Conference-Asia
2. 12th IEEE PES Innovative Smart Grid Technologies (ISGT) Conference-North America

7 References

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8 Annex

8.1 List of Figures

8.2 List of Tables