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Charge Scheduling Optimization of Plug-In Electric Vehicle in a PV Powered Grid-Connected Charging Station Based on Day-Ahead Solar Energy Forecasting in Australia

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Abstract: Optimal charge scheduling of electric vehicles in solar-powered charging stations based on day-ahead forecasting of solar power generation is proposed in this paper. The proposed algorithm's major objective is to schedule EV charging based on the availability of solar PV power to minimize the total charging costs. The efficacy of the proposed algorithm is validated for a small-scale system with a capacity of 3.45 kW and a single charging point, and the annual cost analysis is carried out by modelling a 65 kWp solar-powered EV charging station The reliability and cost saving of the proposed optimal scheduling algorithm along with the integration and the solar PV system is validated for a charging station with a 65 kW solar PV system having charging points with different charging powers. A comprehensive comparison of uncontrolled charging, optimal charging without solar PV system, and optimal charging with solar PV system for different vehicles and different time slots are presented and discussed. From the results, it can be realized that the proposed charging algorithm reduces the overall charging cost from 10–20% without a PV system, and while integrating a solar PV system with the proposed charging method, a cost saving of 50–100% can be achieved. Based on the selected location, system size, and charging points, it is realized that the annual charging cost under an uncontrolled approach is AUS $28,131. On the other hand, vehicle charging becomes completely sustainable with net-zero energy consumption from the grid and net annual revenue of AUS $28,134.445 can be generated by the operator. New South Wales (NSW), Australia is selected as the location for the study. For the analysis Time-Of-Use pricing (ToUP) scheme and solar feed-in tariff of New South Wales (NSW), Australia is adopted, and the daily power generation of the PV system is computed using the real-time data on an hourly basis for the selected location. The power forecasting is carried out using an ANN-based forecast model and is developed using MATLAB and trained using the Levenberg–Marquardt algorithm. Overall, a prediction accuracy of 99.61% was achieved using the selected algorithm.

Keywords: electric vehicles; plug-in electric vehicle; charge scheduling; time-of-use pricing; EV charging infrastructure; solar charging of EVs; solar forecasting; EVs in Australia

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1. Introduction

In recent years, there is an increasing trend in the use of plug-in electric vehicles (PEVs), hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs) rather than ICE vehicles, mainly due to environmental concerns and rapid depletion of fossil fuels. Electrified transportation has reduced the reliance on petroleum imports for transportation, thereby boosting energy security. EVs provide several distinct advantages from a financial standpoint. To begin with, the electricity cost of operating an EV is much lower than the fuel cost of operating a comparable ICEV over the same distance. Due to the durability and simplicity of a battery-electric motor system against the IC engine and subsystems, the periodic maintenance of EVs is far less. Since the current generation of EVs reached the market, automotive battery technology has advanced at a fast pace [1].

The increased use of electric vehicles affects the power quality of the distribution network, which includes voltage imbalance, off-nominal frequency problems, undesirable distortion, network congestion, and other technical, economic, and security concerns [2–5]. Electric vehicles are considered high-power loads that have a direct impact on the power distribution infrastructure, particularly distribution transformers, fuses, and cables. If charging occurs during peak hours, the system will be overloaded, which leads to equipment damage and protection relay trip. Adding an electric vehicle to the grid for fast charging is equivalent to adding many houses to the grid. As the distribution networks are constructed with specified numbers of households in mind, the addition of such massive loads will cause serious network problems.

Implementing a scheduling algorithm for charging electric vehicles is one of the most cost-effective ways to mitigate the negative impact of EVs on the power grid. Scheduling algorithms provide an efficient manner of charging using the available infrastructure. Different charging strategies are implemented to manage the time and frequency of EV charging, such as un-controlled/un-coordinated, controlled/coordinated, delayed, and off-peak charging [6]. Uncoordinated charging, uncontrolled charging, or dumb charging [7] refers to charging without regard for when power is drawn from the grid. In a controlled charging approach, EVs are charged at times when demand is low and/or charging cost is less, such as after midnight. Several constraints are taken into account when formulating scheduling algorithms. Vehicle profile, vehicle configuration, aggregator parameters, and grid parameters are some of the most critical constraints. The vehicle profile contains information about the vehicle, such as arrival and departure time, vehicle power rating, the energy required, and state of charge (SOC), which are essential for charge scheduling [8].

The optimum EV charging schedule in the electricity market has been studied extensively with a wide range of objectives. The EVs charging priority is set up in [9] based on the difference in the EVs' parking duration. The charging time of electric vehicles is scheduled in [10] to increase the utilization rate of the feeder terminal load while reducing power loss in the distribution network. The multi-agent system is used in [11] to schedule EV charging in order to achieve peak shaving and three-phase equilibrium. To reduce the voltage drop and power loss during EV charging, a real-time load management system is proposed in [12]. An intelligent technique for controlling EV charging loads in a controlled market in response to Time-Of-Use pricing (ToUP) is represented in [13]. Effective EV charging methods in the day-ahead market from several aspects has been formulated in [14]. In [15], optimum EV charging operation for both day-ahead and real-time scheduling has been analyzed. The impact of PEV penetration on the load profile of the distribution network was investigated in [16], with different models of vehicles and charging methods being considered. In [17], an intelligent charge scheduling algorithm (ICSA) is described with the inclusion of Henry gas solubility optimization (HGSO) to reduce the charging station operator's total daily pricing. Using linear programming, [18] developed a real-time optimization program based on an energy management model for EV parking lots (EVPL), where the scheduling algorithm provides a peak load limitation centered demand response (DR) program to increase the EVPL's load factor. A global intelligent technique for finding optimal cooperation charging/discharging techniques for EVs based on particle swarm optimization (PSO) is investigated in [19]. A centralized charging method for EVs by using the battery swapping setup by using both PSO and genetic algorithm is presented in [20], which considers the optimal charging priority and charging. A day-ahead electric vehicle charge scheduling using an aggregative game model is presented in [21]. The heuristic algorithm-based optimal charge scheduling of EV is discussed in [22]. EV charging scheduling based on various configurations is represented in [23,24].

The cost of charging is the prime factor that encourages customers to use electric vehicles. The charging station is an important part of the electric vehicle industry's operation [25]. The operating cost, specifically the charging cost of EVs, is not only a key criterion for vehicle purchasers to choose EVs over ICVs, but it is also the primary means for operators to cover the expenses of charging infrastructure investment [26]. Energy service providers use time-dependent tariffs in a price-based demand response (PBDR) program so that electricity cost, higher rate during peak demand periods and lower during off-peak periods. Time-Of-Use pricing (ToUP), Real-Time Pricing (RTP), and Critical Peak Pricing (CPP) are examples of time-based tariffs [27]. The hours in ToUP are separated into various time blocks, each with a particular tariff. The prices in RTP are updated hourly to match the actual wholesale cost of electricity. Electricity is costlier in CPP during peak demand periods [19]. This time-dependent tariff, on the other hand, will not result in a shift in loads. To schedule the load, efficient optimization procedures are required. Furthermore, consumers should be aware that by utilizing these programs, they will be able to reduce their electricity expenses.

With EVs in the picture, renewable energy utilization becomes more appealing. Parking lot rooftops have a lot of potential for installing PV panels that can charge the vehicles parked below as well as feed the grid in the event of excess generation [28], assisting in the commercial deployment of RESs. By integrating the RESs and Energy Storage Systems (ESS), a convex optimization problem of energy scheduling is developed in [29], while taking into account the uncertainties of EV load and the real-time price market of grid electricity in order to maximize renewable energy consumption through direct load control of EV charging. In [30], the paper illustrates a two-stage energy scheduling in office buildings with PV systems and workplace EV charging. Based on a two-stage model, the work reported in [31] examines the influence of high renewable sources and electric vehicle penetration on generation scheduling and overall cost. A reliable, optimal week-ahead generation scheduling technique for Plug-in Hybrid Electric Vehicles (PHEVs) is provided in [32], which takes into account unpredictability in loads, renewable energy sources, and PHEV charging behavior. An energy management scheme (EMS) is depicted in [33] for the optimal charging and discharging of EVs in a distribution network with photovoltaic based on solar energy and grid power availability. Table 1 summarizes some of the other charge scheduling of EVs presented discussed in the literature. From the above discussion and also from Table 1, it can be understood that the deep learning approaches and AI-based optimization tools are used for the development of charge scheduling algorithms. The deep learning and AI-based approaches guarantee accuracy in optimization. However, the tradeoff is implementation complexity and processor requirement for algorithm development.

Though RES is one of the promising solutions to avoid grid issues and make EV charging more sustainable, there exist some challenges. The power generation of solar PV systems depends on environmental conditions, mainly irradiation and temperature. Due to the variability of irradiation and temperature in nature, the power generated by the solar PV system is intermittent. Figure 1 shows the daily power generation of a 65 KW solar PV system for random days 1 May 2020–30 April 2021 in New South Wales, Australia. From the figure, it can be realized that power generated by a solar PV system varies over time and also from season to season. The fluctuating nature of RES, which is solar power in this case, affected by time, weather, location, and other factors, causes voltage stability and resilience problems for the power system. An effective prediction analysis should be carried out to understand the energy generation behavior of RES.

Table 1. EV Scheduling methods by integration of RES.

Reference	Year	Renewable Energy Type	Algorithm/Method	Remarks
[34]	2019	Solar energy	Elitism simulated annealing	The charging demand of each electric vehicle can be satisfied with minimum electricity cost.
[35]	2019	Solar energy	Particle Swarm Optimization (PSO)	The analysis is performed on a real low-voltage distribution network with real load data, and the results indicate that under a proper charging schedule both the voltage profile and the energy losses of the DN could be improved.
[36]	2020	Solar energy	Integer Linear Programming (ILP)	This article considers a photovoltaic (PV)-powered station equipped with an energy storage system (ESS), which is assumed to be capable of assigning variable charging rates to different EVs to fulfil their demands inside their declared deadlines at minimum price.

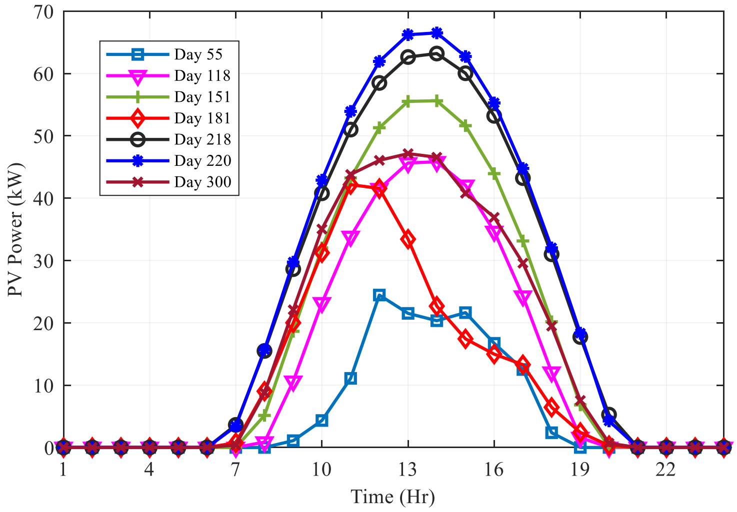


Figure 1. Power generated by a 65 kW PV system on different days during a year.

In the context of solar-powered EV charging stations, for effective scheduling of EV charging with minimized cost, knowing the power generation of the solar PV system in advance is a mandate. To know about the power generation behavior of the PV system, effective prediction of the weather data must be carried out. The following subsection describes the day ahead forecasting. Since the prime focus of this paper is the EV charge schedule, a brief review of forecasting methods and the predicted results are presented.

Numerous tools and techniques are adopted in literature to predict the weather parameters such as solar radiation, temperature, and wind speed to estimate power generation of renewable energy systems. Soft computing and bio-inspired approaches such as an artificial neural network (ANN), genetic algorithm (GA), particle swarm optimization (PSO), and the learning approaches such as a support vector machine (SVM), long short-Term memory recurrent neural networks (LSTM) are used for prediction [37,38]. ANN is the most commonly adopted approach for prediction due to its reliability and suitability for multidimensional spaces over empirical methods [39,40]. This is one of the five classes of the nonlinear model-based approach, which uses gradient descent-based learning [41]. A variety of ANN-based models proposed for forecasting are discussed in detail in [37–39]. Hence, artificial neural network (ANN)-based forecast model is used in this paper.

In this paper, an optimized charge scheduling algorithm for a solar PV-powered grid-connected PEV charging station is proposed. A proposed charging approach is an uninterruptable approach. The main objective of the proposed approach is to minimize the charging cost by optimizing the charging schedule by considering the PV generation.

Day-ahead prediction of solar PV generation helps to optimize the scheduling accounting for the PV generation. The main contributions of the paper are:

- Modelling of solar PV system for a PEV charging station.
- Day-ahead prediction of irradiation, temperature using ANN, and computation of solar power generation.
- Development of optimal uninterruptible charge scheduling for PEVs considering solar PV power generation.
- Validation of proposed algorithm using the different vehicle's parameters.
- Cost comparison of the proposed algorithm with uncontrolled charging, optimal scheduling without PV and with the integration of PV.
- Annual cost analysis and feasibility study of charging station with 65 kW solar PV system under different scenarios.

The diagrammatic representation of the proposed system is given in Figure 2. The proposed architecture comprised of a solar PV system, and the utility grid to power the EV charging units. Based on the availability of solar power and the power required by the charging stations at any instant, the grid will either supply power or receive the power via a point of common coupling. The main objective of the proposed algorithm is to reduce the overall charging cost of PEVs by scheduling the charging hours according to the power generation of RES. The algorithm monitors the function of sub-components of the charging infrastructure and schedules the charging of vehicles accordingly so that the overall charging cost can be reduced along with proper utilization of power generated by the solar PV system to make the charging sustainable and cost-effective.

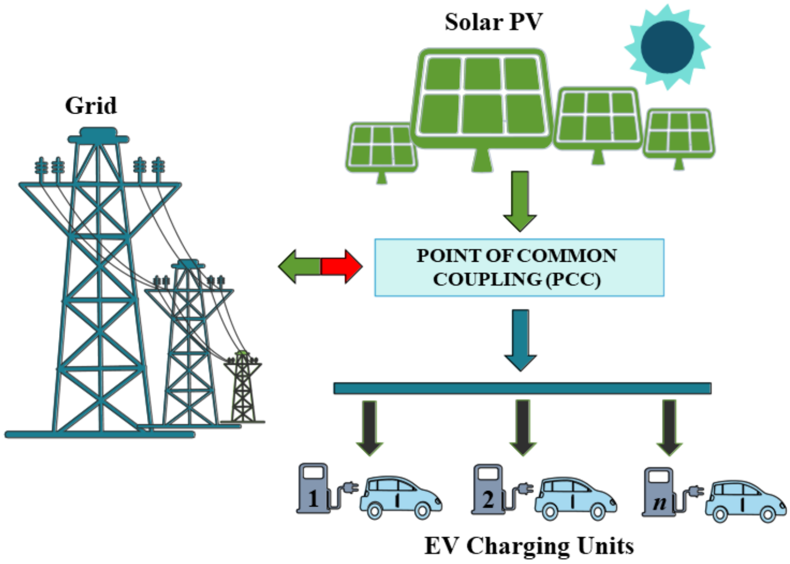


Figure 2. Diagrammatic representation of a proposed system.

The rest of the paper is organized as follows. Section 2 analyses the daily driving behavior between home and office, the site selection of the proposed study and modelling of a solar PV system as well as the day ahead forecasting of PV generation. Section 3 describes the development of the proposed scheduling algorithm based on an improved placement algorithm. Section 4 analyzes the simulation results and charging cost obtained under different approaches for single and large-scale charging stations. Lastly, Section 5 concludes the paper.

2. Analysis of Driving Behavior, Site Selection, PV System Modeling, and Day-Ahead Forecasting

Based on the charging power and time taken to charge the batteries, EV charging is mainly categorized as slow charging and fast charging. Slow charging is usually an on-board charging with AC supply and for fast charging high power off-board charger is used [42]. In slow charging, the rated charging power is 3 kW in most of cases. The typical rate of fast chargers is 7 kW and 11 kW. DC fast charges with higher capacity are also available. The battery capacity of Tata Nexon EV is 30.2 kWh [43]. In the case of Tata Nexon EV, it takes nearly 9 h to fully charge (100%) the battery from 10% in slow charging mode. Under fast charging mode, the same battery can be fully charged in approximately 4 h when connected 7 kW charger and it may take only 2.5 h to charge the vehicle when connected to 11 kW fast charger.

2.1. Driving Behavior

As mentioned earlier, the EV loads are unpredictable, and the uncertainty of these loads will cause several issues to the utility grid. However, optimal scheduling will help to overcome the grid-related issues and also to reduce the overall charging cost. The daily travel characteristics, i.e., the commuting of vehicles from home to office and office during a day based on the U.S. NHTS dataset are analyzed in [44]. The travel pattern of vehicles is shown in Figure 3a. Likewise, the vehicle mobility pattern in the office parking of Beijing University, China presented in [45] is shown in Figure 3b.

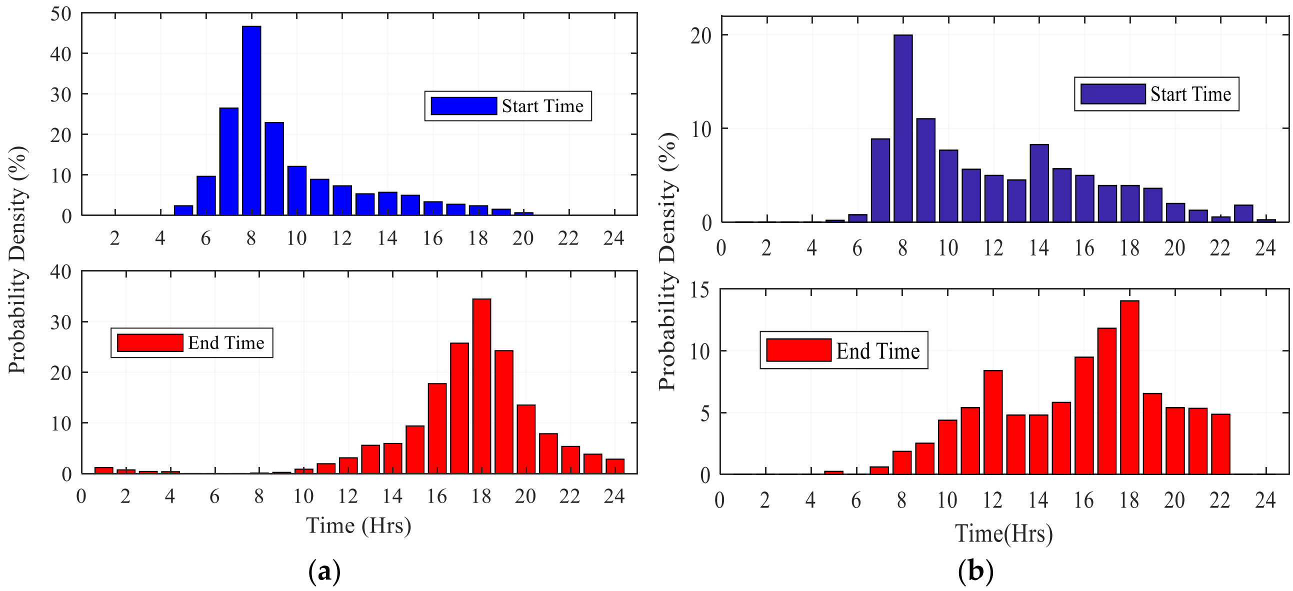


Figure 3. Vehicle Travel Pattern (**a**) U.S NHTS dataset (**b**) Beijing University dataset.

The start time indicates the vehicles traveling from home to office and the end time show the vehicles traveling back from work to home. From the figures, it can be realized that the maximum vehicles leave from home between 7 AM−10 AM and then return back to home between 4 PM–7 PM. Thus, the EVs can be effectively charged in an office parking environment for 8–12 hours. However, for residential parking, the scenario will be the opposite and vehicle charging will be mostly overnight.

In this paper, a rooftop PV system installed over the car parking roof is considered for analysis. The work presented in [46] discusses the off-grid solar-powered EV charging station. A 320 kW solar PV system is considered as a source for analysis in the presented work and 10 PV panels with a capacity of 320 W_P is accounted for a parking space of one vehicle. The size of the selected PV panel is 1.6 m^2 and hence, the area considered for parking one vehicle is 16 m^2 in this case. According to the Dutch regulation, 12.5 m^2 is the minimum area required for parking one vehicle [47]. The work presented in [48] discusses the feasibility of PV-powered EV charging station. The PV-powered charging station installed in the Université de Technologie de Compiègne, France is considered for analysis. A total of 84 SunPower SPR X21-345PV panels were mounted over the parking shade, which has a capacity for parking nine cars. The area covered by one PV panel that is

1.6 m^2 [48]. Hence, the parking area per vehicle is nearly 15 m^2 in this case. Based on the above discussion, the parking space per vehicle is considered as 15 m^2.

2.2. Site Selection

The State of Electric Vehicles report released in August 2021 has stated that the Australian EV market experienced a tremendous rise in EV sales in 2021. The NSW government has been continuously taking several initiatives to increase EV adoption in the state. Based on state and BudgetDirect reports, 30% of total EVs accounted for in Australia are from NSW there are around 6400 EVs in the state. NSW is ranked as #1 in making EV policies among the other states in Australia, with a score of 9 out of 10. According to the EV strategy announced by the NSW government, the entire passenger fleet of the NSW government will be transformed into EVs by 2030. Further, the NSW state government has decided to invest nearly 500 million dollars in the next four years as incentives for electric vehicle purchases. Along with that, an investment of 171 million dollars is allotted for building the ultra-fast EV charging infrastructure across the state [49].

The potential of renewable-based power generation is promising in the selected region, particularly solar power generation. Moreover, the utility services are offering separate solar feed-in tariffs as well as a ToUP tariff plan for EVs. Considering all these facts and figures, New South Wales (NSW), the southeastern state of Australia is selected as the location for analysis in this study. A PV powered On-grid EV charging station with a capacity of 20 parking spaces considered in this paper. The total area of parking space is 300 m^2 and the capacity of the solar PV system taken into account 65 kWp. The complete specification of the PV powered charging station is given in Table 2.

Table 2. Specification of the PV powered charging station.

Parameter	Value
Location	New South Wales (NSW), Australia
Latitude	32.533° S
Longitude	148.931° E
Parking area per vehicle	15 m^2
PV Module	SPR–X21–345-COM
Maximum Output Power (P_{max})	345 W_p
Average Efficiency of Module (η_s)	21.5%
Temperature co-eff (γ)	$-0.29\%/°C$
Cell Type	Monocrystalline Maxeon
Total Capacity of the PV System	65 kW_p
Total Area of parking shade	300 m^2
No. of Parking	20

2.3. PV Modeling

A photovoltaic cell converts solar energy into electrical energy. The power produced by a photovoltaic cell depends upon the solar radiation and temperature data. The expression for output power P_{pv} is given by,

$$P_{pv} = \eta_s \times A \times 0.9 \times SI \times (1 + \gamma\,(t_o - 25)) \quad (1)$$

where, P_{pv} is PV module's output power and η_s is the efficiency of the PV module. 'A' represents the area of the PV module, whereas 'SI' denotes the solar irradiation (W/m^2). γ and t_o represent the temperature coefficient of PV module (%/°C) and outdoor temperature (°C), respectively. Value of γ differs depending on the manufacturing parameters and PV technology used [45]. Solar radiation and outdoor temperature are the key parameters for modeling the solar PV system. Power generation of the proposed PV systems considered in this study is computed using Equation (1).

2.4. Day-Ahead Weather Forecasting for Solar PV Generation Using ANN

The concept of artificial neural networks (ANN) is derived from the information processing of biological nervous systems. ANN process the information with a help of interconnected elements, which are called neurons. ANN is most widely accepted for forecasting due to its high approximation capability and the accuracy of prediction. Hence, ANN is adopted for forecasting weather data in this work. Figure 4 shows the multilayer perceptron network of NN with one input layer, one hidden layer, and one output layer. As shown in the figure, all the inputs are connected to each and every neuron in the hidden layer. At the initial stage, the weights are randomly assigned based on the relation between the input and output. Then, during the training process, NN adjusts the weights, and the outputs are updated in each stage. This process is repeated, and weights are adjusted in the layers until the error between the output of NN at the output layer and the expected output are minimized. The following subsections discuss the various stages of model development of ANN.

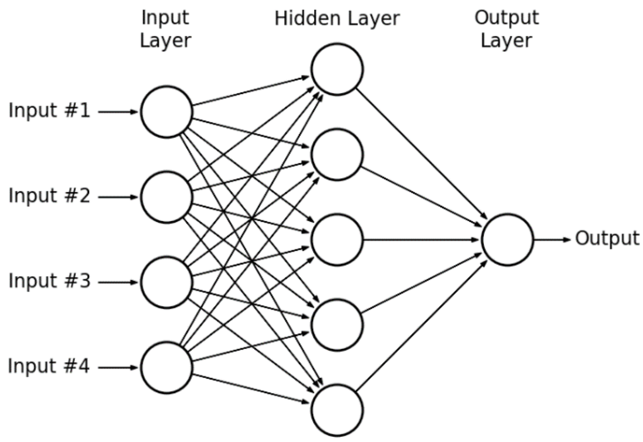


Figure 4. Architecture of multilayer perceptron network.

The ANN model development for forecasting has a number of stages such as (i) Data Collection & Generation of Data for Training and Testing (ii) Data Pre-processing & Normalization and (iii) Training & Testing of Neural Network.

(i) Data Collection & Generation of Data for Training and Testing

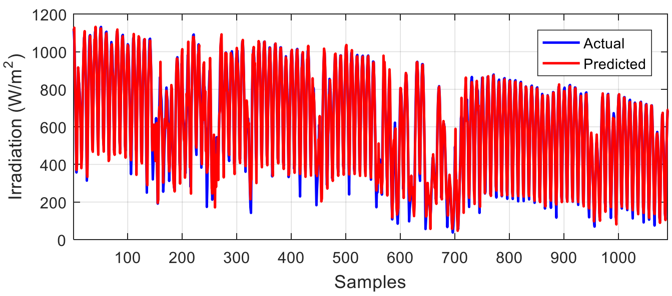
The typical operating conditions of the system are represented by the data. The first step in ANN modelling is the collection of data and the generation of training and testing data from the collected data. In order to schedule the vehicle charging optimally, knowing the power generation in advance is mandatory. As mentioned in the previous section, power generation is computed using weather data. Thus, the weather data is predicted and the power generation is computed using the predicted data. The hourly data of solar irradiation and temperature for s one year period from 1 May 2020–30 April 2021 for New South Wales, Australia (Latitude: 32.533° S, Longitude:148.931° E) is collected from Solar Irradiation Data (SODA) [50]. To build the ANN model, the data is further processed and separated for training and testing. From the processed data, 70% of data is used for training and the rest is taken as test data. The following subsection describes the data pre-processing and normalization of raw data.

(ii) Data Pre-processing & Normalization

The hourly data of temperature and irradiation collected for the selected region have 8460 samples of each datum. In the case of irradiation, the data are zero during the period when there is no sunlight. The variation between the minimum and maximum values of the and zeros in the data will create a great impact on the training of the neural network. Moreover, the network will be saturated quickly during the training process with such raw data. Hence, data is generally pre-processed and normalized to increase the robustness of training and prediction accuracy. In this case, the irradiation data is pre-processed to remove zeros and the very low irradiation values. For irradiation data, samples between 9 AM to 7 PM are sorted and collected. A total of 3650 samples are used for prediction. However, for the prediction of temperature all the 8460 samples are used.

(iii) Training & Testing of Neural Network.

An ANN-based forecast model is developed using MATLAB and trained using the Levenberg-Marquardt algorithm. The ANN model consists of one hidden layer with 10 hidden neurons is used. The number of hidden neurons is selected by the trial-and-error method. The actual and predicted output for Irradiation, and Temperature, are presented in Figure 5a,b, respectively. The mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the correlation coefficient (R) are presented in Table 3.



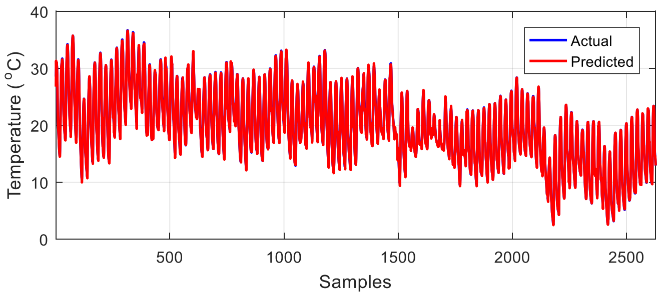


Figure 5. The actual and predicted outputs using ANN: (**a**) Irradiation; (**b**) Temperature.

Table 3. Simulation results of forecasting.

	Irradiation	Temperature
MSE	2.2295×10^3	0.2294
RMSE	47.2176	0.4790
R^2	0.9949	0.9995
MAPE	7.9048	1.7067

From the Table 3, it can be understood that the correlation coefficient (R^2) of all the selected parameters is very close to "1". This confirms the efficiency of the prediction and reliability of predicted data. Using the obtained results, the power generated by the Solar PV system is calculated and these results are used for scheduling the vehicles for optimal charging.

3. Improved Placement Algorithm

In [51], Arif et al. presented and discussed a placement algorithm for EV scheduling. The main limitation of the algorithm is its time restriction for entry and departure time of the vehicle. In residential parking, the charging is done mostly overnight. However, the algorithm proposed in [51] is not suitable for scheduling overnight charging. In the paper, the placement algorithm is modified in such a way to offer flexibility for the user to enter and exit the charging point at any time of the day. Further, it is improvised to make it capable of scheduling overnight charging, which allows the vehicle to continue charging in the next day starting from 0100 h also. Moreover, the proposed algorithm considers the hourly PV generation also into account vehicle scheduling for optimal and cost-effective charging. Formulation of the proposed algorithm is presented in the following sub-section.

Formulation of Optimized Scheduling Algorithm

The proposed algorithm collects the vehicle information required to schedule the charging once the vehicle is plugged in for charging. Here, the vehicle arrival time is considered as a plug-in time of the EV. Likewise, the charging must be stopped before the departure time of the vehicle and the vehicle must be charged with the required amount of energy before the vehicle leaves the station. Considering these factors and the predicted hourly generation of solar PV, the algorithm should assign a slot at which the charging cost will be minimized. The main factors considered in the algorithm development are as follows:

- Availability of power generated by solar PV based on the predicted data
- Vehicle arrival time (EV_{at})
- Vehicle departure time (EV_{dt})
- Length of charging duration (L_{ch})
- Vehicle charging power (P_{ev}) and
- Consumption Tariff rate (R_{grid}) and PV tariff (R_{pv}).

Here, the algorithm follows uninterruptible charging i.e., once the charging process is initiated, it will be terminated only upon completion of the charging duration. Initially, the placement algorithm generates the charging slot between the arrival time and departure time based on the length of charging duration.

Let us consider that the i^{th} vehicle is plugged in for charging at EV_{at} h., the vehicle will depart at EV_{dt} h. and it should be charged for L_{ch} h. Then, the total number of possible charging slots of the i^{th} vehicle can be obtained using,

$$q^i = \begin{cases} EV^i_{dt} - EV^i_{at} - L^i_{ch} + 1 \text{ for } EV_{dt} > EV_{at}(\text{same day}) \\ 24 + EV^i_{dt} - EV^i_{at} - L^i_{ch} + 1 \text{ for } EV_{dt} < EV_{at}(\text{next day}) \end{cases} \tag{2}$$

Then, the algorithm calculates the total charging cost for all the possible slots. For each slot, the hourly required power is computed based on the PV power generation for every hour between the starting time and end time. From that, the slot at which the cost incurred for charging is identified by the algorithm using Equation (3), and the vehicle is scheduled to charge in that slot.

$$\arg min C^i_{ch}\left(q^i\right) \tag{3}$$

Since, the PV-generated power is predicted in advance, the algorithm can optimally schedule the EV charging by effectively utilizing the PV power. In addition to that, the excess power from PV generation is supplied to the grid when there is no requirement or the required power is less than the generated power. The step-by-step procedure for finding optimal slot for EV charging using improved placement algorithm with predicted PV power is given in Table 4. The algorithm initially collects the vehicle information and PV power generation. Then, the power required from the grid is computed for each hour during the period between start and end time of charging. The charging cost is calculated for each slot between the arrival and leaving time of the vehicle and the slot at which the minimum cost incurred is identified using Equation (3). Finally, the vehicle will be scheduled to charge during the minimum cost slot. This way, the solar power is effectively utilized to reduce the overall grid cost and the burden to the grid is also minimized.

Table 4. Step by Step procedure of the proposed optimal charging algorithm.

Steps	Procedure
Step-1	Load the arrival time (EV_{at}), departure time (EV_{dt}), charging duration (L_{ch}) and charging power (P_{ev})of the electric vehicle
Step-2	Load the electricity consumption charge (R_c) and PV tariff (R_{pv}) tariff (R_{ch})
Step-3	Load the predicted data of irradiation and temperature for the selected day and calculate PV Power using Equation (1)
Step-4	for i^{th} vehicle
Step-5	Find the number of possible charging slots between EV_{at} and EV_{dt} using, $$q^i = \begin{cases} EV^i_{dt} - EV^i_{at} - L^i_{ch} + 1 \text{ for } EV_{dt} > EV_{at}(\text{same day}) \\ 24 + EV^i_{dt} - EV^i_{at} - L^i_{ch} + 1 \text{ for } EV_{dt} < EV_{at}(\text{next day}) \end{cases}$$
Step-6	Find charging cost for all the slots from x^i = 1:q^i Charging Start Time $C^i_{st} = EV^i_{at} + x^i - 1$ Charging End Time $C^i_{ft} = EV^i_{at} + x^i + L^i_{ch} - 2$
Step-7	for x^i = 1:q^i for $t = C^i_{st} : C^i_{ft}$ Find the required power using $$P_{req}(t) = P_{ev}(t) - P_{pv}(t)$$ Calculate the charging cost $$C^i_{ch} = \sum_{t=C^i_{st}}^{C^i_{ft}} R_{ch} \cdot P_{req}$$ $$R_{ch} is R_{pv}\ if\ P_{req} < 0$$ $$R_{ch} is R_{grid}\ if\ P_{req} > 0$$
Step-8	Find the slot at which cost incurred for charging is minimum $$min \sum_{t=C^i_{st}}^{C^i_{ft}} R_{ch} \cdot P_{req}$$
Step-9	Schedule the vehicle to charge at $$\text{arg}min C^i_{ch}\left(q^i\right)$$
Step-10	End

4. Simulation Results and Analysis

Two different case studies are conducted. In the first case, a residential parking shade for one car (16 m^2) with 3.45 kW PV system is considered. In this case, the effectiveness of the scheduling algorithm is analyzed using data of the three vehicles with different power rating. The charging power and charging time of slow and fast charging considered for analysis is presented in Table 5. The cost incurred to charge the vehicles with unscheduled and proposed optimal charging under different scenarios is compared and analyzed. In the second case, a charging station with a capacity of charging 20 vehicles in a day is considered. The charging station is integrated with a 65 kW PV system. In case 2, three different scenarios are considered for the analysis. In both cases, the analysis is carried out as follows: (i) Uncontrolled charging with grid power, (ii) Uncontrolled charging with grid power and PV power source, (iii) Optimized charging with grid power, and (iv) Optimized charging with grid power and PV power source.

Table 5. Type of Electric Vehicle Charging.

Type of Charging	Charging Power	Duration of Charging	Avg. Time Duration
Slow Charging	3 kW	7–9 h	8 h
Fast Charging I	7 kW	4–6 h	5 h
Fast Charging II	11 kW	1–3 h	2 h

Time-of-Use pricing (ToUP) scheme is adopted for analysis in this study. The utility service providers in Australia offer independent Time-of-Use pricing (ToUP) schemes for EV users. EV ToUP pricing scheme of NSW is presented in Table 6. Apart from this, all the service providers offer a solar feed-in tariff for the customers. The solar feed-in cost of 7 cents/kW is offered by most of the service providers in Australia. Hence, 7 cents/kW is considered as a feed-in tariff for Solar PV and wind power in this study. Other than the usual off-peak, shoulder, and peak prices, a special tariff is offered to EV users between 12–4 h [52]. EV ToUP of NSW is depicted in Figure 6.

Table 6. ToUP Tariff data.

Slot (Hr)	1	2	3	4	5	6	7	8	9	10	11	12
Cost (₵)	7.98	7.98	7.98	15.95	15.95	15.95	28.6	28.6	23.1	23.1	23.1	23.1
Slot (Hr)	13	14	15	16	17	18	19	20	21	22	23	24
Cost (₵)	23.1	23.1	23.1	23.1	28.6	28.6	28.6	23.1	23.1	15.9	15.9	7.98

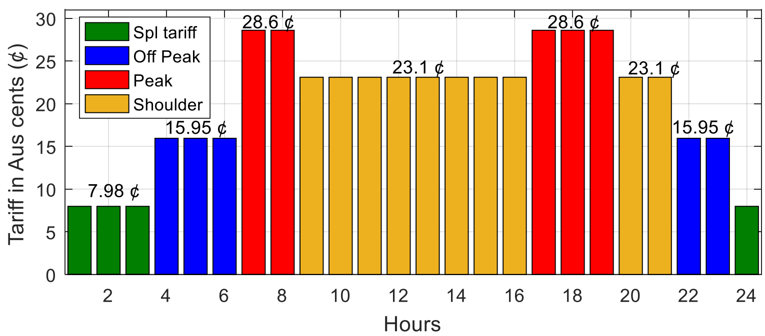


Figure 6. ToUP tariff of New South Wales (NSW).

4.1. Case 1. Analysis of Optimal Charge Scheduling of EV in Residential Paring Shade

For the first case study, the 305th day of the year, i.e., 2 March 2021, is considered. Using the predicted weather data, the expected power generation of 3.45 kW PV system for 305th day is computed. The actual power generation on the selected day is also calculated to validate the accuracy of the prediction. The actual and predicted power of the PV system is shown in Figure 7. The actual and predicted power computed for the selected day is listed in Table 7. The prediction efficiency is also presented in the table.

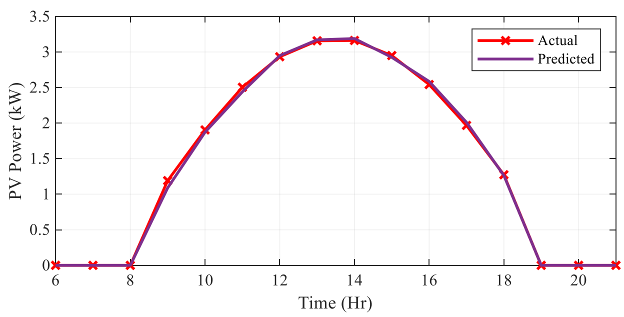


Figure 7. Actual and Predicted power of 3.45 kW PV system for 305th Day.

Table 7. Total output power of Solar PV system based on Actual and Predicted data.

Actual Power	23.5851 kW
Predicted Power	23.4927 kW
Efficiency	99.61%

Three plug-in electric vehicles with dissimilar power ratings and charging rates are taken to analyse the algorithm. The simulation data of EVs are given in Table 8. The table shows the departure time, arrival time, charge duration, and charge rate of the selected vehicles. To refer to the vehicles, a short name is given as ID for all the selected vehicles. For example, "Nissan Leaf" is referred to as "NL".

Table 8. Simulation Data for Electric Vehicles.

Vehicle	ID	Vehicle Arrival Time (A_t)	Vehicle Departure Time (D_t)	Charging Duration of Vehicle (h)	Rate of Charging of Vehicle (kW)	Total Energy of Vehicle (kWh)
Kia EV6	KA	11 h	18 h	3	11	33
Nissan Leaf	NL	7 h	19 h	8	3	24
Hyundai-IQNIQ	HD	16 h	24 h	5	7	36

Vehicle "KA" arrives at the charging station at 11 h. It will leave the station at 18 h. It must be charged for 3 h duration before it leaves the station. Figure 8a shows the charging schedule and charging power without PV in uncontrolled charging mode. In uncontrolled charging mode, the charging process is initiated immediately after the vehicle is connected to the charging station (11 h) and continue to charge for the required charging duration which is 3 h in this case. Figure 8b shows the grid power which represents the hourly grid power of the charging station integrated with 3.45 kW solar PV system. Negative power indicates the excessive power supplied to the grid and positive power indicates the amount power of power taken from the grid. For the selected case, the proposed algorithm also schedules the vehicle to charge from 11 h since the charging cost is minimized in that slot. Therefore, the charging slot remains the same for both uncontrolled charging and the proposed optimal charging for the vehicle "KA". Hence, the graphs for optimal scheduling are not presented again. Thus, for vehicle "KA" the cost incurred for charging with an uncontrolled charging approach and optimal charging remains the same.

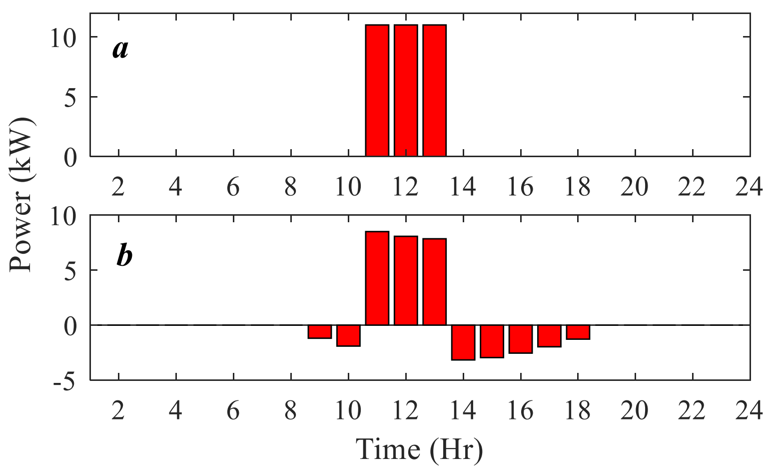


Figure 8. Grid Power (**a**) Uncontrolled Charging without PV (**b**) proposed charge scheduling with PV for vehicle KA.

Now, for vehicle "NL", under uncontrolled charging, the vehicle is charged between 7 h to 14 h as shown in Figure 9a. But the proposed algorithm scheduled the vehicle to charge between 9 h to 16 h to reduce the cost as shown in Figure 9c. The grid power with the PV for "NL" under uncontrolled and proposed method are shown in Figures 9b and 9d respectively.

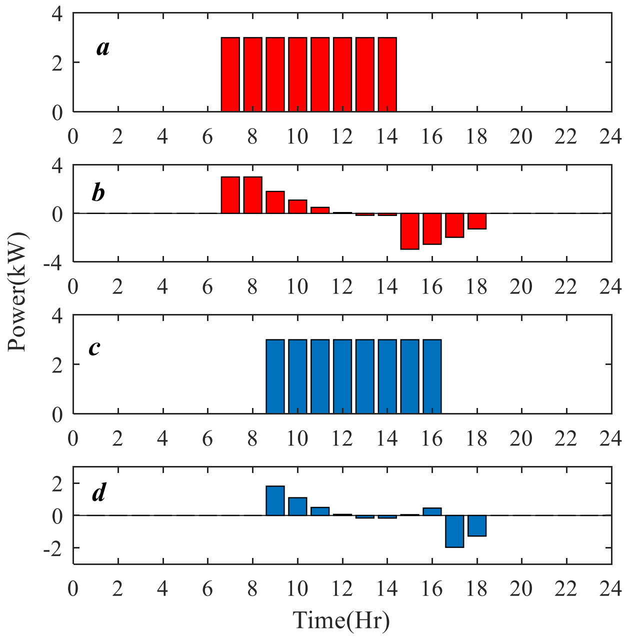


Figure 9. Grid Power (**a**) Uncontrolled charging without PV (**b**) Uncontrolled charging with PV (**c**) Proposed charge scheduling with PV, and (**d**) Proposed charge scheduling without PV for vehicle NL.

Likewise, for vehicle "HD", under uncontrolled approach, the vehicle is charged at a higher cost. However, the proposed algorithm optimized the charging schedule in such a way as to reduce the charging cost. Figure 10 shows the charging power and grid power of "HD" with uncontrolled, and proposed charging approach without and with PV integration. A detailed cost comparison between different methods with different sources of power to charge the vehicle is presented in Table 9. For vehicle KA, the cost incurred for charging is the same with and without scheduling since the charging cost is low in the first slot. For vehicles NL and HD, it is evident from the table that the proposed algorithm optimally schedules the charging of vehicles in such a way to reduce the cost incurred for charging. Further, the integration of solar PV systems helps to reduce the overall charging cost.

Table 9. Charging Cost Comparison.

	Uncontrolled Charging Method			**Proposed Charging Method**		
Vehicle	KA	NL	HD	KA	NL	HD
Grid Only	7.6230	5.8740	9.2400	7.6230	5.5440	7.4690
Grid & PV	4.5884	1.8833	6.4796	4.5884	0.6691	5.8180

From the above results, it can be inferred that nearly 10% of cost-saving is achieved for charging "NL" and the cost saving is more than 20% in the case of "HD" when charged only from the grid. On the other hand, with the integration of PV system, 50% to 100% cost-saving can be achieved depends on the power rating, charging requirement, tariff schemes, and capacity of PV system integrated into the charging unit/station, i.e., in certain cases, the energy generated by the PV system will be sufficient fulfil the requirement.

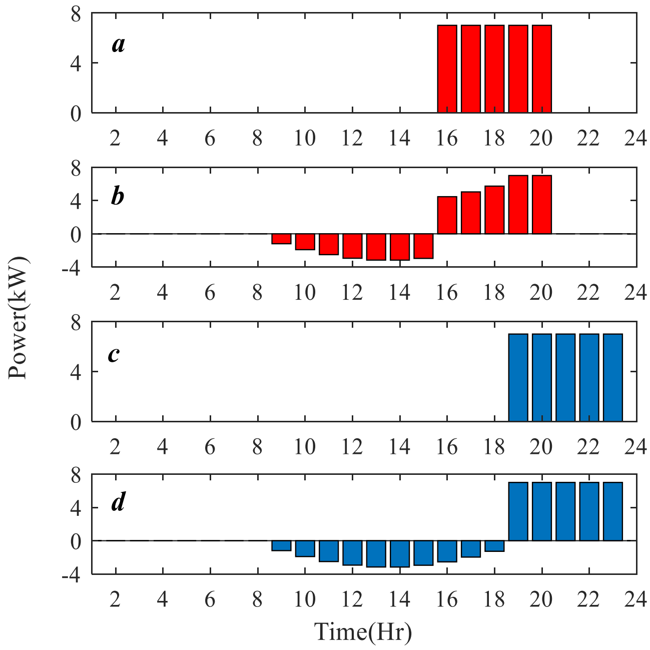


Figure 10. Grid Power (**a**) Uncontrolled charging without PV (**b**) Uncontrolled charging with PV (**c**) Proposed charge scheduling with PV and, (**d**) Proposed charge scheduling without PV for vehicle HD.

4.2. Case 2: Large Scale Analysis of PEV Charging from Solar PV based Charging Station

In this case, a long-term analysis of PEV charging station with 65 kW solar PV system is carried out. The economic benefits of integrating solar PV systems in large-scale public charging stations with the proposed charging approach are analyzed. To conduct the analysis for a period of one year, initially the daily generation of solar PV system for one year between 1 May 2020 to 30 April 2021 is obtained using the weather data collected from the selected region. The daily generation of the selected solar PV system is shown in Figure 11. The average power generated by the 65 kW solar PV system per day is 321.8417 kW. The generation is computed using the predicted data.

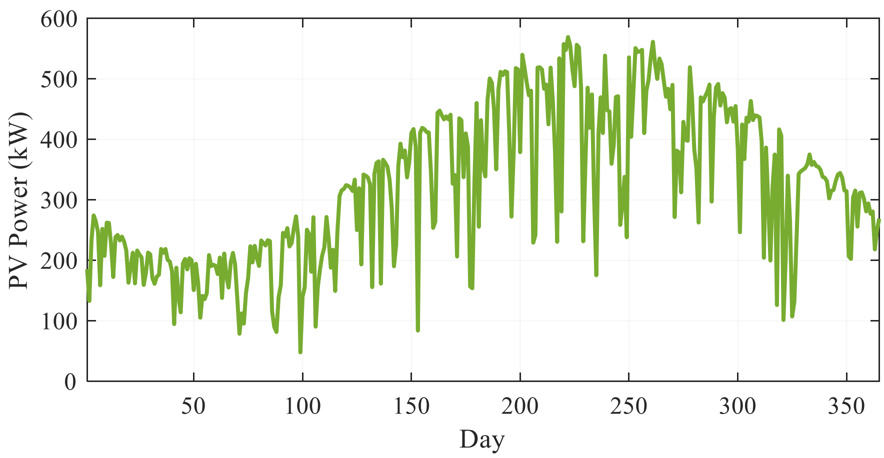


Figure 11. Daily Generation of the 65 kW PV System.

The vehicle data consist of vehicle arrival time, departure time, duration of charging and charging power is generated for 365 days and analysis is carried out for PV powered grid connected charging station with 10, 12 and 15 charging points. The number of slow chargers, fast charger I, and fast charger II in each scenario are given in Table 10. To generate the vehicle data, it is assumed that the vehicles will enter the station between 7 h–11 h and depart from the station between 17 h–20 h. In each set, the arrival time, departure time of each vehicle is randomly generated based on this assumption. Likewise, the duration of charging for different charging power are also randomly generated based on the charging duration. A sample dataset of one day for scenario 2 is listed in Table 11. Vehicle data for 365 days is generated in a similar fashion.

Table 10. Number of chargers selected for large scale analysis.

	Scenario 1	**Scenario 2**	**Scenario 3**
No. of Charging Points	10	12	15
Slow Charging (3 kW)	5	6	8
Fast Charging I (7 kW)	3	4	4
Fast Charging II (11 kW)	2	2	3

Table 11. Sample of random vehicle data.

Charging Power	**3 kW**						**7 kW**				**11 KW**	
Arrival time	7	7	7	8	9	9	9	11	11	9	10	9
Departure time	18	19	20	20	19	19	20	20	19	18	17	18
Charging Duration	7	7	7	8	8	9	6	4	6	5	1	2

The annual charging cost under different scenarios using proposed charging methods without PV, and proposed charging method with PV are given in Table 12. From the analysis carried out with 10, 12 and 15 charging points as given in Table 10, a solar powered charging station with 12 charging points includes 6 slow charges (3 kW), 4 fast charger I (7 kW) and, 2 Fast charger II (11 kW) is found to be a sustainable net-zero energy solution with the proposed algorithm based on the annual charging cost. The daily cost of charging station for scenario 1 under different approaches for a period of one year is shown in Figure 12.

Table 12. Annual charging cost under different scenarios.

<table>
<tr><th rowspan="2">No. of Charging Points</th><th colspan="3">10</th><th colspan="3">12</th><th colspan="3">15</th></tr>
<tr><th>3 kW
5</th><th>7 kW
3</th><th>11 kW
2</th><th>3 kW
6</th><th>7 kW
4</th><th>11 kW
2</th><th>3 kW
8</th><th>7 kW
4</th><th>11 kW
3</th></tr>
<tr><td>Optimized</td><td colspan="2">Grid Power Only Cost
2.2817×10^4</td><td>Grid & PV Cost
-5.3170×10^3</td><td colspan="2">Grid Power Only Cost
2.7851×10^4</td><td>Grid & PV Cost
-283.4445</td><td colspan="2">Grid Power Only Cost
3.3739×10^4</td><td>Grid & PV Cost
5.6051×10^3</td></tr>
</table>

The annual charging cost is AUS $28,131 when charging is carried out using uncontrolled charging method. In this case, the station is powered only from the grid. However, a reduction of AUS $280 is achieved with the proposed charging approach. With the integration of 65 kW solar PV system, the charging station becomes self-sustainable for the selected conditions. The net annual charging cost has become negative (AUS $ (-)283.4445) in a 65 KW solar powered EV charging station with proposed algorithm. Hence, the operator can make a net profit of AUS $28,134.445 annually. The key reason is that the utility services charge the peak and off-peak tariff between 7 AM–7 PM and the solar PV system also produces power during this period. From these results, it can be inferred that the solar powered grid connected charging station with the proposed scheduling algorithm significantly reduces the overall charging cost and burden on the utility grid during peak hours.

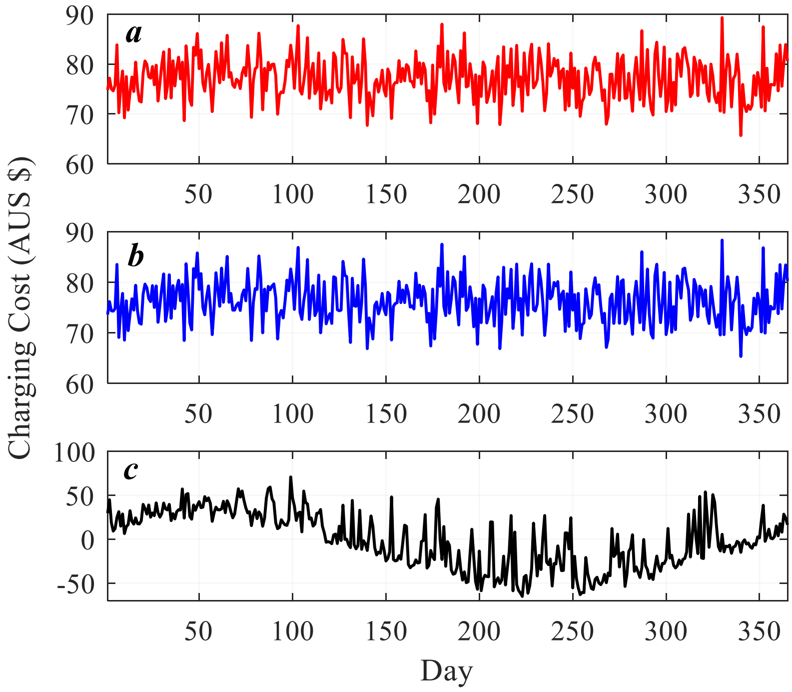


Figure 12. Daily charging cost for charging 12 EVs; (**a**) uncontrolled charging without PV, (**b**) proposed charging without PV, and (**c**) proposed charging with PV.

5. Conclusions

In this article, the authors proposed a novel scheduling algorithm for charging of EV to reduce the overall charging cost and to eradicate the negative impact on the power grid. With the proposed technique, charging of EV is completely managed based on day-ahead forecasting of connected renewable power generation source. A dedicated artificial neural network model is developed to forecast power generation. The proposed algorithm schedule charges in such a way to effectively utilize the solar PV power. The effectiveness and accuracy of the proposed scheduling algorithm is validated through extensive simulation studies under different scenarios. A 3.45 kW solar powered charging station in residential parking for charging one vehicle and an office parking space charging station with 65 kW PV systems are modelled for the analysis. An extensive comparative with uncontrolled charging without and with a PV system, optimal charging without and with PV for different vehicles, and different time slots for different scenarios is carried out. The study reveals that the residential charging system reduces the cost by 10–20% with the proposed algorithm. Further, the cost incurred for charging a vehicle with 30 kWh battery capacity from 10−90%, i.e., 80% charging is nearly zero (0.6691 cents) when it is charged from a 3.45 kW solar powered residential system with the proposed algorithm. The cost analysis of the commercial charging station is carried out with and without solar PV system by incorporating the proposed algorithm. From the analysis, it can be observed that the annual electricity tariff of the charging station with 12 charging points is AUS $27851.00. However, on the other hand, the vehicle charging becomes sustainable with a profit of AUS $28,134.445 in the65 kW solar powered charging station with proposed algorithm for the selected conditions. From the results and analysis, it is concluded that the proposed charging algorithm optimally schedules the vehicle charging and the charging cost is less compared to the uncontrolled approach. In addition to that, Solar PV power forecasting aid to optimally schedule the charging and this helps to reduce the burden on the grid and peak demand issues. Thus, the solar powered EV charging system with the proposed optimal charge scheduling algorithm makes the EV charging more sustainable and cost effective.

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