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T. T. Lie, Xiuli Liang*, and M. H. Haque

# A Cost-Effective Electric Vehicle Charging Method Designed For Residential Homes with Renewable Energy

**Abstract:** Most of the electrical infrastructure in use around the world today is decades old, and may be ill-suited to widespread proliferation of personal Electric Vehicles (EVs) whose charging requirements will place increasing strain on grid demand. In order to reduce the pressure on the grid and taking benefits of off peak charging, this paper presents a smart and cost effective EV charging methodology for residential homes equipped with renewable energy resources such as Photovoltaic (PV) panels and battery. The proposed method ensures slower battery degradation and prevents overcharging. The performance of the proposed algorithm is verified by conducting simulation studies utilizing running data of Nissan Altra. From the simulation study results, the algorithm is shown to be effective and feasible which minimizes not only the charging cost but also can shift the charging time from peak value to off-peak time.

**Keywords:** Electric Vehicles (EVs), EV Charging, Photovoltaic (PV)

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## 1 Introduction

The rising demand on finite energy sources, coupled with an increasing environmental awareness in the public consciousness means that Electric Vehicles may see wide scale proliferation in the near future. Similarly, the uptake of Photovoltaic (PV) energy sources in residential homes is driven by similar forces, and is likely to become increasingly common. Battery Electric Vehicles (BEVs) and Plugin Hybrid Electric Vehicles (collectively referred to as EVs in this paper) play an important role in reducing greenhouse gas emissions and the dependence on oil. However at this time, EVs have relatively low penetration into the domestic vehicle fleet. This is in part due to the high cost and limited lifetime of batteries, the lifecycles of which are impacted by charging/discharging rate, temperature changes, and chemical degradation over time. Currently, the most commonly utilized charging method is 'plug in and charge', which leaves the battery without reasonable protection. Overcharging a lithium battery will cause overheating problems that have an impact on the battery's lifespan or may even explode.

There is a clear need for a method that can reduce charging cost and improving the electrical efficiency as well as extend the lifetime of the internal battery of EVs. This will result in huge benefits such as helping to promote EVs, reducing oil demand, protecting the environment, decreasing the electricity demand on grid and leads to further economic benefits. This paper proposes a smart and cost effective EV charging methodology for smart homes combined with renewable energy such as Photovoltaic (PV) panels. The proposed charging strategy is coupled with a central information control system which can manage historical electricity consumption data, storage, and processing of the energy generated by the PV panels. This data can be used to manage the battery charging operation to reduce the strain on the electrical grid, the cost to the consumer, and extend the lifetime of the battery. Electricity generation is typically focused on providing for peak loads. This means contemporary grid infrastructure does in fact have enough spare capacity to service the load required to charge EVs [1]. However a sufficiently high load demand caused by simultaneous charging of electric vehicles with desirable charging speed can possibly result in damage to the power grid [2].

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In [3, 4], the authors proposed a method by encouraging EV owners to shift their charging time away from peak load periods which has the dual benefit of reducing cost to the consumer and flattening overall load demand. This can in turn offset peak demand. However, in practise customers are not well equipped to manually select the optimal off-peak charging period. Additionally, the risk of overcharging is present when charging is unsupervised for long periods of time, for example overnight. To mitigate these issues, the proposed algorithm automatically delivers optimal charging energy from both the main electrical grid and a smart grid, while minimising cost to the consumer.

Within the existing body of literature, there is much research regarding the charging of large numbers of EV and its effects on the grid. However, very little has been published on charging individual EVs with respect to residential electricity consumption and generation resources. In [5, 6], weather forecasting is used to predict the amount of renewable energy available from a PV panel in a Smart Home or Building. In [5], historical weather data is used as an input to the algorithm when determining the available PV generation. The authors show that this technique improves power savings by 6% when charging EVs as soon as they are parked, and 15.2% when EVs are charged after lunchtime. However, the predicted PV output may not match that well with the actual output because the proposed technique is based on historical rather than real-time weather data. Consequently, the algorithm may suffer from accuracy problems as variations in solar radiation at different times of the day, and external environmental changes influence the amount of electricity generated by solar power installations.

State of Charge (SOC) is an important parameter for correctly determining the charge time. In the existing literature, the problem of determining the state of charge is overlooked or is outside the scope of the study. For example, in [5], the initial SOC is determined manually by the user. In [6] , the initial SOC is estimated from the distance travelled by the EV since the last charge. This information is extracted from a GPS device on board the vehicle and processed with the Google Maps API. However, the authors do not make it clear how this impacts the actual charging strategy. Charging of a single EV is mentioned in [7] which shows both single and multi EV charging scenarios. The initial SOC is modelled as a Gaussian distribution of possible initial charges. In the single charging case, the model is run over a 12 hour charging period starting at 20:00 hours, and the algorithm attempts to shift as much of the charging time as possible into the load valley.

In this study an algorithm is proposed to address the SOC parameters, allowing the battery of an electric vehicle to be charged to a specified SOC. The algorithm automatically optimises for price over the charge time based on known time-of-day electricity prices, as well as the availability of charge on an attached Photovoltaic (PV) in order to reduce load. A smart meter will be introduced to get the real time data. In addition, a dynamic algorithm is designed to capture the whole process.

In this paper, the SOC parameter is calculated and it is considered as a primary parameter. The proposed algorithm was simulated using MATLAB taking in account power consumption of home appliances, off peak time, SOC, departure time and other parameters. Thus, it will be able to deploy an EV at a reasonable cost as well as reducing the pressure of peak time electricity demand on the electricity grid. The proposed research will systematically demonstrate some related parameters such as state of charge (SOC) to avoid overcharging, optimize charging time and take advantage of the off-peak charging benefits. Moreover, the proposed method has the advantage of prolonging the lifetime of the EV's battery. An overview of the technique is given in Section 2 and simulation studies are explained in Section 3, followed by the simulation study results and conclusion which are expressed in Sections 4 and 5 respectively.

## 2 The Development of the proposed Algorithm

The algorithm proposed targets a residential dwelling equipped with a central management and control system capable of regulating the input, output, storage of energy. In particular, this algorithm focuses on homes which are connected both to the grid, and to another renewable source of energy. For the purposes of this study, it is assumed that the dwelling has a Photovoltaic panel and an energy storage mechanism such as a battery. The proposed algorithm depends on the presence of a programmable controller embedded in the residence which can make decisions as when to charge an electric vehicle from the grid, the PV source, or both according to

1. The end user's preference.
2. The residual PV energy.
3. Energy consumption of other home appliances.
4. The current electricity price.
5. Charge information from the connected EV.

The algorithm is designed to provide sufficient power for general domestic appliances using a charging rate calculated by the scheduling algorithm. In this section, rele-

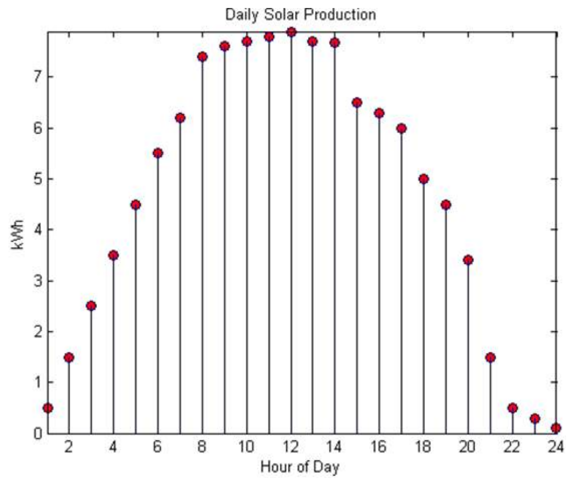


**Figure 1:** Daily Solar Production [8].

vant parameters like PV output, battery characters, SOC, and the mathematical model of charging cost will be presented.

## 2.1 PV Output

Figure 1 depicts the typical daily production and it is taken from [8].
The output of the PV panel can be expressed as

$$Q_{D_{Tol}} = Q_{(D-1)_{Tol}} + \sum_{t=1}^{T} Q_{pv}(t) \tag{1}$$

where $Q_{D_{Tol}}$ is the total PV output till time $t + T$ at date $D$; $Q_{(D-1)_{Tol}}$ is the remaining energy on $(D-1)^{\text{th}}$ day; $Q_{PV}(t)$ is the electricity generated by PV at time $t$. Using the smart meter significantly improves the precision of the measurement of PV output, irrespective of the weather condition or PV panel state.

## 2.2 Characteristics of Lithium-ion Batteries

### 2.2.1 Charging Lithium-ion Batteries

Most appropriate lithium-ion battery charging processes can be divided into at least three stages: constant current charging, constant voltage charging and charge termination. These charging methods are described briefly as follows:

**Stage1: Constant Current Charging**
When the battery voltage rises to the trickle charge threshold, the charging current is increased to a specific value. The battery is then charged with a constant current. Normally a constant charging current is between 0.2C to 1.0C (the C-rate signifies a charge or discharge rate equal to the capacity of a battery in one hour.) [9]. Constant current charging requires the current be maintained at a constant level to mitigate the issue of heat transfer through switching components in a linear charging system.

**Stage 2: Constant Voltage Charging**
When the battery voltage rises to a specific point, the constant current charging will stop and the constant voltage charging starts. Since the voltage is constant during this phase, the current will drop as the charge time increases.

**Stage 3: Charge Termination**
Unlike with charging nickel batteries, lithium-ion batteries are not recommended for continuous trickle charge. Continuous trickle charge will lead to the appearance of lithium metal plating effects which will cause the battery unstable and may lead to a rapid automatic disintegration [10].
Currently, constant current and constant voltage charging are used more extensively in lithium-ion battery charging process and will be applied to the proposed charging algorithm. A default SOC or a desired SOC is used to terminate a charging process.

### 2.2.2 SOC Determination

Many EVs are powered with lithium-ion batteries which have high energy and power density. However, an excessive charging or discharging of the battery has serious implications with respect to lifespan and durability. In order to protect the battery and avoid the over-crossed discharge phenomenon, the state of charge (SOC) parameter is introduced.
The SOC reflects the remaining capacity of a battery, which is defined as the ratio of the current remaining capacity and the total capacity of battery [9]. This can be expressed as follows:

$$S(T) = S(0) + \frac{\delta_c}{C_N} \int_0^T i_t d_t \tag{2}$$

where $S(0)$ indicates the initial state of charge or the state of charge when the EV is connected to the grid; $C_N$ is the rated capacity, $i_t$ is the battery current, (it is positive while under the charging process, negative when it is discharging),$\delta_c$ is the current loss coefficient (the value is between 0.98-1 in general) [11].

Using the Coulomb counting method [12] to achieve the estimation by integration the current, has the benefit of being simple and easy to implement and is widely applied in practical applications. However, due to the accumulated error, some calibration method is required. More details about this will be presented in a later section.

## 2.3 Charging Cost and Energy Balance

One of the objectives of the proposed algorithm is to minimize the charging expenditure. When a certain quantity of electricity is taken from the grid $Q(t)$ at time $t$ at a cost of $P(t)$, the corresponding cost of electricity at time $t$, the total cost of each time charging a EV can be expressed as follows:

$$C = \int_{t_0}^{t_0+T} Q(t)P(t)dt \tag{3}$$

where $t_0$ is the start charging time and $C$ is the total electricity costs over the actual charging time $T$. At a specific time $t$, the energy consumption of home appliances and EV charging capacity are either from grid or from the electricity generated by PV or combination of grid and PV. It is expressed as follows:

$$E_{Grid}(t) + E_{PV}(t) = E_{Load}(t) + E_{EV}(t) \tag{4}$$

where $E_{Grid}$ is the electricity supplied by the grid, $E_{PV}$ is the electricity supplied by the PV at time $t$, $E_{Load}$ is the total electricity consumed by the residence at time $t$, not including the EV, $E_{EV}$ is the electricity consumed by the EV.

### 2.3.1 Charging Rate

Depending on the type and condition of a battery, the controller can charge EV with different charge rate according to customer's preference and constrained by the following equation:

$$\text{Min charging rate} \le \text{Charging rate} \le \text{Max charging rate} \tag{5}$$

### 2.3.2 Possibility of V2G

A Vehicle to Grid (V2G) system is a form of demand response system in which a plug-in electric vehicle throttles its charging rate or returns electricity to the grid in response to peak energy demand [13, 14]. V2G is a discharge procedure in which electricity is taken from the grid during charging and sold back to the grid when demand is high. Selling the electricity back to the grid necessarily depletes the charge in the EV battery, which requires electricity to be taken from the grid again at a later time. There are two main reasons which limit the uptake of V2G, government policy and degradation of battery itself. With respect to policy, V2G is hugely dependent on whether or not there exists a favourable sell-back electricity tariff. This parameter is normally the domain of government policy. With respect to technical effectiveness, this is limited by the fact that the battery can only withstand a finite number of charge and discharge cycles. The number of cycles is determined in part by the charging capacity and depth of discharge. Therefore, an increase in charging and discharging cycles will shorten the lifespan of the battery. For V2G to be successful, there should be a strong economic incentive for the battery owner to overcome the cost of degradation which results in a further replacement of battery. Based on those two reasons this paper will not take V2G into consideration, as its value is only realised when it brings profits to the owner.

# 3 Simulation Studies

Charging an EV to the optimal charge level within the user allocated time depends on the amount of energy the PV Cell can provide, the grid electricity price at the time of charging, and the total load in the dwelling. Since the grid price and the available PV output are not constant throughout the day, each 24 hour period is divided into sub intervals into which PV output, and domestic power consumption are quantized. The SOC in this study is calculated from the charging profile data for the Nissan Altra lithium-ion battery.

The following subsection focuses on solving the charging scheduling problem for the EV. In addition to power consumed by the EV, there are basic domestic power loads contributed by all other electrical appliances which alter the load curve for the dwelling. This domestic load must be estimated from historical data as it contributes to the total power load. The hourly load curve (Figure 2) was drawn from the RELOAD database [15]. Load curves in the RELOAD database are given as hourly fractions of the yearly load, and must therefore be scaled by the annual household consumption divided by the number of hours

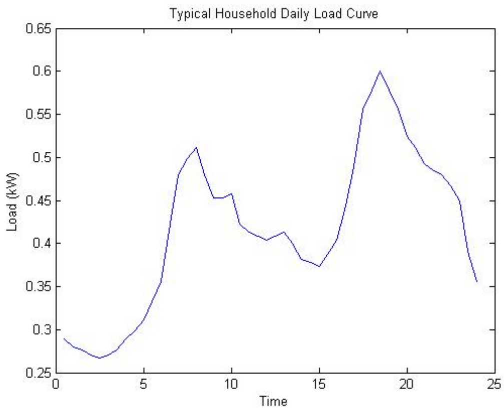


**Figure 2:** Typical Household Daily Load curve.

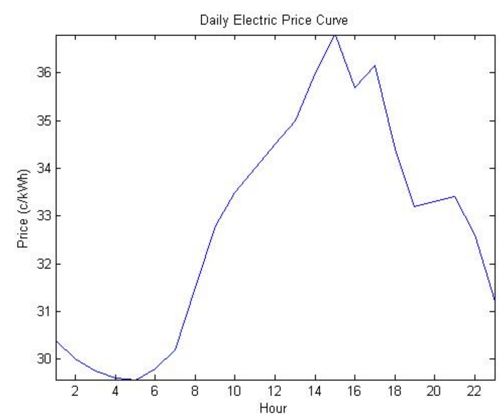


**Figure 3:** Daily Electricity Price Curve [16].

per year, leading to the scaling figure for the load shown in (Figure 2).

## 3.1 Historical Energy Usage and Price Data

The total power consumed strongly depends on time of year, particularly seasonal variations in temperature. To improve the estimated power consumption, historical power consumption for the user can be loaded to choose the correct seasonal load curve. A reasonable estimate is given in Figure 2 which shows the load curve for a family with a daily electricity demand of approximately 20 kWh.
An example Time of Use (TOU) curve is shown in Figure 3. This curve shows the price of electricity as a function of the time of day. The highest points on this curve correspond to the periods of the day that experience peak electricity demand. The grid electricity cost in [16] represents the whole sale price which means an average fixed component of \$0.255 is added for a market value including transmission costs, facility costs, and other network costs.
The optimised model (eq. 3) from the previous Section is discretised into n intervals over the total charging time, each with a period of $\Delta t$. Thus, equation (3) is rewritten as follows:

$$\min C = \sum_{i=1}^{n} Q(t_i)P(t_i)\Delta t \tag{6}$$

## 3.2 Capacity Calibration

The capacity of a battery will fade due to ageing and external environment variation. The battery deterioration process will be faster with higher temperature. Usually at less than 25°C a li-ion battery may loss 10% of its capacity after 1000 charge cycles [17]. The battery is considered to be due for replacement when the capacity drops below 80% of its rated value. By using capacity calibration a more accurate SOC would be formulated.
When the initial value of the battery is static, it is assumed that the SOC is $S_1$. After charging the battery, the current integration method is used to obtain the energy charged $Q_{in}$. The battery is left for some time to allow the SOC to settle, at which point $S_2$ is obtained. The battery temperature must be kept constant for the duration of the test procedure to prevent error due to temperature induced internal resistance changes. The total capacity of the battery pack can be derived according to the above parameters while $Q_{max}$ is expressed as follows [12]:

$$Q_{max} = \frac{Q_{in}}{S_2 - S_1} \tag{7}$$

While considering the corresponding cost increase of a certain accuracy improvement, this article [12] only calibrating capacity to improve EV's charge accuracy, more precise results can be achieved by calibrating initial SOC and charging current which are proposed in this paper.
The data for the battery performance characteristics are taken from [18], in which the charge parameters for a 1999 Nissan Altra-EV are experimentally determined. Figure 4 shows the AC Demand versus Time curve for the charger in this study. The start of charging is marked by a rapid increase in AC Demand, which then remains flat for the majority of the charge time, followed by a steep decline. The state of charge increases linearly over the same period, levelling off as the AC Demand begins to drop. From the graph, the peak instantaneous power consumption is around 6.6kW. This curve can be used to estimate the charge time [18].

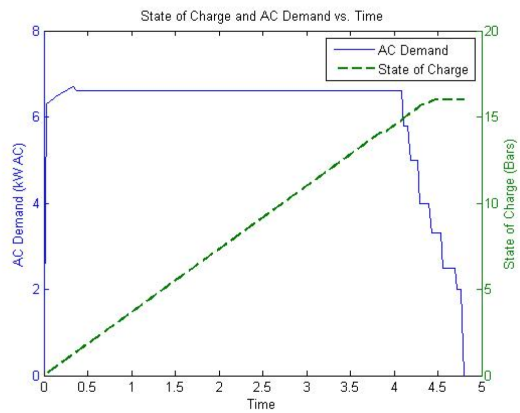


**Figure 4:** AC Charging Profile for Alta's lithium-ion battery [18].

## 3.3 Charge Scheduling

The following section describes the procedure for the charge scheduling algorithm and a flow chart is also provided in Figure 5.

**Step 1:**
The optimized charging algorithm supervises the charging time from electricity generated by PV and grid to obtain minimum charging cost while maximise usage of PV. In addition, the algorithm tries to ensure that some minimum amount of charge is always present so that the vehicle can be driven again at relatively short notice. Only data required to make the programming more customised is preloaded, such as $SOC(0)$, $SOC(f)$, arrival time, departure time, and $SOC(s)$, a parameter used to ensure some minimum amount of energy is available for emergency uses. The full time required to charge the EV is obtained from this information.

**Step 2:**
Confirm that the desired charging time is long enough to charge an EV. Using the preloaded electricity consumption files, real-time PV output and grid price, arrival and departure times and so on, the desired charging time is calculated such that full charging of the EV within the allowed time is guaranteed. This is expressed in equation (8) as

$$t_d - t_{al} \geq t_{rq} \tag{8}$$

where $t_d$, $t_{al}$, $t_{rq}$ indicates departure time, arrival time and required charge time respectively. If equation (8) is true, the algorithm shall go to the following steps. Otherwise, customer will be informed to re-load a departure time.

**Step 3:**
Check whether the current $SOC$ is less than $SOC(f)$. If it is true, the algorithm shall go to the next step. Otherwise go to step 13.

**Step 4:**
Check whether $SOC(s)$ is greater than the current $SOC$. If it is true, the algorithm shall go to the next step. Otherwise go to step 6.

**Step 5:**
Charge the battery to $SOC(s)$, prioritising PV energy over grid energy if possible.

**Step 6:**
Calculate the number of remaining charge intervals I based on required charging time.

$$\frac{t_{rq}}{t_p} = I \tag{9}$$

where $t_{rq}$ is updated required charging time, $t_p$, which is the smallest units of a day than can be measured in the smart metering system.

**Step 7:**
Check the energy stored in PV system according to equation (10), and determine the number of charge intervals $N$ which can be taken from PV. This number depends on $M$ (the PV storage energy), the charging rate of the EV, and load information.

$$\sum_{inputtime}^{t} \left(Q_{pv}(t) - Q_{load}(t)\right) = M \tag{10}$$

$M$ is constrained such that its minimum bound is guaranteed to be sufficient for the entire duration of a charge interval. When $M$ is insufficient to provide charge for a period, energy is taken from the grid.
Time $t$ is restricted by equation (11) as follows:

$$t_{al} \leq t \leq t_d \tag{11}$$

**Step 8:**
If $I \leq N$ this indicates there is enough electricity in the PV to charge the EV to the desired SOC without the need for any electricity from the grid. In this case the PV is always selected as the charge source for the current interval. Up-

date cost, SOC and then go to Step 3. Otherwise, the algorithm moves to Step 9 to determine the charge source for the next interval.

**Step9:**
The time interval required to charge from grid satisfies the following equation (eq. 12)

$$G = I - N \tag{12}$$

where $G$ indicates the remaining charging intervals from grid.
From eq. 12, the algorithm chooses $G$ to be continuous intervals with the lowest grid cost (according to the real time or preloaded electricity price, a sample is shown in Figure 2) in the interval $(t, t_d)$, where $t_d$ is the departure time. During the charging process, $T_g$, is defined as the minimum start charging time from the grid to charge EV (which means from $T_g$ to $T_g + G$ is the grid charging time). Then go to step 10.

**Step 10:**
If $t < T_g$ and $N = 0$
$t < T_g$ indicates current time $t$ has not reached the best grid charge time $T_g$. Between $t$ and $T_g$ the algorithm will check whether or not to charge EV by PV. When $N = 0$, it indicates that the residual electricity in PV system is not enough to charge EV for a time interval. As a result, the algorithm will wait for another time interval and go back to Step 3.

**Step 11:**
If $t < T_g$ but $N > 0$
$t < T_g$ indicates current time $t$ has not reached the best grid charge time $T_g$ but an adequate amount of electricity is available from PV. The EV is charged with the electricity from PV system for a time interval. Then calculate the cost and SOC and return to Step 3.

**Step 12:**
If $t \geq T_g$, then this interval is the best for charging from the grid. The EV should be charged using electricity from the grid for the current time interval. Then update the cost, SOC and go back to Step 3.

**Step 13:**
Check battery capacity $C$ based on equation (7) and update to mitigate the error of calculating SOC caused by battery degradation.
If demand charging time is less than the duration of parking time (which means equation (8) is negative), the algorithm will send notice to inform user of the impossibility of charge completion within the time along with one or two choices: 1) charge EV without considering about price variation and target SOC (or request end user load another departure time), or fast charging.
If the selected charging parameters are sufficient (i.e.: the charging time is long enough), the system will automatically select the best charging interval with remaining PV energy and electricity price. The accuracy of the charging prediction is improved by updating the charging profile for the dwelling with data gathered from the smart meter over the course of the day. This data is updated at midnight every night.
According to the U.S. National Electrical code and SAE International standards, three standards were developed: Level 1, AC energy to vehicle's on-board charger commonly used with a 120 volt outlet; Level 2, AC energy to vehicle's on-board charger at around 208-240 volt and Level 3, DC energy from an off-board charger with very high voltages (300-600 V DC) [19]. Charging with level 1 requires more time but with much lower infrastructure investment expense. In comparison, a faster charge can be applied to homes with upgraded electrical outlets. The upgrade refers to charging equipment cost, installation cost and so on. Level 2 charging allows for a wide range of charging speeds with a maximum of 19.2 kilowatts, providing up to 112.6 km driving distance per hour of charge [20].
Charge at Level 3 requires approximately 30 minutes to charge an EV battery up to 80 percent to fulfil short distance travelling requirements [21]. Furthermore, for many customers are apprehensive about purchasing an EV because the charging process will normally take several hours. With this method the flexibility of charging an EV is greatly increased, however with a higher voltage or current the cost may be not the best compared with the method mentioned above.

## 4 Simulation Results

Digital simulation studies are carried out in MATLAB to show the effectiveness of the proposed method. Charging results for the proposed method both with and without PV are compared against non-optimised charging. Nu-

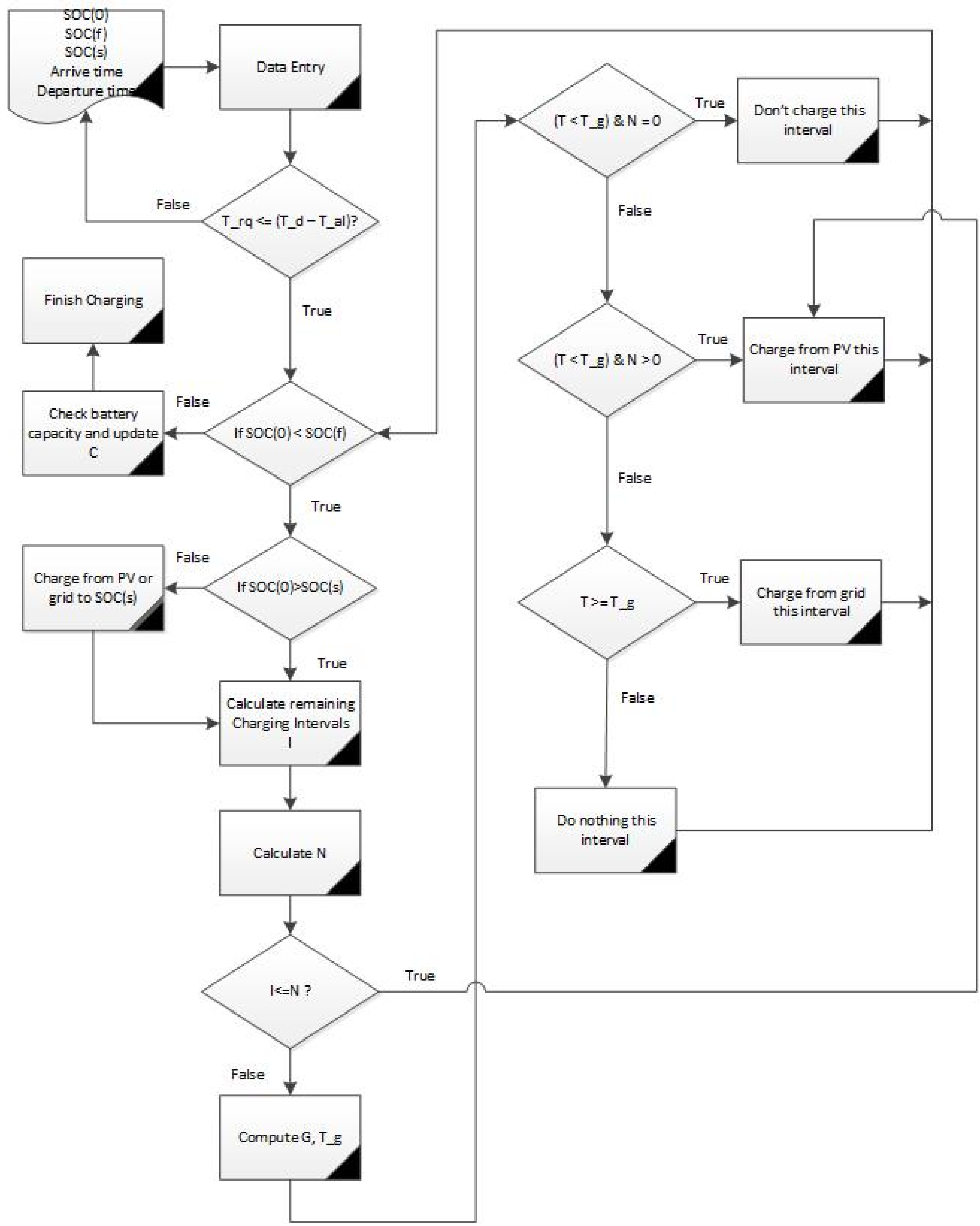


**Figure 5:** Flow chart of this optimized charging algorithm

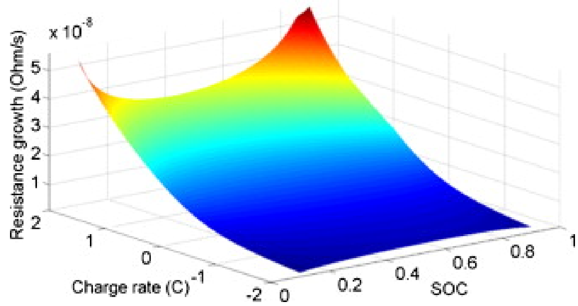


**Figure 6:** Resistance growth versus Charge rate and SOC [22].

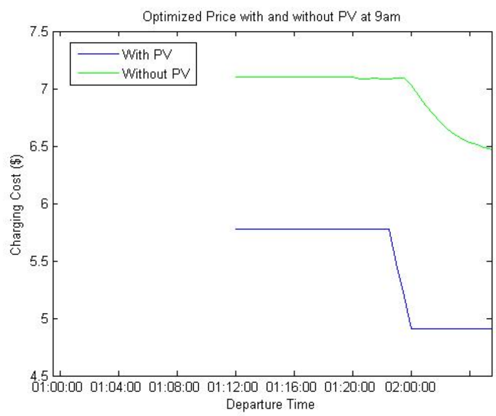


**Figure 7:** Optimized price with and without PV at 9am.

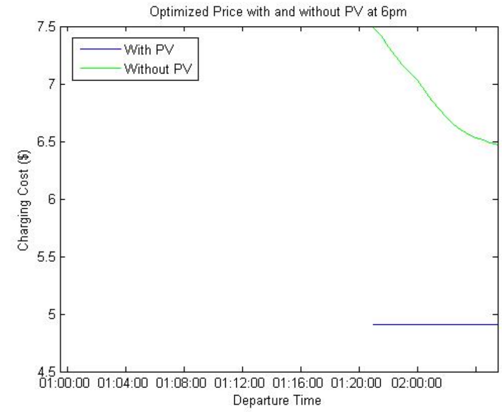


**Figure 8:** Optimized price with and without PV at 6pm.

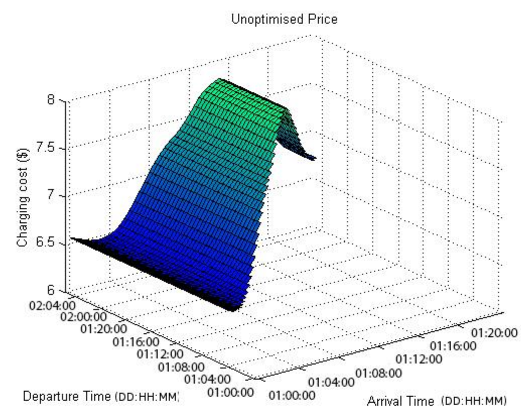


**Figure 9:** Non-optimised Charging cost.

merical cases are presented to validate the effectiveness of the designed algorithm. Cost is compared with unmanaged charging (with the normal 'plug and charge pattern') for the same scenario. In order to compensate for possible short-notice trips, the SOC(s) parameter can be set which in turn instructs the algorithm to ensure the battery is charged to some minimum level. The parameter SOC(s) should be set based on not only daily statistics, but the range of the vehicle itself. Around 90% of the commuters drive within a distance of 75 km [24], which suggests that setting SOC(s) such that the battery will deliver 75 km driving distance is a reasonable choice. The Nissan Altra has an all-electric range of approximately 196 km. Therefore in this paper, SOC(s) is set to 40%. In order to make a better comparison between different scenarios, all figures are produced with an initial SOC of 20% and a final SOC of 90% for each random simulation studies.

Figure 7 compares the charging price with and without PV with the same start charging time 9am. It can be seen that both results have a similar tendency to stay flat from 12pm to approximately 11pm followed by a sharp drop after that. However with PV the optimized price is much lower than the charging price without PV. More often individuals will start to charge their vehicle just after they arrive home. In Figure 8, the charging results at 6 pm indicate that without PV the total charging reduces dramatically from the charging cost of $7.5 to $6.5. The departure time increases whereas the results with PV remain the same. This is because after a day the PV system can collect enough power to charge the vehicle in these conditions as long as the departure time is longer than the minimum required charging time. In this case, the charging cost will stay at approximately $5.

Figure 9 shows the non-optimised charging cost. The input charging time is chosen randomly ranging from 00:00 till 24:00 with different departure times and charge durations. Without optimisation, the price is higher overall and it's less sensitive to changes in charge duration which is explained below.

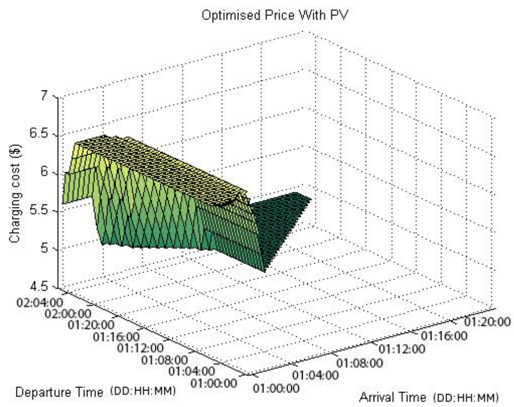


**Figure 10:** Optimised Charging cost with PV.

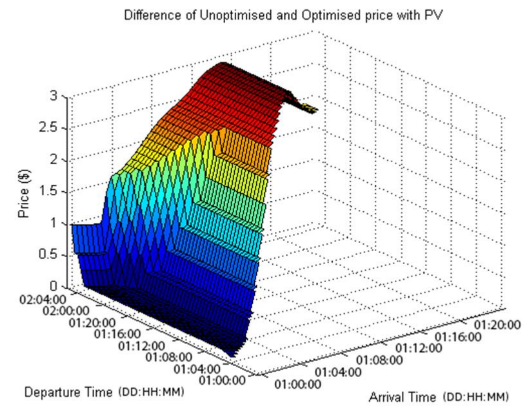


**Figure 11:** Difference of non-optimised and optimised price with PV.

One case is chosen as an example. Assume that residents arrive home at 18:30 and plug in the charger at the same time with an initial SOC of 20%. Without the optimized charging algorithm, the system will begin to charge the EV which will take approximately three and a half hours. After that the battery is in the trickle charge condition until the charge is not connected to the grid.

To incentivise consumers to consume electricity during off-peak generation time when excess capacity is present, some countries implement Time of Use pricing (TOU). Broadly, TOU shapes the price curve to such that the price is higher during peak, and lower during off peak. From Figure 3, it can be seen that the peak time is from 10:00 to 22:00. In comparison, 00:00 to 08:00 will be measured as the off peak electric time. The remaining time is called flat time. The main charging time for the above case is from 18:30 till 22:00 which occurs during peak time and the corresponding charging cost can be seen form Figure 7 which is approximately $7.5.

In the proposed algorithm, the remaining PV output and the optimal charging time are automatically checked. To analyse the performance of the algorithm an average cost of $0.23/kWh is applied for electricity generated by PV. The average cost is calculated using an off-grid simulation in RET Screen, which is a clean energy project analysis software tool that helps decision makers determine the technical and financial viability of potential renewable energy, in the Auckland region with a system lifetime of 20 years and a break-even time of 14 years. This figure is derived by factoring in the lifetime operational costs of the PV system, including the up-front capital cost of installation, maintenance costs, electricity cost, and break-even time.

Figure 10 shows the optimised charging price when energy is available from the PV cell. The flat region in the top-right

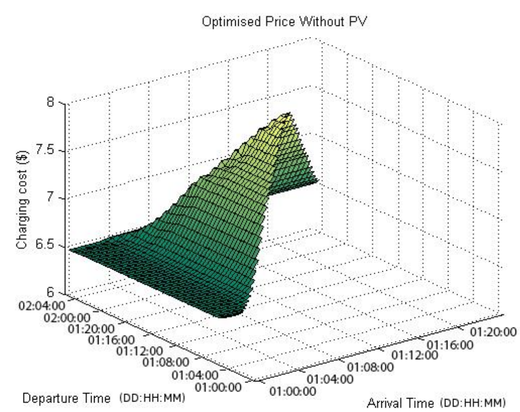


**Figure 12:** Optimised Charging cost without PV.

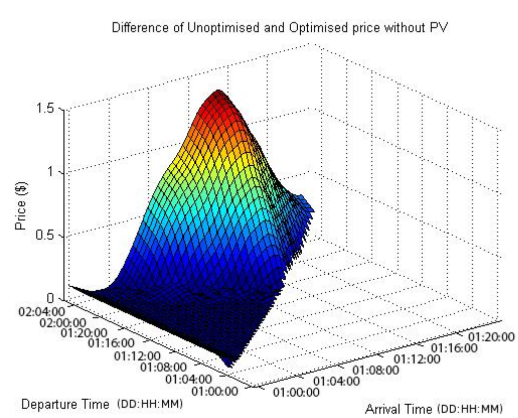


**Figure 13:** Difference of non-optimised and optimised price without PV.

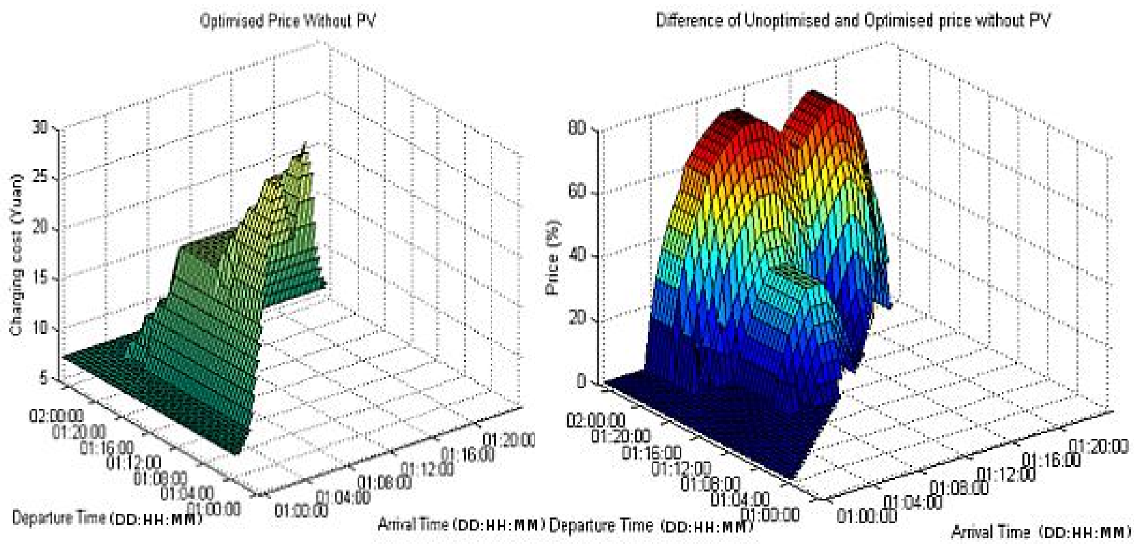


**Figure 14:** Optimised price without PV for Beijing Data and Percentage difference of non-optimised price for Beijing TOU data.

of the graph shows the lowest prices attainable using this setup. These occur when the input time is late in the day as there is enough energy left in PV. The optimised charging algorithm therefore selects the PV exclusively to charge the EV as this represented the lowest cost. No additional energy is needed from the grid, which in turn reduces the overall load pressure. The simulation is carried out with a charge time in the order of 3.5 hours [18] which places a lower bound on the price that can be obtained with or without the aid of PV. This lower bound manifests itself as the flat region in the top-right of the graph, indicating that after a certain amount of time, it is not possible to reduce the charging costs any further. Figure 11 shows the difference of non-optimised and optimised price with PV which demonstrates that adding PV to the system reduces the sensitivity to the grid price, and lower overall.

When there is no electricity generated by PV or there is a large amount of domestic consumption the electricity is taken from the grid. The price curve for this scenario is shown in Figure 12. While the cost is higher without the additional electricity provided by the PV, the value of any optimised price is lower overall than the cost of charging without the optimised algorithm as shown in Figure 13. This demonstrates the proposed smart charging method has the ability to shift the charging time from peak time to off peak time. Regional variations in power pricing will affect the maximum performance of the algorithm. There are many factors which contribute to the retail price of electricity, and elaborating on all of these is outside the scope of this paper.

In regions where a TOU scheme is available and with a great variation on price, the proposed algorithm can deliver even larger savings to the end user. To demonstrate this, the optimised method is compared against the algorithm in [7], which is designed for a similar purpose and is tested on electricity price data in Beijing, China. This provides further opportunity to reduce the price by taking advantage of the comparatively lower off-peak electricity cost.

In the previous analysis, the maximum difference in the price curve is \$0.066. This difference is relatively small, and places some limits on the percentage savings that can be accumulated using the proposed technique. To further establish the algorithm performance, the analysis is re-run with the pricing data for the Beijing area. The price curve has a maximum difference of 0.978 Yuan. The percentage saving in [7] for charging a single EV is given as 51.52%. The algorithm proposed here generates a maximum percentage saving of 73.25%, with an average saving over all random scenarios of 22.09%. The analysis is not performed for the case where a PV is available, as a comparison with [7] under these conditions is not possible. Figure 14 shows the optimised charging cost and percentage savings curve as a function of arrival and departure time for the Beijing price data. It should be noted that the above analysis only applies in a regulated electricity market where the wholesale costs are determined in advance, such as in Beijing.

# 5 Conclusion

The improvement of EV and gradually increasing penetration of renewable energy will benefit society in terms of significantly cut oil consumption, reduced environmental pollution, and improved traffic efficiency and public living standard.

In this paper, an EV charging method for a smart residential dwelling which has a renewable energy system such as PV is introduced with the aim of taking full advantage of renewable energy and transferring the charging pressure from the grid under peak demand to other time to minimize the charging cost. A proper charging rate, ampere hour counting method and a suitable error estimate method are proposed to obtain a desired SOC while preventing the battery from damage due to overcharged and subsequently extending the lifetime of the battery. This paper also introduced a fast charging strategy as an additional solution to improve the reliability and flexibility.

From the simulation results, one can conclude that the proposed charging method takes advantage of the available renewable energy, and the charging time can be efficiently changed from peak to off peak time or shifted to a time interval with the lowest electricity price. Additionally, there is a significant price difference between unregulated plug and charge pattern. In electricity markets where there is a large price differential between peak and off-peak time, the algorithm can deliver significant savings to the end user.

Since the charging condition of each EV is different there is a diverse range of parameters affecting the charging cost including battery specification, input time, departure time and initial and final states of charge. However under any situation the algorithm has the capacity to select the best schedule prior to the departure time and PV output.

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