

Optimal Charging of Electric Vehicles using a Stochastic Dynamic Programming Model and Price Prediction

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ABSTRACT

The idea of grid friendly charging is to use electricity from the grid to charge batteries when electricity is available in surplus and cheap. The goal is twofold: to avoid putting additional load on the electricity grid and to reduce the cost to the consumer. To achieve this, a smart meter and a tariff with variable electricity prices has to be in place. In Day Ahead tariff (DA), prices are announced in advance for the next day, and this information can be used to select the cheapest times to charge the battery by the required amount. The optimization method is very simple, and it only has to be run once per day. However, the balance of supply and demand is not fully known in advance. Therefore Real Time Pricing (RTP) tariff supplies electricity at spot market rate depending on the current balance. This makes the charging process less predictable because it adds a stochastic element, but it does offer the potential of higher savings if future prices can be predicted with a reasonable degree of accuracy.

This paper proposes an optimal controller based on a stochastic dynamic program (SDP), which predicts future price changes from available data. The controller takes into account price variability via a simple grid model that allows of unexpected price rises and a gradual return to a normal grid price. The DP algorithm has two variables, the state of charge (SoC) and the current electricity cost. It traces the expected total cost based on the stochastic model and makes a decision 'to charge or not' to minimize the expected (average) total cost. The results show that in case of a positive probability of price rises, the time to charge is chosen slightly before the lowest expected cost during the night. This is a rational solution, because waiting longer does increase the risk of an unexpected price spike. In the trivial case of a zero probability of unexpected price rises, the solution converges to the one found by the previous deterministic optimization algorithm.

CITATION: Mody, S. and Steffen, T., "Optimal Charging of Electric Vehicles using a Stochastic Dynamic Programming Model and Price Prediction," *SAE Int. J. Passeng. Cars – Electron. Electr. Syst.* 8(2):2015, doi:10.4271/2015-01-0302.

INTRODUCTION

Electric Vehicles (EV) are becoming more popular and abundant, as the requirement to reduce carbon and greenhouse emissions increases. Charging of EVs is a time and power consuming affair; the effects of which can be widespread on the Electricity Grid of the future. Electricity grids are going through a revolution as well in the aim to reduce the carbon footprint of generating energy. The smart grid vision is quickly spreading to all sectors of energy distribution and consumption that are currently dominated by fossil fuels. It will become important to align the transport and electricity sectors in order to maintain grid stability in the future; when grids are dominated by renewable generation, high power appliances (like EVs) and other problems which already exist.

Hybrid EV (HEV) have been mildly successful in the past decade with the major producer, Toyota (Prius) selling 2 million units by 2009. Whilst it is widely accepted that market forces alone have not been able to make the EV a first choice for many consumers; government policy support, research to make EVs less expensive and economy improvement will improve their market significantly [1][2]. Although, electric driving ranges are limited for all three HEV, Plugin

Hybrid EV (PHEV) and pure EV (BEV); surveys have indicated that 47-55% of single vehicle usage in a single day is less than 20 miles, with 82-88% of vehicles travelling less than 60 miles [3]. Kang and Recker's 2009 [3] study concludes that it is possible to convert between 80% to 90% of daily mileage to electric when using PHEV with a 60 mile range in California; under the condition that both home and public place charging stations are in use. These numbers indicate that EVs are more feasible than previously thought. JP Morgan performed a study in 2009 which forecasted 11.28 million EVs worldwide by 2020 and 20% of the total cars sold in North America [4].

A change from ICEVs to EVs' main impact will be that on the already stressed electric grids. The batteries of these vehicles require long times and high power and currents for charging. For most domestic users, charging will take place overnight at their homes. Moreover, the tendency to plug the vehicle in as soon as they reach home is high. Other typical charging loads could be concentrated in office or public car parks depending on the actual use of the vehicle during the day. Studies like [5], [6], [7], [8], [9] highlight the impact of EVs on electricity distribution in the future in more elaborate detail.

The subsequent effect will be to electricity market: generation methods, infrastructure and prices in the future will change significantly. In most countries the industrial sectors are on wholesale electricity prices- buying electricity at lower rates during off-peak hours. There is a possibility for such ‘spot-markets’ even for domestic electricity consumers as is case in Portugal, Germany, some parts of continental Europe and a few states in the USA. In such markets, the consumers are encouraged to shift their electricity usage to off-peak hours through high-price updates/alerts either hourly or daily. Advances in ‘Smart-Grid’ technology can allow this elastic behavior from households, helping them to reduce costs.

The meter records hourly consumption and also alerts the consumers of the latest and future prices. The smart grid is being promoted and provided to consumers in the U.S.A. for some time now. Electric utility providers in California, Colorado, Florida, Illinois, Indiana, Ohio, Texas, Washington and some other states have already been introducing smart grids to many customers. There is also a strong financial incentive being provided for both smart grid research and introduction via the Energy Independence Act of 2007 and the US Stimulus Package of 2009 [10].

The state of Illinois is a good example where RTP has been available to customers since 2003. The RTP programs have been successful in reducing the participating consumers' electric usage and bills and shifting usage to non-peak times of the day [11]. The two electricity providers which allow the choice of RTP are Amaren and ComEd. Amaren's Power Smart Pricing (PSP) and ComEd's Residential Real Time Pricing (RRTP) programs have reduced their peak demand in the range of 15% and achieved participant bill savings between 10-15% [11].

The above discussion shows that there are two problems to consider: Firstly, it will be important to manage the electricity loads and peak demands due to user profile of EV charging. Some load may have to be shifted from peak times to others either by persuading or enforcing the consumer to charge earlier or later. Secondly, charging the vehicle without control might also be a disadvantage for the consumer due to the possibility of a future with RTP. However both these problems can be looked as an opportunity for EVs. The flexibility of charging time can be looked as an advantage for load shifting and when smart-grid infrastructure is in place, communication with it can not only allow automatic flexible charging but can also be used to provide electricity from the vehicle to grid (V2G).

The following paper progresses from the idea in [13] taking into consideration the need of more complex prediction methods to provide an optimal solution to the charging problem. The idea is to automatically manage the charging time once the vehicle is plugged in to provide a full charge when required but at the lowest cost (hence at low demand hours). This paper treats the EV charging problem as dynamic and stochastic. Therefore, a stochastic optimization algorithm is used to design a controller and the simulation results are presented towards the end. The subsequent advantage of this can be to the grid in a way of load shifting.

Firstly, a literature study explains the motivation and current research in this field. Then the optimal charging problem is explored based on time-discrete solution and then the dynamic problem is introduced.

Secondly, a case is made for using stochastic optimization within a dynamic program (DP), to find an optimal solution to the ‘when to charge?’ problem. The approach is discussed, explained and connected to the grid model for price changes. The controller algorithm and assumptions are described with a typical user charging scenario (evening at home charging) for simulation purposes. Lastly, the results obtained from different simulation scenarios are presented, showing its validity, and a brief outlook to future work is discussed.

RESEARCH LITERATURE

Vehicle Driver Charging Behavior

Morrow et al. [14] performed a study for the U.S Department of Energy on PHEV charging and infrastructure. They looked at two main charging scenarios- at night home charging and opportunity charging at public facilities. The conclusion was that there is a peak in EV charging during the evening when users plug-in at home between 19:00 and 23:00. Wang et al. [15] simulated four charging scenarios which included uncontrolled charging, delayed charging (to promote load shifting), smart charging and smart charging with demand response (where the charging is optimally controlled by the electricity distributor). They concluded that smart and delayed charging can significantly reduce the total cost of the system both on the electric and charging side.

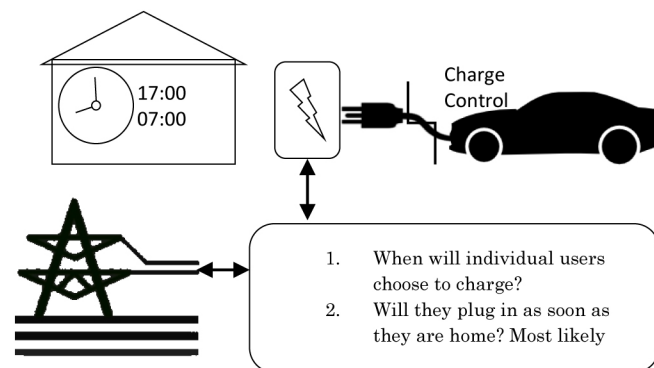


Figure 1. Charging Time of Concern

Kang and Recker [16] developed four theoretical scenarios of uncontrolled home charging, end of day travel charging, controlled (after 10 pm) charging and public infrastructure charging. They concluded that it was important for the electricity charging infrastructure's circuits to be upgraded for faster recharge times, which would allow more of the daily mileage to be electric. Clement and Hasen [17], Parks et al. [18] have also considered both the ‘uncontrolled charging’ and ‘charging with a time delay scenario’ in their studies. However, Clement and Hansen have suggested a ‘coordinated controlled charging’ scenario which should help minimize grid power losses. Mullan et al. [19] also took into account three scenarios: evening time charge (16:00-23:00), night time charge (22:00-7:30) and controlled night time charging using smart meters. They concluded that shifting the EV peak to later in the night can benefit the base-load utilization in Australia up to a limit governed by other effects in daily electricity-grid/transformer maintenance.

Most studies more or less conclude that the tendency to charge vehicles as soon as users reach home is extremely high. It will not be enough to allow users to charge their vehicles as they please without serious effects on the grid's health and power quality or simply the capacity. Most of them highlight the requirement of a 'smart' or 'controlled' way of charging the vehicles, the control of which may be shared between the user and the electricity provider. The charging behavior of users is difficult to predict, although it can be derived from their usage profiles. Charging locations and times will vary on user type, infrastructure and geography. For instance, a company fleet user may opt to do most charging at work, where infrastructure may be provided. However, an individual user would choose to charge both at home and public infrastructure. It is likely though, human behavior will propel users to plug-in their chargeable appliance as soon as they are home so 'it remains charged' by the time they need it. Studies like [20], [21], [19] and [22] conclude that the spike in charging requirements is pronounced between 5:00pm and 7am based on the time majority vehicles arrive home. What is more interesting is that these studies are done in different geographical regions of the world and yet this time period is of concern whether or not the morning period at work may be of charging demand (assuming infrastructure is provided). The current study therefore assumes, the best time to study a simulation for this case would be between 17:00 and 7:00 am. Other assumptions and data sources are listed before the results are presented later in the paper.

Charging Solutions

Studies on the effect of EV penetration to the electricity grid date back to the 1980s. In [23], Heydt discusses the effects on and of electric load management due to EV penetration. The study concludes that it is likely that charging will occur at peak demand times and some form of load management must be introduced to manage the additional EV charging load. Webster's review of electric infrastructure in the UK [24] concludes that in case of high EV penetration, it is likely that battery recharging times will coincide with peak electricity demand. Measures must be taken to avoid this although the electric networks can cope with the additional load. Both these authors consider the user profiles to be of primary impact on recharging times. In a much more recent study, Camus et al. [25] simulate a 2020 scenario of 2 million EVs in the Portuguese spot electricity market, considering different mixes of renewable power generation. They conclude that with low renewables and high cost, charging of EVs during peak times can lead to electricity prices of 17 Euro cents/KWh. This can be brought down to 7 Euro cents/KWh with off-peak charging and with higher renewables and low general costs, down to 5.6 Euro cents/KWh. Mahalik et al. [26] performed a simulation to realize EV impacts on the Illinois grid in 2020 and concluded that on-peak uncontrolled charging would require an additional 400 MW unit to support the state's reserve margin. If off-peak and controlled charging is facilitated, no additional supporting grid would be needed.

Acha et al. [27] present a time coordinated optimal power flow (TCOPF) tool for distribution networks to decide on load control approaches for EVs in the future. The algorithms concentrate on showing different charging strategies to the electricity providers to see how they may have to change energy production to reduce carbon

emissions and cost. They conclude for the UK context that, UK will need to introduce more renewables or non-carbon fuel mix to offset costs and emissions for high EV charging scenarios. Kristoffersen et al. [28] use a linear regression to minimize charging costs based on the Danish (Nørpool) electricity market prices. The study made the assumption of an EV fleet controller who managed the participation of EVs during charging or providing electricity to the grid, based on fleet driving patterns and electricity prices. They concluded that EV driving patterns and hence charging time is highly flexible during the day but not from day to day.

Mody and Steffen [13] presented a study in 2013 describing the need to use automated control for 'optimal' charging of EVs. They observed that the increasing EV population will lead to electricity grid problem if it is treated like a normal appliance. It would be necessary to use a smart method to offset EV charging to lower demand hours by automatically charging the vehicle rather than let it charge instantly when it is plugged in. The paper presented a sub-optimal controller for automated charging based on real time tariffs provided by electricity grid distributors in Illinois (Chicago). The first conclusion was; if prices are known in advance (day-ahead pricing), the optimization only requires picking the cheapest time slots for charging the battery. Further savings can be made by using real time prices that are not known in advance. Although it becomes much more difficult to solve using price prediction strategies, the control can achieve optimal solutions (presented in this paper). The main conclusion was made from the results and case study of the simulation of the sub-optimal controller.

Scholer and Glynn [29] presented a charging solution in the technical paper (2014) with a similar idea to [13]. However, it was mainly a part of a series of technical papers written by the SAE PEV task force. The main theme of their paper was 'smart-charging standards' but their main conclusion also was; it is not necessary to charge the PEV immediately when plugged in and smart charging is required to balance the load and prevent problems in the local distribution circuit. They presented, a price-based smart charging idea based on RTP and smart grid communication very similar to the one presented by Mody and Steffen in [13]. It reacted to the price information and offset charging to lower demand times, still making sure that full charge was provided when needed.

Yunus, Parra and Reza [30] presented a paper on distribution grid impact of fast charging with a stochastic charging model (2011). The stochastic model they used was for a simulation of the effect of many PEVs loading the grid when charging at high power (fast charging). The model results led to a conclusion that widespread fast charging affects the quality of electricity supply and necessary actions need to be taken to continue the use and deployment of such stations for EV charging. In 2012, Druitt and Fruh [21] investigated a comprehensive model and simulation to quantify the integration of additional wind power and electric vehicles in the future electricity network. They suggested a stochastic model for both wind power generation and electricity price market. The study's aim however, was to investigate the role of a 'fleet' of EVs in a future grid to load management and energy storage potential (essentially V2G), with the integration of more wind power.

Zheng and Wang [31] proposed an aggregation model for large number of EVs charging, to control power fluctuation problems. They consider the randomness of the number of EVs charging at any time as a stochastic disturbance and employ a genetic algorithm to obtain these. They simulate this model for a parking lot scenario and show the stochastic feature of the charging characteristics. Their proposed charging strategy is to control (minimize) the influence of many EVs charging simultaneously to the grid power. They conclude their updateable model reduced power fluctuation level in the residential district where EVs in parking lot are being charged. However, their idea does not take into account the effect to SoC and user needs.

Although, there have been studies in the past few years (2010-2014) on future EV charging strategies; none of them have stressed on the need to find an optimal control solution for just the vehicle charging snapshot. Studies concentrate on the system view, including vehicle-to-grid (which may be valid in the future and useful) and on assumptions about grid requirements regarding future regulations. Research so far has not been concentrated on isolating the ‘snapshot’ of charging a vehicle as a user might when they plug it in at home and won't control the time it is switched on. This is more of an issue which must be addressed imminently, as it may affect grids in the near future. Moreover, none of them stress on ‘optimality’ in finding the control inputs.

Hence, this paper explains the use of a stochastic dynamic approach to achieve optimality in the selection of charging power times. The advantage of this approach is that, it separates out the issue of charging hours and puts the confusion out of the user's mind, simultaneously avoiding ‘instant charging’ in case the cost is high, therefore preventing grid problems (high cost means high demand). Secondly, it provides a low overall cost (based on smart-grid information) thus automatically choosing hours when the electricity demand is low but at the same time predicting fluctuations that might occur and change the price. This prediction can help the control system to take a safer route and provide the charge at a low average cost (take penalty in certain situations), if the user needs the vehicle at a certain time. Most importantly, this control system is independent of changes that might occur on a system level; for example: all it requires is pricing data, time the charge is required (ToC) and level of charge (SoC). When the regulations for charging become clearer in the future, this system can fit in where required because parameters like ‘charging-power’ (likely to be regulated differently in the future) are variable in the control system. This means, their limits are pre-defined and the values can be picked when and as required rather than rigidly building a system which conforms to a single standard as it may exist today.

THE CHARGING PROBLEM

Overview

The problem of ‘when to charge?’ is complicated because of the number of parameters which could affect this decision. However, in essence it can be explained in two states in discrete-time. Two variables of concern to the user are SoC and ToC: i.e. how much charge is required and when is it required by? The two states in effect that would change as time goes along are grid cost (due to market forces/electricity demand) and SoC as a result of input. The final cost (which we want to minimize) is the

output of the problem. The basic problem in [13] assumes day-ahead prices are perfect, therefore we know the price in advance. In ‘spot’ electricity markets retailers purchase electricity at the spot price and sell it on at heavily-regulated market prices. This leads to the problem of price-spikes when the spot price changes significantly within a short period of time. Therefore, real time electricity prices can change unexpectedly, so the assumption that they are known in advance has to be revisited. The basic problem is re-explained here in brief followed by its evolution to the dynamic problem of concern in the current study.

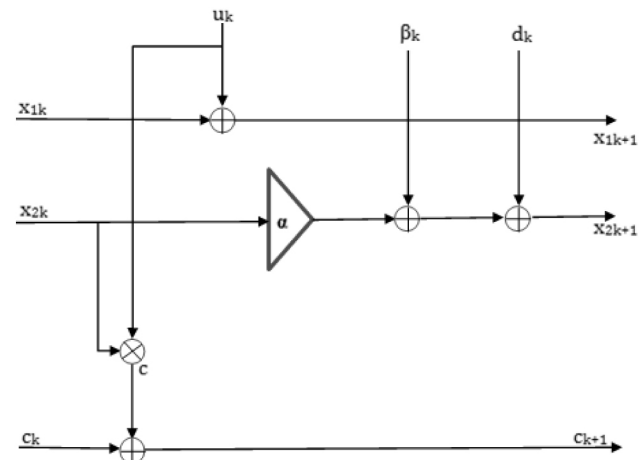


Figure 2. Problem diagrammatic representation

Figure 2 shows the problem block diagram in each time step T_s :

x_1 is the battery SoC (state)

x_2 is the grid cost (state)

c is the cost at each time step

u is the input (here: charge power)

d is the random disturbance causing price fluctuations

The problem has two distinct parts, one is the disturbance which changes the basic problem into a stochastic one. The deterministic or basic problem is symmetric. The summation of each time steps (T_s) evaluation leads to a final cost, say J_N . Where N is the final time-step.

Basic Problem

It has one control variable: the charging power u . The power is subject to two constraints: it cannot be negative and there is a constant maximum power $\bar{u}$ such that $u \in [0, \bar{u}]$.

The behavior of the system is determined by two separate dynamics: the battery state and the total cost. Both accumulate (integrate) over time and the only difference is the coefficient.

The battery state X_1 is an integral of the charge power over time:

$$X_{1k+1} = X_{1k} + T u_k$$

assuming that the self-discharge and charging losses are negligible.

The cost c_k is also an integral of the charge power but weighted by the current electricity price:

$$c_{k+1} = c_k + TX_2 u_k \quad (2)$$

$C_0 = 0$. The price is a disturbance for the system, for the deterministic approach, it is assumed that it is known in advance.

The total number of steps N to consider with $k = 0 \dots N$ are also defined in advance.

The basic optimal charging problem is defined by the cost function $J = c_N$ representing the total electricity cost and the boundary condition $X_{1N} = X_{1full}$ which requires the battery to be fully charged at the end of the charging process.

Because no discharge is allowed, it is not necessary to impose limits on the charge state. The advantage of using this simple model is that the final state and cost can easily be calculated as:

$$X_{1N} = X_{1|0} + \sum_{0 \dots N-1} T \cdot u \quad (3a)$$

$$c_N = \sum_{0 \dots N-1} T \cdot X_2 \cdot u \quad (3b)$$

Self-Discharge and Resistive Losses

Every battery has losses which are associated with both charge and discharging. It can be assumed that the efficiency of the battery pack therefore, will be less than 100% and the battery loses a certain part of its charge at every time step. This modifies the basic battery model:

$$X_{1|k+1} = \delta X_{1|k} - \omega + \phi T u_k \quad (4)$$

Where $1-\delta$ is the relative discharge coefficient for each time-step, ω is the absolute discharge energy per time step and ϕ is the charging efficiency. This leads to the following battery SoC:

$$X_{1N} = \delta^N X_{1|0} - \omega \sum_{0 \dots N-1} \delta^k + \phi \sum_{0 \dots N-1} \delta^{N-k-1} T u_k \quad (5)$$

Resistive losses within the battery (and the electricity supply) can be the dominating factor for charging losses. These resistive losses are proportional to the square of the current, assuming a constant voltage:

$$u_{in} = u_{out} + R u_{out}^2 \quad (6)$$

where R is the resistance normalized for the charging power. In terms of the optimization problem, the losses can be included either in the power going into the battery or in the cost of the electricity depending on whether u_{in} or u_{out} is the wanted variable. The latter produces an easier problem definition:

$$c_{k+1} = c_k + TX_2 (u_k + R u_k^2) \quad (7)$$

These resistive losses in effect will tend have an influence in the decision to charge because practically the battery will only receive a part of the charging power. Secondly, losses are proportional to charging power, therefore they will be higher at higher charging powers (fast charging).

Dynamic Problem and Random Disturbance

The basic problem has a sub-optimal solution [13] but this is only applicable if the dynamics of decision problem are not taken into account. Once, the dynamic nature of the state variables are taken into consideration, the problem becomes a lot more complex. In this case, the varying nature of the grid-cost is important to the decision made by the controller and can be termed as the state which is affected by the stochastic disturbance (fig. 2). Therefore, this problem turns into a 2 state dynamic problem with a stochastic element.

By definition a dynamic programming problem is one which has both inputs and outputs which change dynamically with time [32]. This problem fits perfectly to this definition because we don't want to view the decision of 'when to charge' in isolation. The time varying grid cost (and potential unpredictable disturbance) make the decision requirement dynamic. Dynamic programming helps to balance the trade-off between low present cost and need for reduction of high future costs. Taking figure 2 as a guide; the ultimate aim is to minimize the summation of c (from each time step) and the final c_N .

The problem with state X_2 is its dependence on the random disturbance d whose nature is therefore, stochastic. The disturbance basically describes price 'spikes' or fluctuations which can change the trajectory of grid-cost and is dependent on market forces and electricity demand. The nature of the electricity market (purchase and sale) leads to unpredictable real time costs. This is what causes the difference between day-ahead prices and real-time prices when a smart-grid and smart-metering tariff is in question. By adding the stochastic element to the dynamic program, a solution for price prediction in context of EV charging (to try and minimize final cost) can be obtained as explained in further sections.

New Grid Cost Model and Possible approaches

To describe this nature of the electricity grid we can call the price 'spikes' as events and associate a probability to the occurrence of these events. Describing the cost model as a standard first order linear process where:

d is an uncorrelated random variable with a normal distribution. It can be possible to define this as Gaussian and make solutions more accurate but this needs to be tested after the simulation stage