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Price Steering For Households with Electric Vehicles and Solar Panels

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Design of a robust charging controller

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Abstract - This paper describes a robust charging controller for households with electric vehicles and solar panels using a multi-stage architecture and scaling of the solar prediction using a factor α. This controller is tested in simulations and in an experiment. The simulations give an average charging cost of 0.185 €/kWh which is 0.04 €/kWh more expensive than the optimal cost and 0.13 €/kWh cheaper than uncontrolled charging. The controller also achieves a PV utilisation of 100% and has the low average of 0.046 kWh of not reached charging demands. The controller is tested on a charger and this shows that the controller is able to adapt within seconds to changing PV production, helping to reach the charging demand within time.

1 Introduction

In 2021 33% of the electricity in the Netherlands was generated by renewable sources [1]. A larger increase of renewable power sources is needed to reach the European climate goal of 55% carbon emission reduction in 2030 by comparison with 1990 [2]. The increasing amount of installed renewable energy installations leads to fluctuating power supply and fluctuating electricity prices which sometimes are even negative [3].

Rooftop PV has the potential for producing 70 TWh/y of electric solar power in the Netherlands [4]. Beside the increases in solar power, there is also a large increase in Electric Vehicles (EV), with a ban on the sale of new fossil fuel passenger cars in 2030. This leads to increase of installed charging points up to 1.7 million in 2030 [5]. Both the new charging points as well as the solar panels need electric grid connections. However in the largest part of the Dutch grid operators are not able deal with the higher demand leading to grid congestion [6]. For example, PV installations have to be turned off when the voltage on the grid is higher than 253 V [7]. These turnoffs become more frequently because of the grid congestion. Because the Netherlands has the second highest solar power installed per capita of the world [8] and one of the highest EVs per capita [9], it can expected that other countries will also experience those problems in the coming years.

With a smart charging station EV charging can be used for local Demand Side Management(DSM) to match the production of the PV installations to prevent local congestion [5]. In 2030, due to the rise of charging points and renewable energy installations, local DSM, by means of EV charging, will frequently be used delivering in total 9 % of the demand response in the Netherlands [10].

The Dutch smart charging requirements set by the nationale agenda laadinfrastructuur requires car manufactures and public charging point operators to at least support some form of smart charging [11]. According to this standard all cars should be able to charge with a lower speed if this is set by the charging point or to stop with charging and start again if this is mandated by the charging point.

Besides preventing local congestion also other smart charging objectives can be reached. Those objectives can be divided into technical and economical objectives(minimizing costs or maximising profits). The following technical objectives are frequently used in literature: increasing PV utilization, reducing peak loads, balancing the grid, avoiding grid congestion (local and regional) and reducing grid losses (related to peak shaving) [12].
Smart charging can achieve multiple objectives at the same time. It is assumed that optimizing for low charging costs also means that (national) grid balance is maintained, the European power markets are specifically designed for this [13]. Also if solar panels are turning off due to too high voltages, minimizing costs also means maximising solar power utilisation.

1.1 Price steering

Multiple methods exist for creating a suitable DSM system. This research focuses on the popular approach of dynamic price steering. For example, the coupled European grid uses a multi-region dynamic energy

market called the EPEX spot market [14]. In dynamic price steering all the different electricity consumers and producers bid their required electricity volumes with their associated price on an exchange.
The most commonly used trading practice in Europe is a so called "coupled day-ahead market". In a day-ahead market the price is set day-ahead on a hourly basis for each bidding zone (the Netherlands is one bidding zone). The different markets are linked together to enable cross-border flow. This price steering algorithm has the specific requirement that the price should ensure grid balancing [13]. Therefore the price set by the spot market is a good steering signal for balancing the grid.
Balancing Responsible Parties (BRP) need to match the electricity consumed and produced by their consumers. Therefore to prevent fines they should reliable predict this a day-ahead or try to match their imbalance on the continuous intraday-market [15].

1.2 Solar power

For ideal bidding behaviour from BRPs the solar power should be perfectly predicted. Multiple algorithms exist for predicting solar power. Machine learning and Kalman filters are common used approaches.
Kalman filters require little computing power but have the drawback that only short term predictions are possible (at maximum 60 minutes) [16]. Also this algorithm is tested in Nevada which has a very dry and stable climate [17]. Therefore it can be assumed that this method has more errors in more variable weather conditions.
The machine learning approach predicts the daily generated solar power accurately but it assumes a known surface solar radiation [18]. At this moment reliable day-ahead predictions for the solar radiation in climates with changeable weather do not exist. For example, current state-of-the-art research for predicting solar radiation in the Netherlands has a relative root mean square error of 50% for a 3 hours forecast. Only on sunny days this forecast is better [19]. A DSM algorithm should therefore be able to handle large uncertainties in the prediction of solar power.

1.3 Households

Currently consumers mostly have an energy contract with a fixed price for their electricity. By means of a directive, the EU hopes to simulate flexible price contracts for consumers, enabling them to shift their consumption based on dynamic prices [20]. Therefore in the future, it can be expected that many consumer will have a flexible energy contract and that their consumption will shift in time in a reaction to price incentives as the EPEX price and PV production. If a simple controller is used, a charging pattern than looks like the one shown in Figure 1.

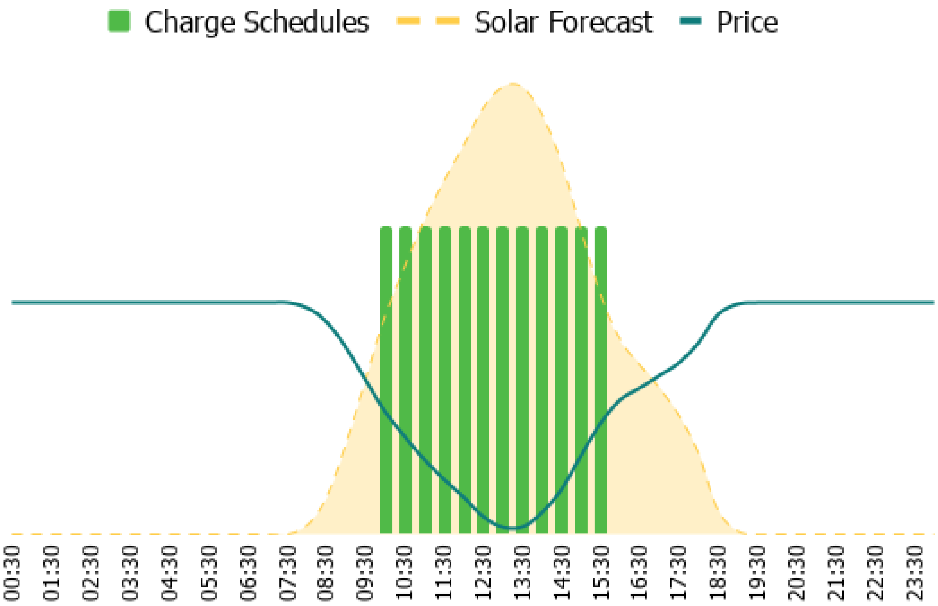

Figure 1: Simple smart charging load shifting [21]

The solar power that is produced and directly consumed by a consumer is not taxed in the Netherlands. Currently the consumer can deduct electricity that is delivered to the grid from the electricity that is taken off the grid, this practise is called net metering and will be abolished in a few years, making an end to these tax benefits [22]. With the abolishment of net metering it becomes more important for consumers to consume their own PV power directly.
In the near future there will be a demand for DSM algorithms that use the flexibility offered by domestic device to let households profit from the variable electricity prices and to optimally utilize their PV power.

With price steering every domestic device controller tries to maximise the profits or minimise the costs while staying within both user and device specific constrains. When uniform pricing is used, all (flexible) devices try to shift their loads to moments with lower prices. This could create large peaks and unbalanced grids. However, this research assumes that the induced demand is not large enough to influence the grid balance. Therefore the effect that the induced demand has on the price is not taken into account.

Flexible devices have some user constraint they need to reach, for example a EV needs to be charged before a certain departure time. Due to the uncertainty of the PV power the device can come in a must run state to stay within user constrains. In a must run state devices have to use electricity independent of the price. This could lead to higher costs for devices than without any price control and to grid instabilities.

1.4 Research questions

At this moment there is no proper controller for the charging of an EV in a household situation with solar panels and hourly varying electricity prices that takes the uncertainty of the PV production into account. For a proper DSM solution using price steering the following question needs to be answered.

What is the best way to charge an electric vehicle in a household situation (with solar panels) and hourly varying electricity prices that takes the uncertainty of the PV power into account and what side effects does this charging pattern have?
We will do so in steps according to the following sub-questions.

1. How can the uncertainty in solar power prediction be taken into account?
2. What effect does the PV production uncertainty have on the charging costs?
3. What is the effect of the cheapest scheduled charging pattern on the other objectives such as self-consumption, peak shaving, CO_2 emissions and grid congestion?
4. How do different experimental phenomenons such as time delay, rounding errors and limited discrete charging levels effect the charging costs and other smart-charging objectives?

The report is structured as follows: first an analysis of mathematical optimization methods will be giving. Secondly the used model is explained and the evaluation of this method is described. Thirdly the results are shown and discussed. Finally a conclusion is drawn and recommendations are given.

2 Analysis

2.1 Design requirements

The algorithm should minimize the charging costs for a household while fulfilling the expected charging service to the car. Therefore it should also always handle the following constrains:

1. The charging speed set by the controller should never be higher than the maximum charging speed of the car
2. The power taken from the grid should never be higher than the capacity of grid connection.
3. The algorithm should handle uncertainties in the availability of solar energy.
4. The charging demand needs to be reached before a certain departure time.

The following additions can be made to the controller.

1. Fulfilling the charging demand can be dropped for a certain cost.

2.2 Control methods

For reaching the smart-charging objectives two different methods are frequently used in literature: mathematical optimization methods and rule-based methods [12]. The rule based methods use simple rules for determining when and how to charge.

2.2.1 Rule based methods

A commonly used ruled based method is "valley filling". A valley filling algorithm tries to shift the charging load to moments that the uncontrollable loads are lower, based on predictions of the uncontrollable loads, therefore it avoids peaks. This method is researched frequently and it leads to lower grid losses [23]. Another form of a rule based method is a two tariffs systems as proposed by [24]. It has a high and a low tariff and cars change their charging to the low tariff period. This is a simple system but it lacks possibilities for more optimization and it can lead to a synchronized charging peak [25].

2.2.2 Linear programming

Multiple solvers have been developed that can solve all optimization problems in a linear programming(LP) format [26]. Therefore, writing the problem as a LP problem means that a general solver can be used. LP can be used to make a charging schedule.
However, LP has the problem that it doesn't deal explicitly with uncertainties. The EPEX spot day ahead price is known beforehand. But the prediction of solar power has great variability. This is a drawback of this mathematical optimization methods.

2.2.3 Quadratic programming

Quadratic Programming(QP) is an optimization method that uses a quadratic cost function with linear constrains. This is a frequently used approach in controlling smart charging. This is method is mostly used when smart charging is used to reduce grid losses. As can be seen in equation 1 the grid losses scale quadratic with the current and thus power consumption. In this equation r is the resistance of the electricity cables and i(t) is the time-varying current.
Adoptions to QP can be made to stay within grid boundaries as done by [27] with node voltage analysis. However also QP does not explicitly deal with uncertainties.

$$E_{lost} = \int_0^T r \cdot i^2(t)dt \tag{1}$$

2.2.4 Multistage programming

Multistage programming is a mathematical optimization technique to deal with uncertainty. The most simple model is a two-stage model. In this model there are two stage. In the first stage a decision is made with uncertainty. In the second stage, with known information. the decision that was made is adapted to minimize the cost. In context of smart charging it means that first the decisions are made with a prediction of the PV power and latter this decision is adapted with actual measurements of the PV power.
A linear two-stage problem can be expressed as:

$$Min_x,\ c^T x + E[Q(x, \xi_{(\omega)})]\ s.t\ Ax \leq B$$

$Q(x, \xi(\omega))$ is the optimal solution in the second stage biased on decisions in the first stage [28] .
If on multiple moments more information becomes available two-stage problems are not sufficient anymore. Multi-stage models are a generalization of the two-stage model where on certain moments information becomes available. The decisions that can be taken in a certain stage depends on decisions in earlier stages.
Multi-stage problems can be solved in a certain way if there are finite many scenarios K. Each scenario has a associated probability p_k. Also every scenario k has a sequence of decisions $x^k = (x_1^k, x_2^k, ..., x_m^k)$. With scenarios the stochastic problem can written as a LP problem this can be seen in equations 2 and 3.

$$Min \Sigma k = 1 K p_k[(c_1)^T x_1^k + (c_2)^T x_2^k + ... + (c_T^k)^T x_T^k] \tag{2}$$

$$\begin{aligned} s.t\ A_{11} x_1^k &= b_1, \\ A_{21}^k x_1^k + A_{22}^k x_2^k &= b_2^k, \\ A_{32}^k x_2^k + A_{33}^k x_3^k &= b_3^k, \\ &..., \\ A_{m,m-1}^k x_{m-1}^k + A_{m,m}^k x_m^k &= b_m^k, \\ x_1^k &\geq 0, \\ x_2^k &\geq 0, \\ x_3^k &\geq 0, \\ &..., \\ x_m^k &\geq 0, \\ k &= 1, .., K \end{aligned} \tag{3}$$

3 Model

3.1 Approach

The design of an ideal charge controller is made first without taking the uncertainty into account. Such an ideal charge controller is then adopted to handle the uncertainty. This stochastic controller is first tested in simulations and then it is tested in experiments with physical cars and chargers.
For not reaching the charging demand in the specified time a certain penalty will be applied in [€/ kWh].

3.2 Linear programming

There are multiple moments to charge at in a charging session and at each moment there are two different sources, of the electricity grid or from PV panels. At the same moment there is thus a possibility to charge both from the grid and from the PVs, only from the PVs, only from the grid or to not charge at all. Then the optimization problem follows: find the moments and sources to charge from on while respecting the constrains. The cost is money and is therefore linear.
These problems can be rewritten in a LP problem. Therefore there is a set Q consisting of $Z \cup Y$ of points at which can be charged. Z denotes the power from the grid, Z_0 is the first moment to charge from the grid and Z_k the latest therefore $Z = \{z_0, z_1, ..., z_k\}$. The set Y denotes the power from the PV installation, $Y = \{y_0, y_1, .., y_k\ \}$. Every point in the set has an associate price. The set Z has an associated price set C_z and the set Y has the price set C_y. In total the price set C_q is $C_z \cup C_y$
The goal is to minimize $Q^T x$
The following constrains are set:

- $0 \leq z_i \leq min(P_{evmax\_grid,i}\ , P_{gridmax,i})$
- $0 \leq y_i \leq min(P_{evmax\ , P_{pv,i}})$
- $\sum x = E_{demand}$
- $P_{evmax\_grid,i} = max(0, (P_{evmax} - P_{pv,i}))$

With the variables:

- $P_{pv,i}$ The PV production on moment i
- P_{evmax} Maximum charging speed of the EV(kW).
- $P_{evmax\_grid,i}$ Maximum charging speed that can be used on moment i for charging of the grid [1] .
- $P_{gridmax}$ Maximum power from the grid(kW)
- E_{demand} is charging demand (kWh)

This problem has both a linear cost function as well as linear constrains meaning that it can be solved by general LP solvers.

3.3 Stochastic multi-stage programming

Due to the uncertainty in PV power the charging scheduling can be expressed as two-stage problem. In the first stage a schedule will be made with an uncertain PV production. In the second phase, called the charging phase, the charging is adopted to the actual PV production.
The charging phase adapts the charging to the PV production. If it plans to use the entire PV production then the charging speed will follow the PV production, while satisfying the constrains.

The two-stage programming algorithm can be changed into an N-stage programming algorithm by executing the planning phase multiple times. This schedule is changed due to the energy demand that is

[1] Priority is given to PV power

different than expected because the PV production was different than expected.
To optimize the N-stage programming algorithm, a number of finite scenarios can be made. At each moment there is a chance that the PV production is higher or lower than expected. For example, the PV production at each moment can be expressed in 100 discrete different levels. In this case there are 100^N different scenarios (with an associate chance for each scenario), N is the amount of periods. This problem becomes quit big and therefore practically unsolvable.
The uncertainty in PV production is not a problem if the total usable predicted PV production equals the total usable real PV production. Only when the PV production is lower than predicted, the car is not charged full. A higher PV production than expected means that the car will stop charging after some time. In this case the car is maybe not charged in the best way possible but the user constrains are met.

To handle the uncertainty in the solar panel production with a workable amount of scenarios the optimization problem is changed by adding a factor α. This factor express how much the PV production is over or underestimated during the planning phases. A value of 1.1 means that the solar prediction is scaled with a factor 1.1 and a value of 0.9 means that the solar prediction is scaled with 0.9. Expressing the uncertainty of PV production in one single scalar is based on a in literature known way of expressing uncertainty in household consumption [23]. With this factor a new problem can be written: find the α values that minimizes the averaged cost in different scenarios.

The best charging pattern can be found by first calculating the charging pattern using a certain α factor. Secondly this charging pattern is used in the charging phase. In the charging phase the charging is adopted to the PV production if it is planned to use the PV production to charge. If the PV production is higher than expected the charging power is higher, otherwise the charging power will be lower, while staying within the constrains. After some time the planning phase is rerun with the same α value. This continues until the charging demand is reached or the time is done. When the charging demand is not reached at the end a penalty for not reaching the demand can be given.

What is needed in finding the right α value is a data of predicted PV power and measured PV. The different alpha values can be evaluated using the historical data to find the best α value.

3.4 Taxes

This research focuses on the Netherlands therefore the Dutch tax system is used. In the Netherlands there are multiple taxes on electricity. First of all, a consumption tax on electricity expressed in €/ kWh is applied. The tariff depends on the total usage of electricity. Secondly a tariff for developing sustainable energy called Opslag Duurzame Energie(ODE) is applied. And thirdly there is a Value-added tax(VAT) that is taken on top off the other two taxes. For every grid connection there is a fixed tax deduction [29] [30]. The assumption made in this research is that the user of this algorithm is a household therefore the household consumption tax tariffs are used.

In 2022, due to the Ukrainian-Russia war gas prices rose high leading to a tax reduction in the Netherlands [31]. Because of this reduction and because most data came from 2021, the tax tariffs of 2021 are used. Meaning the taxes used are 0.124 €/ kWh plus a 21% VAT. The fixed tax deduction is not included in those tax tariffs, because the assumption is made that in all simulated cases the fixed tax deduction will entirely be used, see appendix A.1 .

4 Evaluation method

4.1 Data used

For the evaluation of the method historical data is used for the solar production and solar prediction. This data comes from slimpark, a demonstrator site for the combination of EV charging and PV production, at the University of Twente [32]. In total this is about half a year of data from 30 August 2021 to 22 April 2022 with a timestep of 15 minutes. The electricity prices are the hourly EPEX spot prices that are taken from the ENTSOE for the same time period as the solar production [33]. This dataset was split into two sub-sets, one from 30 August 2021 to 22 March 2022 called training data and one from 22 March 2022 until 22 April 2022. All code for this thesis was written in Python using the CVXPY library for solving the LP problems.

4.2 Calculating α

Multiple scenarios are used to calculate the right alpha values. In the main scenario the maximum charging speed of the cars is set as 11 kW because this a common maximum charging speed for cars using AC charging (see the appendix section A.2). An standard Dutch household grid connection is 17 kW [34] and most households have a peak load of 5 kW or less [35] therefore the charging of a car is not limited by the grid connection in a normal household in the Netherlands. The charging demand is 30 kWh a charging session, this is based on normal commuter behaviour (see appendix section A.3). Not all house have enough grid connection available and grid operators want to reduce the EV charging peaks on the grid. Therefore also an scenario is made with a congested grid here the grid connection is just 5 kW. All the scenarios can be seen in Table 2.

The best α values are found by calculating the charging cost for all α values in a range between 0.1 and 1.8, with the training data, and picking the α value with the lowest associated cost. This is done two times for all scenarios, one time with an explicit penalty of €/kWh for not reaching the charging demand, called α_1 and 1 time without a penalty called α_2.

For the scenarios default and congested grid also the best α values are calculated, with the training data, when net metering is implemented.

Table 1: Different charging scenarios

Scenario name	charging demand(kWh)	Charging power car (kW)	Grid connection (kW)
Default	30	11	12
Lower charging demand	10	11	12
High charging demand	50	11	12
High charging power	30	22	12
High demand and high charging power	50	22	12
Congested grid	30	11	5

4.3 Testing the controller

The algorithm with the found value of α_1 is tested on the test data to measure the performance of the multistage algorithm with α_1 is compared with both uncontrolled charging, a multistage with an α value of 1 and the optimal charging pattern. The optimal charging pattern is calculated by using LP as described in section 3.2 but the actual PV production is used instead of the PV prediction, this can obviously only be done in hindsight. The following objectives are compared: charging costs(with penalty for not reaching

the charging demand), peak loads and PV utilisation. PV utilisation is defined as $max(\frac{\Sigma y_i}{E_{demand}}, \frac{\Sigma y_i}{\Sigma P_{pv,i}})$
The multistage algorithm with α_2 is compared with α_1 and $\alpha = 1$ for the charging cost without an penalty using the test data.
The α values found for the scenarios default and congested with net metering are simulated with the test data to measure their performance.

4.4 Physical chargers

The algorithm is also implemented on the slimpark chargers [32] by charging an Volkswagen ID.3. The chargers used are Mennekes AMTRON Professional plus which can be controlled by a Modbus connection. Grid parameters and charging speed are the same as in the scenario congested grid. The performance on those chargers is compared with the performance in simulations.

5 Results

5.1 Charging costs

In Figure 2, a graph with the charging costs vs α can be seen for the default scenario made with training data. It can be seen that it is a convex graph, with a minimum cost for a α value of 0.3. The charging costs and optimal α_1 values for all scenarios can be seen in Table 2. Also the cost of uncontrolled charging is included as a reference. Those costs are the costs in calculated with the same data set as for the calculation of the optimal α_1. As expected the controlled charging results are in all scenarios better than greedy charging.

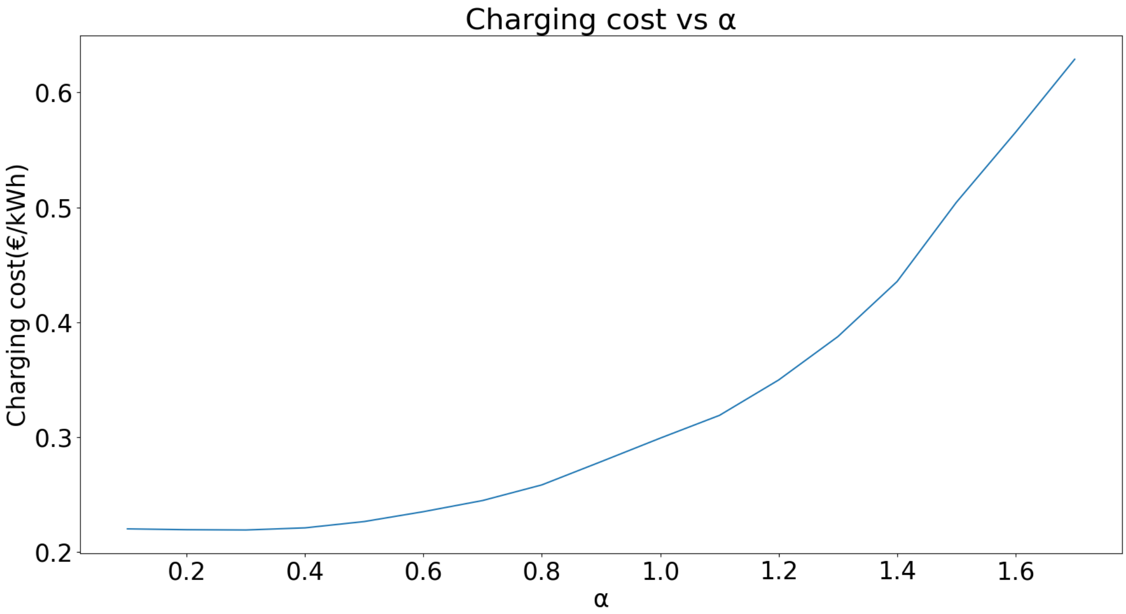

Figure 2: Charging costs vs α_1 for the default scenario without net metering

Table 2: Best α value for different scenarios

Scenario name	Best α_1 value	Charging cost (€/kWh)	Uncontrolled charging cost (€/kWh)
Default	0.3	0.2647	0.400
Lower charging demand	0.5	0.191	0.412
High charging demand	0.1	0.288	0.370
High charging power	0.9	0.255	0.408
High demand and high charging power	0.7	0.287	0.388
Congested grid	0.2	0.278	0.354

The calculated α_1 values are used in simulations and give the charging costs that can be seen in Table 3. Those costs are compared with the charging costs for $\alpha = 1$, the costs of uncontrolled charging and the optimal costs calculated afterwards. It can be seen that that in all cases the cost with α_1 is lower than uncontrolled charging and charging with $\alpha = 1$.

The charging cost for multistage charging is in some scenarios higher then uncontrolled charging. This is the result of the high penalties for not reaching the charging demand. The average not reached demand can be seen in Table 5. It can be seen that the average not reached demand with a α value of 1 is high. In the case with a high charging demand it is even higher than 10% of the charging demand. This leads to

the high prices in the case $\alpha = 1$ multistage charging. Without the penalty the charging cost are lower . In this case the charging cost in the case $\alpha = 1$ are also lower than with the calculated α_1 value.
The charging costs without penalty can be seen in table 4 [2].

Table 3: Calculated costs for different methods and scenarios

Scenario name	Charging cost with α_1 (€/kWh)	Charging cost $\alpha = 1$ (€/kWh)	Uncontrolled charging cost (€/kWh)	Optimal cost (€/kWh)
Default	0.185	1.253	0.315	0.145
Lower charging demand	0.152	0.503	0.377	0.125
High charging demand	0.184	1.507	0.273	0.165
High charging power	0.203	0.286	0.367	0.143
High demand and high charging power	0.189	0.402	0.339	0.160
Congested grid	0.161	1.30	0.285	0.145

Table 4: Charging costs without penalty

Scenario name	α_2	Charging costs α_2 (€/kWh)	Charging cost α_1 (€/kWh)	Charging cost with $\alpha = 1$ (€/kWh)
Default	1	0.140	0.169	0.140
Lower charging demand	0.8	0.128	0.133	0.122
High charging demand	1.8 [3]	0.139	0.184	0.156
High charging power	0.9	0.149	0.184	0.150
High demand and high charging speed	1.1	0.161	0.167	0.161
Congested grid	1	0.140	0.161	0.140

Table 5: Average not reached demand during a charging session

Scenario name	Average not reached demand (kWh) with α_1	Average not reached demand (kWh) with α_2	Average not reached demand (kWh) with $\alpha = 1$
Default	0.046	2.02	2.02
Lower charging demand	0.018	0.084	0.235
High charging demand	0.000	7.10	5.24
High charging power	0.200	0.440	0.285
High demand and high charging power	0.275	1.86	0.987
Congested grid	0.000	2.10	2.10

[2] Both the optimal charging pattern and the uncontrolled charging pattern never get a penalty
[3] Not an optimum but it is the highest α calculated

5.2 Effects grid objectives

5.2.1 PV utilisation

It can be seen in table 6 that the PV utilisation of both a normal multistage and optimized multistage with the best α value have a high and comparable PV utilisation for nearly all scenarios except the scenario high demand and high charging power. This is significantly higher than uncontrolled charging.
For the default scenario a graph of the PV utilisation vs α can be seen in Figure 3. It can be seen that the utilisation is the highest around $\alpha = 1$.

Table 6: PV utilisation in different scenarios

Scenario name	PV utilisation with optimal α	PV utilisation $\alpha = 1$	PV utilisation uncontrolled
Default	1.00	1.00	0.681
Lower charging demand	1.00	1.00	0.358
High charging demand	0.996	1.00	0.808
High charging power	1.00	1.00	0.322
High demand and high charging power	1.00	1.00	0.436
Congested grid	1.00	1.00	0.500

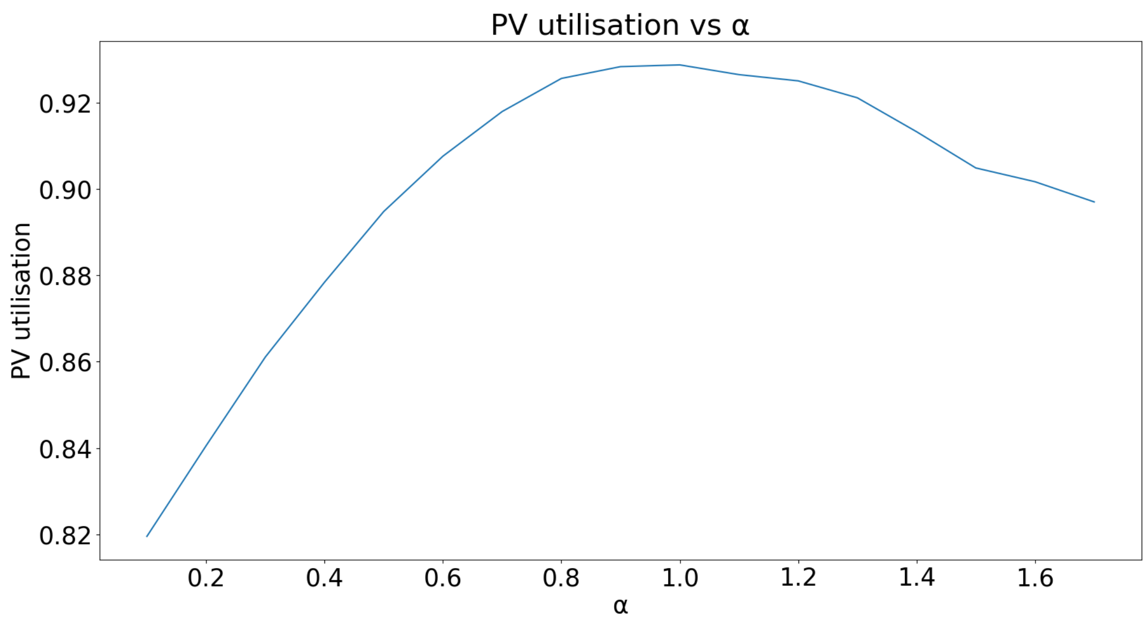

Figure 3: PV utilisation vs α made with training data for default scenario

5.2.2 Squared power peaks

It can be seen in Table 7 that the multi-stage controller decreases the squared power peaks. It depends on the specific scenario if a multi-stage design with α_1 is better than α =1. A graph showing the relation between the squared power peaks and α for the training data can be seen in Figure 4. The peaks are lower in the figure due to a lower amount of PV power in this period (see appendix A.4).

Table 7: Squared peaks of the different charging methods for the test data

Scenario name	Squared peaks with α_1 (€/kWh)	Squared peaks $\alpha = 1$ (€/kWh)	Squared peaks uncontrolled charging (€/kWh)
Default	531	516	1299
Lower charging demand	748	758	1495
High charging demand	347	302	824
High charging power	529	607	1663
High demand and high charging speed	426	447	1552
Congested grid	559	513	1218

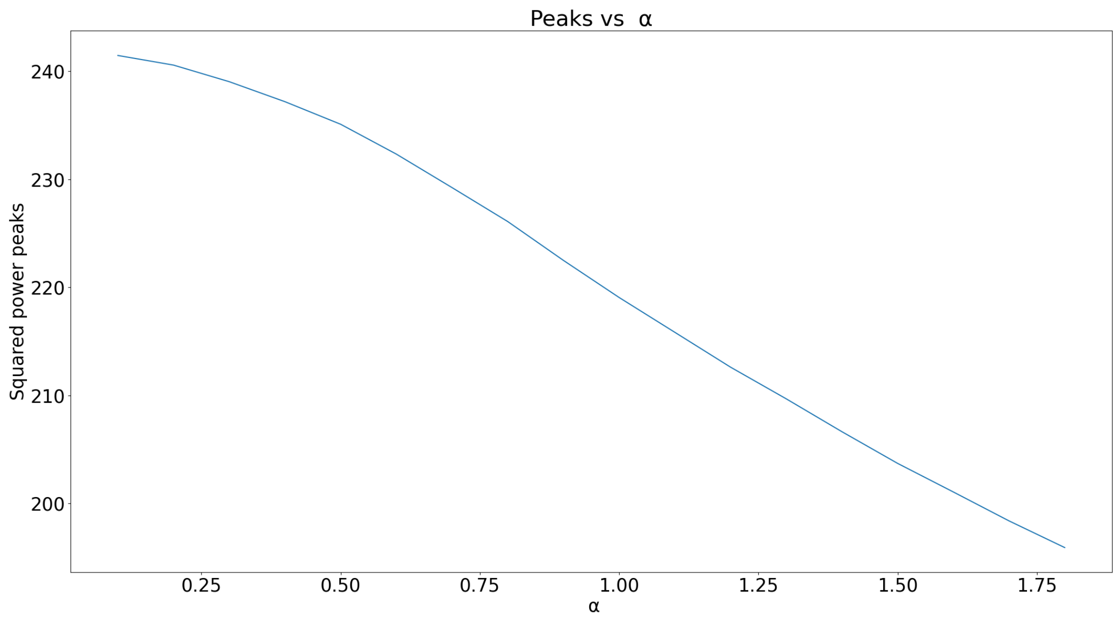

Figure 4: Peaks vs α made with training data for the default scenario

5.3 Net metering

The cost vs α graph for the default scenario with net metering can be seen in Figure 5. It can be seen that an α value of 0 leads to the lowest cost. This cost is, as expected, higher than without net metering because now also taxes are included for the PV power prices [4]. The PV utilisation is for the whole range of α values around 0.53 except for the cause α =0 as can be seen in Figure 6. The peaks are for the whole range around 51000 as can be seen in Figure 7 . In case of the congested scenario the cheapest cost are with an α value of 0.2. In Table 8 the objectives for the default scenario can be seen.

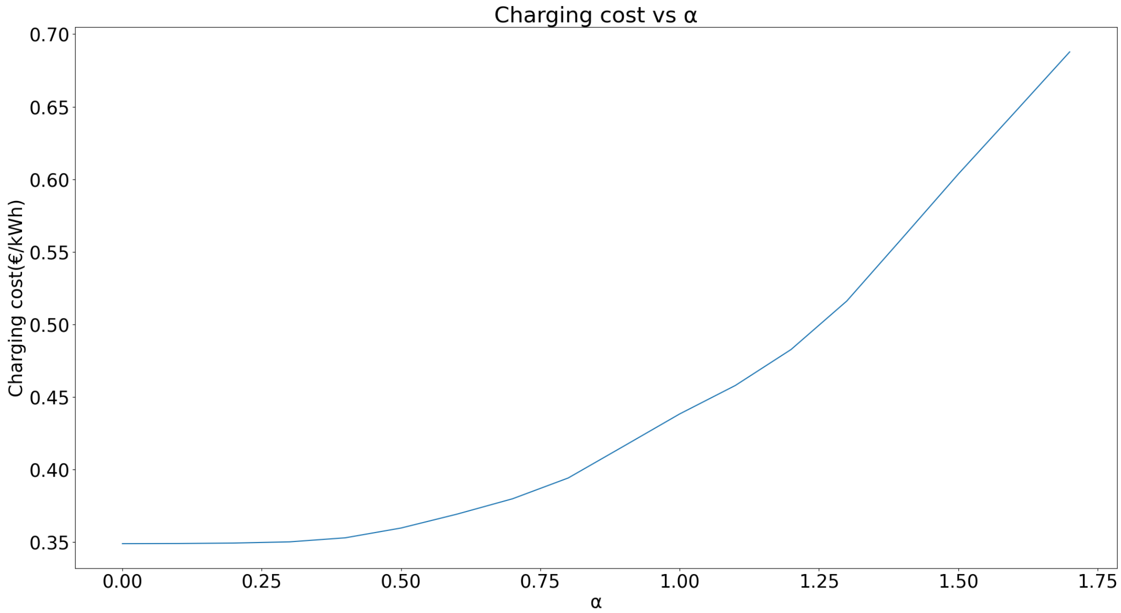

Figure 5: Cost vs α plot with net metering for the default scenario

[4]Assumption is that the total electricity consumption is higher than the total PV production

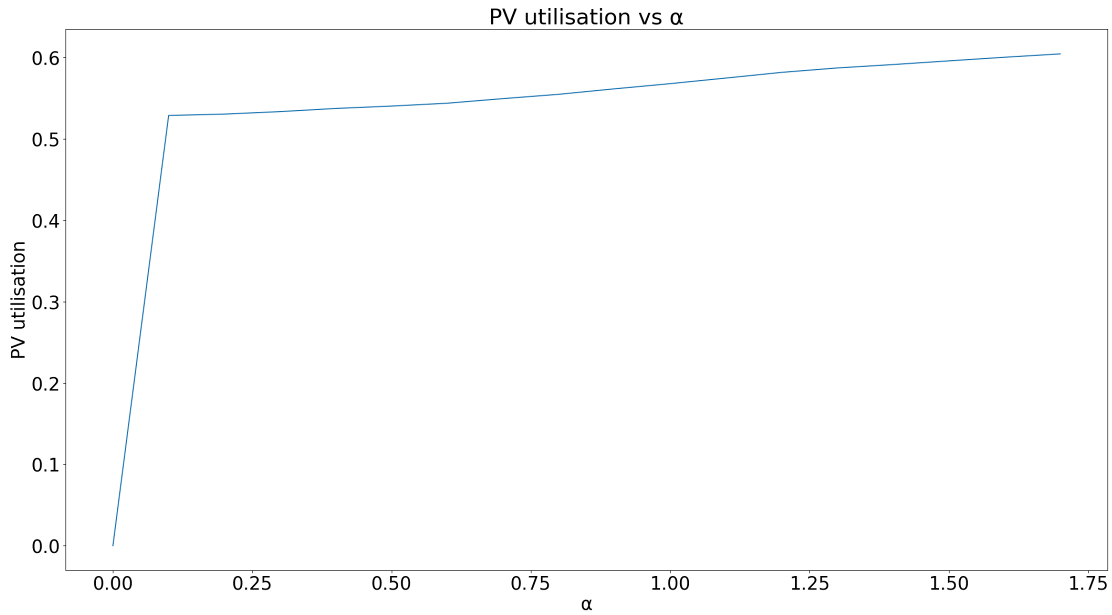

Figure 6: PV utilisation vs α plot with net metering for the default scenario

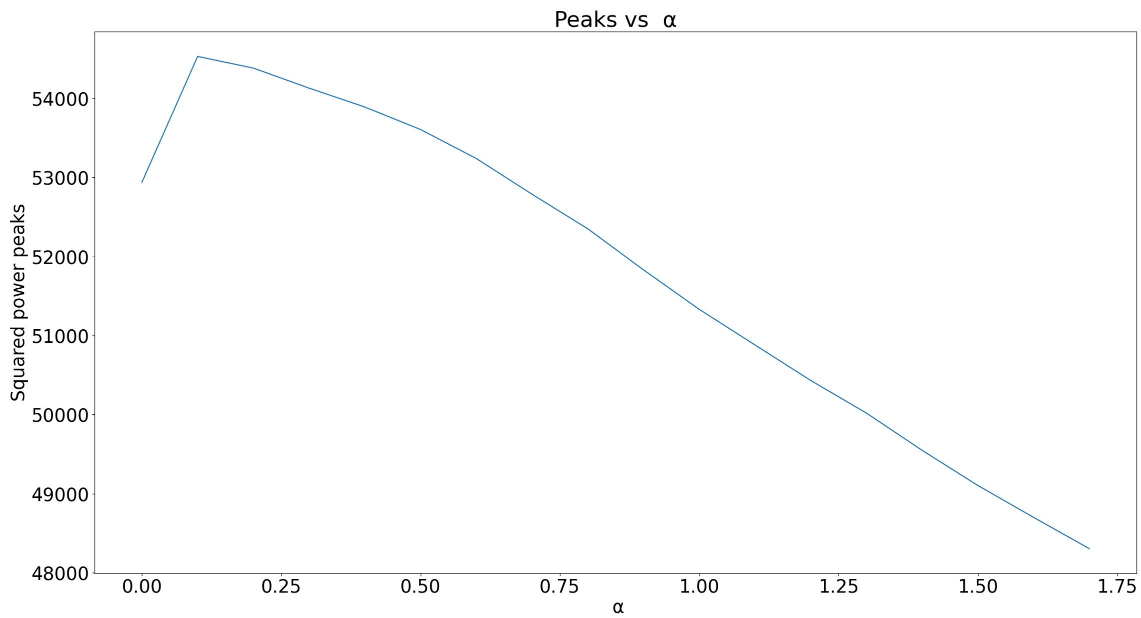

Figure 7: Plotted charging cost vs α for congested scenario with netmetering

Table 8: Different charging objectives for the default and grid congested scenario with net metering made with test data

Scenario	Cost(€/kWh)	Peak shaving	PV utilisation	Not reached demand
Default	0.302	584	1	0
Congested	0.315	527	1	0.02

5.4 Experimental results

In Figure 8 the charging pattern of a car in a experiment can be seen. This experiment was performed on 21-06-2022. During this day the weather was stable and sunny with sometimes clouds, the relative sunshine was 64% [36]. Due to this conditions the PV power was divided by 4 to make the data more comparable to that of a normal household. The PV production shown in Figure 8 is already divided by 4 and the PV prediction in this graph is also multiplied with an α of 0.3.
It can be seen that the charging power follows the PV production. The charging demand in this session was 39 kWh and this was reached. The charging cost in the experiment was 0.28 €/kWh compared to 0.26 €/kWh for an ideal charging pattern.

At the beginning the charging speed of the car was accidentally caped at 5.5 kW leading to the suddenly jump in charging power around 11:15. It can clearly be seen that the controller builds in robustness, it charges more in the beginning of a charging session and it has for-filled the charging demand long before the set end time.
The effects of the limited discrete charging speeds on the charging pattern can clearly be seen in Figure 8. Effects of time delays were not observed, the controller was able to change the charging speeds within seconds. For this experiment a update time interval of 5 seconds was used. During this experiment no problems were observed and the controller was stable. In a small test it was even found that the controller could handle a time interval of 1 second while maintaining stability.

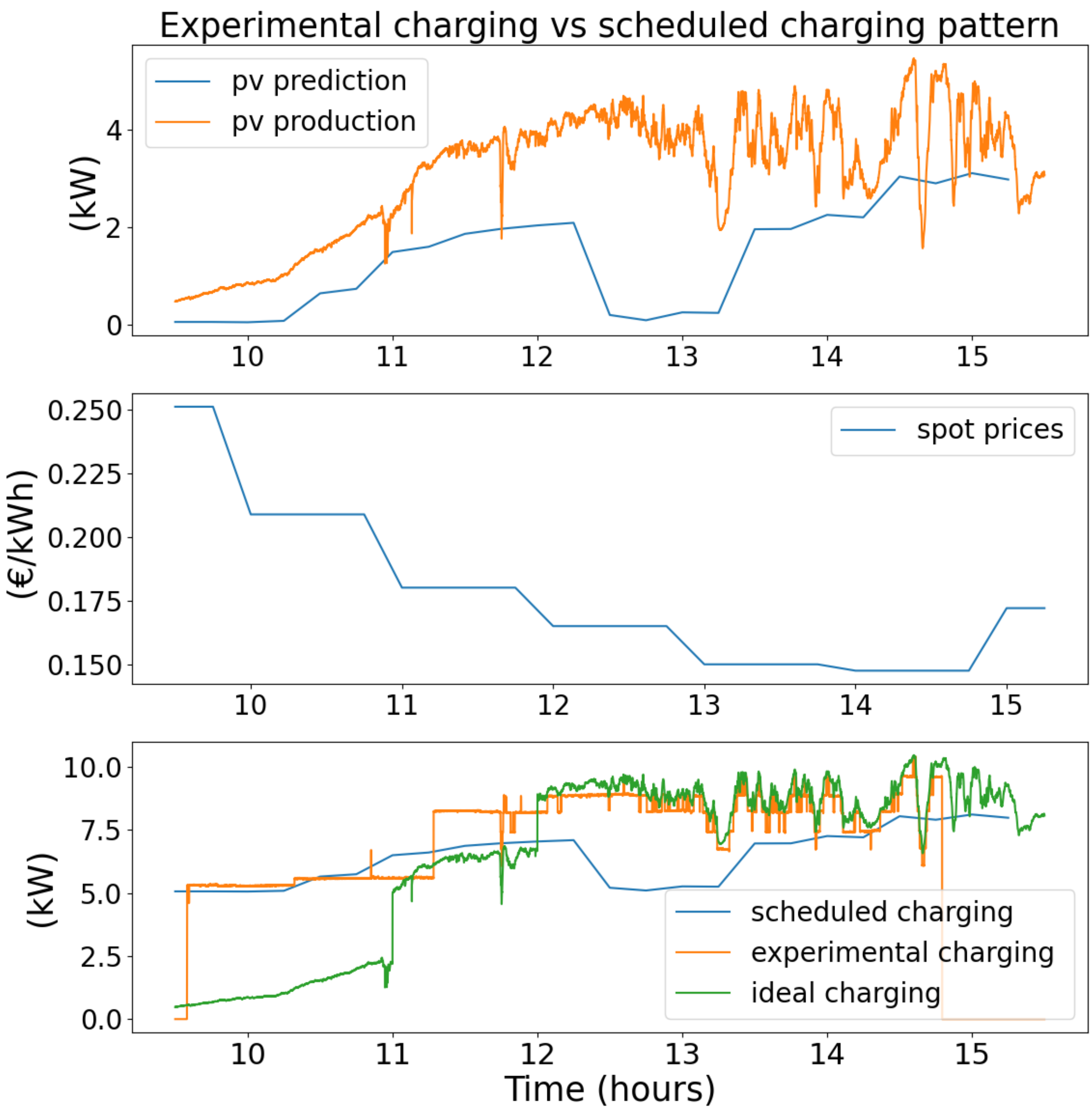

Figure 8: Experimental charging pattern of a EV on 21-06-2022 using the multi-stage controller

6 Discussion

6.1 Charging costs with penalty

The charging costs, including penalties, of the controller using α_1 are 0.02 €/ kWh more expensive than the optimal costs and 0.13 €/ kWh cheaper than uncontrolled charging. Meaning the deployed controller is performing quit well especially considering the uncertainty in the PV production.

The optimal costs decrease when the charging power is higher, the difference is 0.02 €/kWh for the normal scenario and 0.05 €/kWh for the high power. This is not the case for the multi-stage implementation. Here the costs with a 22 kW charging speed are higher than the cost with 11 kW charging power because of the higher not reached demand as can be seen in Table 5. The not reached demand is higher because the charging speed is higher than the grid connection. When at the end of a charging session the PV production is lower than predicted the car can't be fully charged as the available power(PV + grid) is lower than the maximum EV charging. The multi-stage design therefore does not profit from the higher charging speed.

6.2 Charging costs without penalty

The charging costs for α_1 are (without penalty) always more expensive than α_2 and $\alpha = 1$. This clearly means that a price is paid for the extra robustness. For the default scenario α_1 decreases the average not reached demand from 2.02 kWh to nearly zero but it leads to an 0.029 €/kWh increase of the charging costs compared to α_2.

6.2.1 Lower costs than optimal

In multiple scenarios with a multistage implementation with $\alpha = 1$, the charging costs are lower than the optimal costs. This is due to from the high not reached demand. When the usable PV production is lower than expected the multistage implementation do not succeed in fully charging the car. With the optimal charging pattern the car is charged full with power from the grid, which is more expensive than PV charging. The multistage implementation uses less grid power leading to lower costs but it does not charge the car full.

An example of this behaviour can be seen in figure 9, where the PV energy is overpredicted for the given day. The charger has scheduled to charge using cheap PV power. During the charging there is not enough PV power available for reaching the scheduled pattern. This results in charging with full power after a certain moment. But the missing energy is too high to be supplied by the grid, leading to a not reached charging demand of 4.4 kWh. The ideal charging pattern charges at other moments, from the grid, to reach the right demand. Giving a cost of 0.337 €/kWh for the ideal charging pattern and 0.313 €/kWh for the multi-stage implementation.

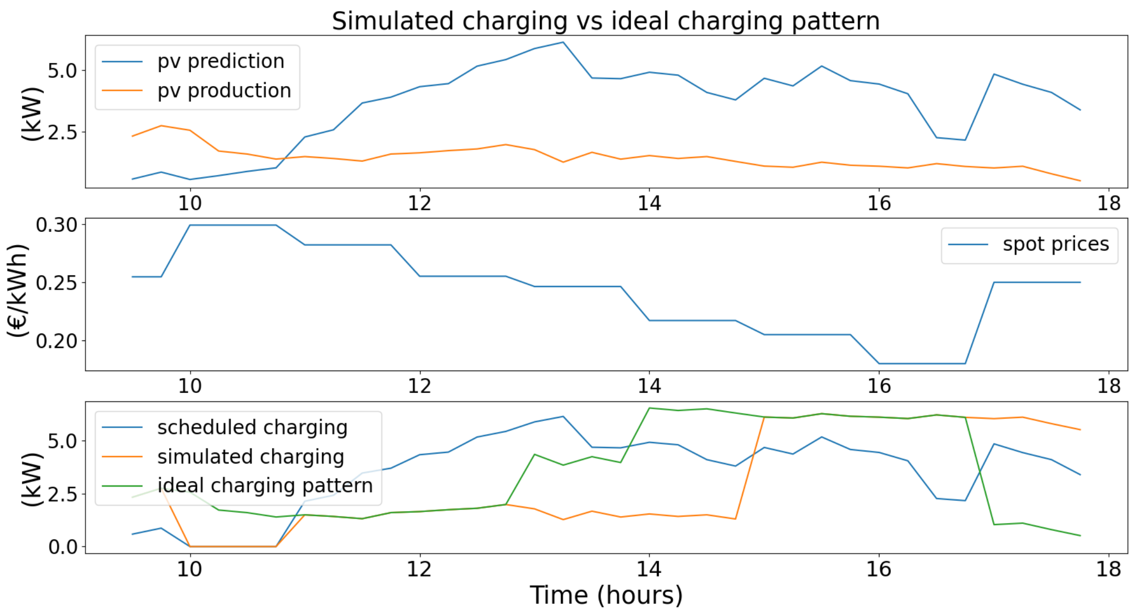

Figure 9: Charging of the car on 04-04-2022 in an congested scenario with α =1

6.3 PV utilisation

In the results, Figure 3 and Figure 4, it can be seen that optimizing for a lower cost means an increase in the peaks and a decrease in PV utilisation. The highest PV utilisation occurs at an α of 1 for the training dataset as can be seen in figure 3. This PV utilisation is significantly higher in the test data for different α values than in the training data. In this period, the winter months, there were moments with a significantly higher wind power production compared with the test data while the average PV power production was on average lower in the training period compared to the test period [1](see appendix A.4). Therefore the spot prices are less depended on the solar production meaning there is a price incentive for using wind energy [37]. In the test period the PV production was in general higher leading to better PV utilisation.

An example from the described behaviour can be seen in Figure 10. At the beginning the spot prices are lower, the car charges there and it is too full to use the solar production entirely. This lead to a PV utilisation of 84%. The PV prediction shows in this graph and in the following graphs is already multiplied with α for the default scenario unless explicitly noticed.

6.4 Peak shaving

The peaks of the grid connection associated with α_1 are lower than uncontrolled charging but higher than charging with $\alpha = 1$ for the default scenario. The underprediction of the PV power leads to larger peaks because at the beginning of a charging session, with typically lower PV production, the car charges from the grid. And at the end of a charging session the PV production will be higher than expected leading to net production peaks.

Due to the multi-stage implementation the schedule gets recalculated meaning that the car will stop charging at some moments because on other moments the price is lower and the EV has already charged enough to charge only on these moments. With an declining prices during the charging period this happens multiple times. Because the EPEX prices are typically higher in the beginning of the morning due to less PV production this behaviour is observed regularly in our experiments. A typical charging pattern depicting this behaviour can be seen in figure 11. Here, PV prediction is the predicted power that the algorithm uses to make a charging schedule so it is already multiplied with α. This behaviour is also the reason that the not reached demand is lower. Shifting more charging to the beginning of the session, by charging faster than expected, also makes the control method more robust.

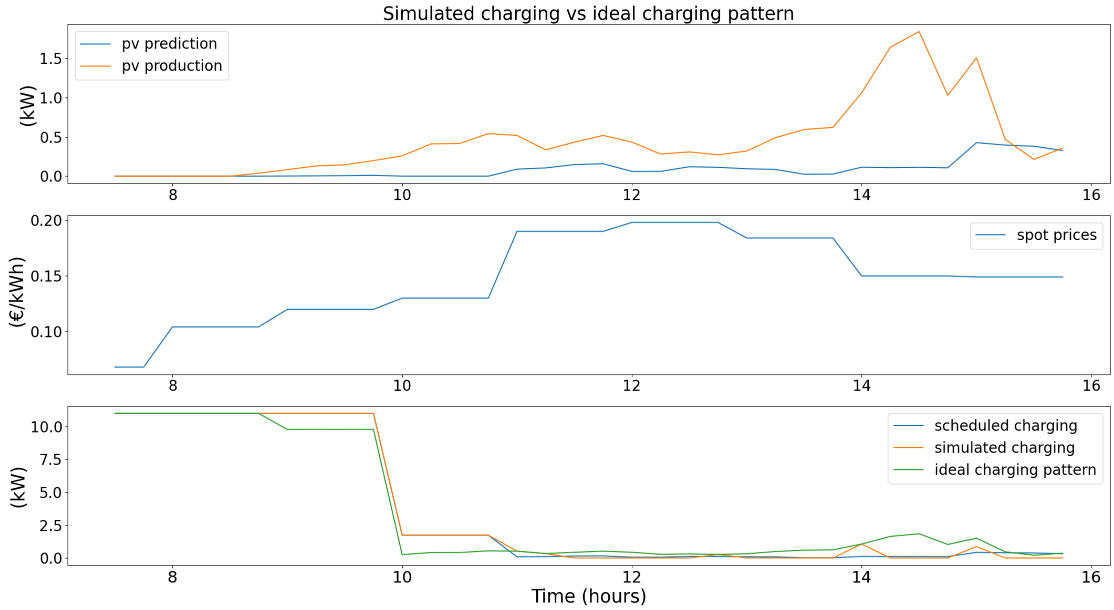

Figure 10: Charging pattern on 6 February with the default scenario

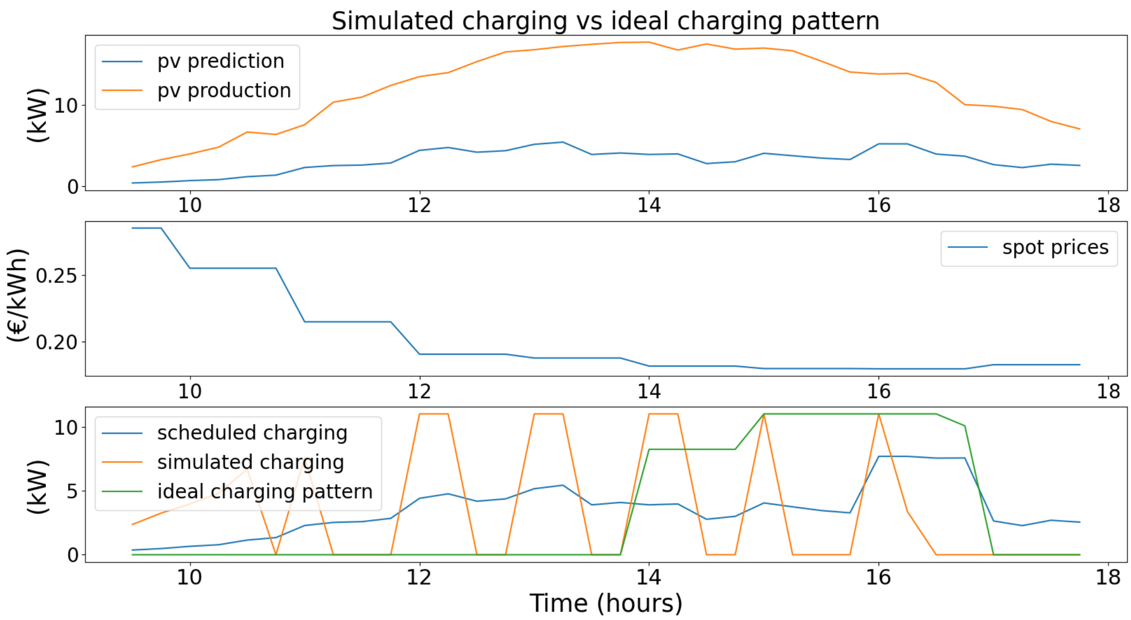

Figure 11: Larger peaks due to the under-prediction of PV power on 11-04 with the default scenario and α_1

6.5 Net metering

Net metering leads to a situation with way less PV utilization and higher power peaks in the training data compared with no net metering. The PV utilization is higher in the test data. This probably is the result of the high amount of solar power in this period. First of all there is enough solar power available to at moments with a low EPEX spot price due to the abundant production. Secondly the spot price reacts more to the sunshine resulting in lower prices on moments of more sunshine.

In terms of costs there is no incentive to use solar power. Only in the case of a congested scenario there is an incentive to use solar power because at cheap moments there is not enough grid capacity to charge the car at full power. This also applies to the scenarios higher charging power and higher demand and higher charging power but those were to a lack of time not tested.

6.6 Negative prices

Negative prices can be handled by the controller but the controller assumes that a PV installation cannot be turned off. Therefore the price used for PV power on these moments stays the spot price, instead of 0 €/kWh if the PV power could be turned off meaning that the charging costs on days with negative prices are too low. But the controller still succeeds into charging the car full on cheap moments as can be seen in Figure 12. Here it can also be seen that it is scheduled to use PV power therefore it reaches high PV utilisation levels.

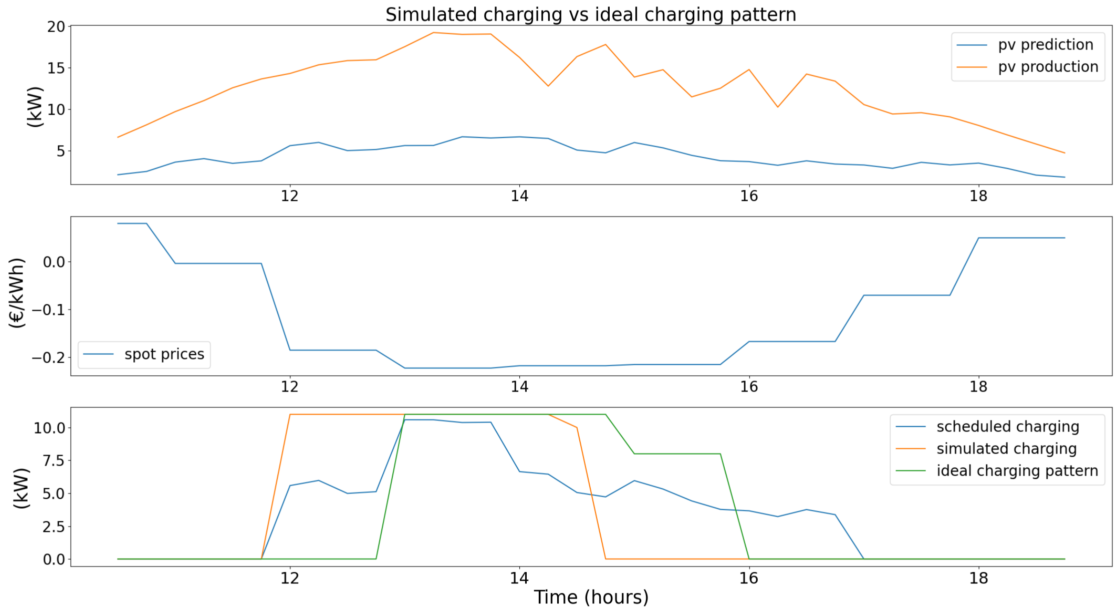

Figure 12: Charging pattern on 23 April, with a total charging cost of -0.207 €/ kWh

6.7 Experimental results

Due to the limited charging power levels that the car supports, the charging level was not able to follow the PV production perfectly. Also the minimum amount of charging the car supports is 4.8 kW, this limits the controller to follow the PV production. But, by chance, the scheduled charging was never lower than 4.8 kW so no effect was observed.

As can be seen in figure 8 the solar power also changes much faster than assumed during the simulations. The PV power can change within a few seconds and the simulations uses a time interval of 15 minutes. Nevertheless, the experimental results show that the controller is able to update the charging within seconds. Therefore, it shows the benefits of the multi-stage design. The scheduling is a fast algorithm, meaning it is able to frequently recalculate the ideal charging pattern. Therefore the method is still applicable, also in simulation, if the sample time decreases.

6.8 Limitations of approach

As can be seen in Table 5 the not reached demand is low while using α_1. In contrast, the not reached demand is higher when $\alpha = 1$ but the charging cost without penalty are lower. The used multi-stage method is not sufficient to further optimize the charging costs. The only factor that can be changed is α which is already optimized.

Secondly there is only a limited differentiation between scenarios that have different charging demands and charging speeds of cars. Especially the controller is not able to use a higher charging speed as can be seen for the scenarios higher speed and higher speed and higher demand.

Thirdly the controller does not differentiate between different weather conditions. On sunny days the car is more depended on PV power to reach the charging demand. Therefore robustness is needed against lower PV productions than predicted. On cloudy days in the winter the EV is less depended on PV power so less robustness is needed. Probably this means that on sunny days the α factor should be lower and on cloudy days the α factor could be higher.

The taxes used in this research are electricity taxes for Dutch households. The taxing system in other countries but also for Dutch companies, including Charging Point Operators(CPOs), is different. Therefore the perfect α factor for them may be different than for Dutch households. However, the rest of the used method is still applicable.

7 Conclusion

This research consists of designing a charging controller that utilizes both PV power and hourly varying prices while taking the PV prediction uncertainty into account. This is done by answering multiple sub-questions:

"*How can the uncertainty in solar power prediction be taken into account?*"

This uncertainty is taken into account by making an addition to a multi-stage design. The multi-stage design is used for scheduling the charging wile using a prediction for the PV power. The charge power is adopted during the charging to the actual PV production.
The PV prediction is on purpose under predicted with a factor α to make the controller more robust against the uncertainty.
The best α factor was found by using historical data from SlimPark. The found factor, called α_1, that had the lowest costs, including penalties, was 0.3 for the default scenario.

"*What effect does the PV production uncertainty have on the charging costs?*"

The costs of the developed controller with α_1 are compared with the optimal charging pattern calculated in hindsight(i.e with perfect knowledge). The differences range, depending on the scenario, from 0.016 to 0.06 (€/kWh) including penalties.

"*What is the effect of the cheapest scheduled charging pattern on the other objectives such as self-consumption, peak shaving, CO_2 emissions and grid congestion?*"

The average not reached demand due to the PV production uncertainty lies between 0 and 0.275 kWh a session. The scheduled charging pattern with α_1 performs with a value of 100% for the PV utilisation (self-consumption) better than uncontrolled charging. The squared peaks are lower with the designed controlled than uncontrolled charging. Both $\alpha = 1$ and α_1 are comparable in PV utilisation as well as peak shaving. The specific amount of CO_2 emissions could not be found but the high PV utilisation means a reduction in CO_2 emissions compared to uncontrolled charging.
A congested scenario was simulated to test the multi-stage design in a congested grid. The simulations show that the controller is still able to charge the car without high not reached demands or too high prices.

A second series of α values called α_2 are found for optimizing costs without penalties. Those values are used in simulation and the costs (without penalty) are lower than with α_1 but show a high not reached demand.

"*How do different experimental phenomenons such as time delay, rounding errors and limited discrete charging levels effect the charging costs and other smart-charging objectives?*"

The controller with α_1 is used to charge an car in a experiment. This controller succeeds in reaching the charging demand with low costs. This experiment also researched the effect of the limited discrete charging steps on the charging pattern, this was not significant. The effect of a minimum charging level of 4.8 kW was, by chance, small in the experiment. Effects of time delays or rounding errors on the overall charging pattern were not observed.

All in all it can be concluded that a multi-stage controller with an under-prediction of the PV power is able to charge the car cheaply and close to the theoretical optimal value. The side effects are limited to an almost negligible not met charging demand of 0.046 kWh in the default scenario.

8 Recommendation

The amount of historical data that was used for this research was limited. For example, it lacks the summer months. More data should be used to improve both the finding of the right α value and the testing of this value. Also mixing the data such that the test data and training data have days from every month will probably increase the reliability of the results.

An addition to the car charging could be made to provide balancing power to Transmission system operators (TSO) and BRPs. When extra generation power is needed the car could stop charging and when more consumption is needed the car could charge at a higher power. Recently it became possible with Equigy to use the flexibility from EV on the balancing market [38]. This means a higher income for charging the car and lower balancing costs for BRPs or TSOs.

The results show that there is a large difference between the charging costs with or without penalties. To improve the charging pattern, robustness could be implemented in an other way. The controller could check during the scheduling if the grid connection is sufficient to catch up with the charging if the PV production is lower than expected. If at some moment the charging power is higher than the grid connection, then the charging should be lower than the grid connection somewhere after this moment. If the PV production is lower than predicted, then on those moments the EV can catch up, with power from the grid, to reach the charging demand.

An other related extension could be a risk factor. With this risk factor, the risk that the user is willing to take can be adjusted. A higher risk means that the expected charging costs are lower but the charging demand is more often not reached due to the higher reliance on PV power. This risk-return trade-off is quite common in investments.
An alternative method would be to set a guaranteed demand and a desired demand. The guaranteed demand will be met even if the solar production is lower than expected, the wanted demand is only met if the expected solar power is available. This is also the charging demand that can be used for positive balancing power(less consumption is needed).

An addition to the charger controller to simultaneously charge with the same chargers is also possible. This can be done by dividing the PV production and grid connection over all the cars, each car could get the same portion or the portion can be set by the ratio between charging demand and charging time.

The designed controller does not support vehicle to grid(V2H). With V2H an EV can supply power back to the grid. This has an great potential to reduce power peaks on the grid and to generate income with an EV.

Integrating other appliances and home batteries into the controller can be done by setting hierarchies of flexibility. First non-flexible loads should use the PV production and the grid connection(such as lights and computers), secondly loads with some flexibility(like washing machines) should use the PV production and grid connection that is left, thirdly it is the turn for flexible loads as EVs and finally the batteries charging and discharging or V2H discharging and charging is planned.

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9 Acknowledgement

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A Appendix

A.1 Average tax payment

According to the CBS the average Dutch person paid in 2021 an total of 1013 €of taxes for their energy, the fixed deduction was 461.62 €[39] . It can be assumed that someone with an EV and a PV installation has a higher electricity consumption than other households despite the solar panels. Therefore the fixed deduction is lower than the taxes making it irrelevant to calculated the lowest charging costs.

A.2 Charging speeds EVs

The common maximum AC charging speed of EV is determined by using the list of the 10 most common EVs in the Dutch fleet [40]. From this list 6 cars have a maximum AC charging speed of 11 kW, the Renault ZOE has a maximum AC charging speed of 22 kW, the Tesla model S has a maximum speed of 17.5 kW, the Nissan leaf 6.6 kW and the Volkswagen e-golf 7.2 kW. The maximum charging speed was taken from ev-database.org [41].

A.3 Charging demands

The assumption is made that households will charge during the day to maximise the use of solar panels. A normal Dutch person travels every day around 30 km to work if they travel by car [42]. With 5 working days this is 150 km and around 25 kWh, based on EV efficiencies tests with affordable cars [43].

A.4 Daily PV production

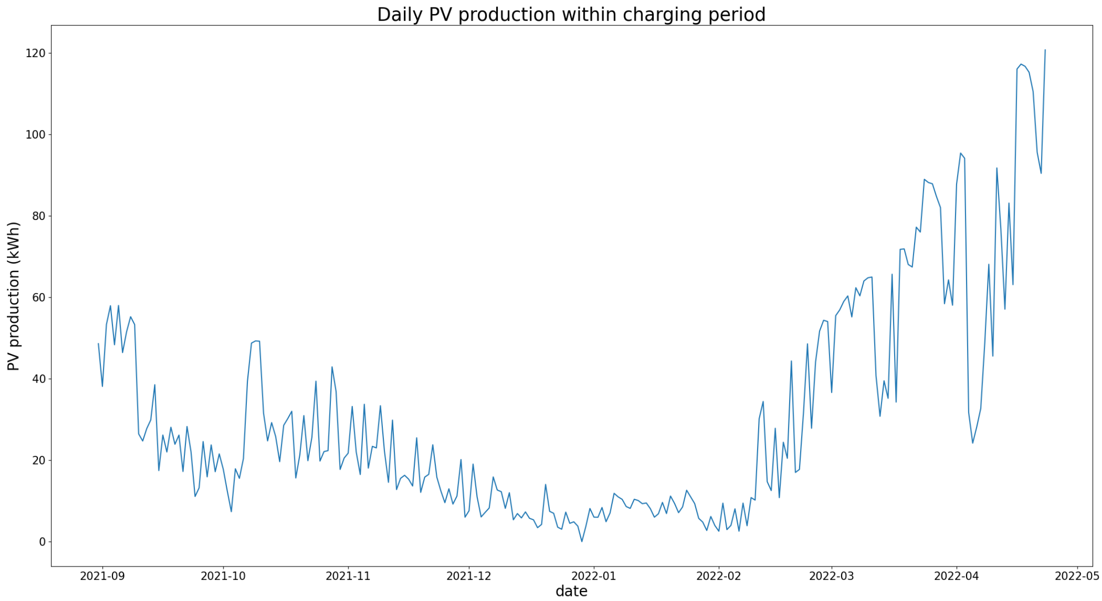

Figure 13: Daily PV production within charging period (8:30-17:00)