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SMART CHARGING OF ELECTRIC VEHICLES BASED ON SCHEDULING THEORY

Heidi S. NYGÅRD
NMBU – Norway
heidi.nygard@nmbu.no

Ingrid Maria MØRCH
NMBU – Norway
ingrid.morch@gmail.com

Olvar BERGLAND
NMBU – Norway
olvar.bergland@nmbu.no

ABSTRACT

Reducing energy related costs by better timing demand for power is a rapidly growing concept due to increased and more fluctuating energy prices. One way to achieve this is through smart charging of electric vehicles (EVs). In the present work, a python-based program has been developed based on scheduling theory and tailored to the specific objectives of charging at a long-term parking facility. Basic building blocks of the theory were assessed to explore the possibility of combining them into a useful model of the problem. The simulation yields example schedules where charging is restricted to night-time and no more EVs than necessary are charged simultaneously, without compromising the constraint of fully charged vehicles at predefined due dates.

INTRODUCTION

The power sector is going through a massive decarbonization process in which electrification plays an essential role. On the power generation side this means replacing fossil energy sources with intermittent renewable energy sources like wind and solar power. On the demand side new load patterns are observed due to for instance the introduction of electric vehicles (EVs) and batteries in the energy system [1]. One of the consequences of this transition is an increased high-intensive decentralized electrical power demand not necessarily coinciding with the production or transmission capacity [2]. This is a driver for greater variations in electricity prices, which in turn strengthens the incentive for consumers to adjust their demand. Typically, this means to move the load away from peak hours (load shifting). The purpose of such demand response in this case is not to balance out an unexpected surge or delay in supply, but rather for the demand to be as evenly distributed over time as possible. This will be beneficial for the grid because the capacity is better utilized, as well as for the consumers, because it may potentially reduce their electricity bills [3].

A possible approach for demand response is smart charging of EVs. Today, charging typically starts as soon as the EV is parked and connected, which may imply buying electricity when the price is high. It may also imply adding demand at peak hours, putting more constraints on the grid. A natural first improvement step is load shifting by better scheduling the timing of EV charging. Many scheduling methods exist, usually requiring data communication and advanced algorithms for full optimization [4].

In this work we have developed a python-based program to demonstrate a proof-of-concept for EV charging schedules that can be implemented at airports or other places offering long-term parking without any additional equipment [5]. The basic building blocks of scheduling theory [6] are assessed to explore the possibility of combining them into a useful model for smart charging.

METHOD

Formulation of the EV charging problem

Scheduling theory is traditionally used for decision making in industrial manufacturing and service industries. It describes scenarios where there is one or more machines that can perform a set of jobs with certain completion times. The goal is to schedule the machines to process the jobs so that the entire set of jobs are completed as soon as possible, so that the production capacity of the machines is used to the fullest. The scheduling problem can generally be described by the following triplet [6]:

$$\alpha \mid \beta \mid \gamma \qquad (1)$$

Here α describes the machine environment, β provides details of processing characteristics and constrains, and γ describes the objective to be minimized.

For the EV charging problem, the chargers can be regarded as machines, while the full charging of one EV can be regarded as one job. The goal is to schedule the charging of each EV in the EV pool based on the following restrictions:

1. All charging is limited to night-time, if possible, on the assumption that demand peaks rarely, if ever, occur during night-time. In addition, the electricity prices normally are lower during night-time than daytime [7].

2. No EVs are charged before they must in order to finish in time, which increases the chance of fitting all charging hours into the defined interval.

3. No more EVs than necessary charge simultaneously, which will spread out the demand used to charge the EVs as much as possible.

Machine environment (α)
Many different machine environments are identified in scheduling theory [6]. The one most applicable for the EV chargers is m identical machines in parallel (P_m). The chargers can be regarded as machines, of which there are several that can operate simultaneously / in parallel.

It could be intuitive to let each machine represent one physical charger, which would make m equal to the number of chargers. However, following the conventions of scheduling theory, that would lead to a schedule in which as many chargers as possible are always in use. That is the opposite of what is wanted for load shifting. The number of machines m is therefore kept flexible in the present problem. To fulfil the goal of reducing load at peak hours, no more chargers than necessary should be in use simultaneously. The chargers are therefore modelled as a minimized number of machines.

Processing characteristics and constraints (β)
The theory defines many different processing characteristics and constraints [6]. One relevant for the charging environment is the release date of job number j (r_j). If this characteristic is present in the β field of the triplet, job number j cannot start before its release date.

It was considered to add r_j to the processing characteristics. However, even though it can be assumed that new EVs arrive every day, it is not known when, how many, or anything about their characteristics, like their charging needs and due dates. It was decided to only include what is known in the triplet, which in this case is by nature a snapshot in time, since the circumstances change daily. It is only known which EVs with their respective charging needs and due dates are parked right now. It is not known how the picture will look tomorrow. It was chosen to disregard the possibility of EV owners notifying ahead of time that they are coming, because that only alleviates the problem to a small degree: that the future is not known.

Another important constraint from the scheduling theory is preemptions permitted ($prmp$). This means that jobs do not need to run continuously from start until completion but can be paused and restarted at will. A full charging of one EV is regarded as one job, but the charging processes of each EV can be stopped and restarted automatically, with no harmful effect to the battery [8]. Hence preemptions should be allowed in the charging problem.

Objectives to be minimized (γ)
There are several objectives to be minimized defined in scheduling theory [6]. The most relevant to the charging problem are maximum makespan (C_{max}) and maximum lateness (L_{max}). Makespan is the time it takes to complete the job, while lateness is the time between the job's due date and its actual completion date. For the charging problem, the maximum lateness is set as the objective to be minimized. It is defined as due date (d_j) plus lateness (z). The due date is the time (in this work: number of days) until the due date of a job, and lateness is the number of days of accepted delay relative to the due date. For the purposes of the charging problem, z is not only minimized, but specifically set to zero. It is a hard constraint that all EVs must be fully charged (or charged to the agreed-upon minimum battery level) upon the EV owners' return. It is unlikely that the EV owners will accept the possibility of delays.

Based on these considerations, the triplet for the charging problem may be described by Eq. (2):

$$P_m \mid prmp \mid L_{max} \quad (2)$$

Solution to the charging triplet

The triplet in the form of Eq. 2 generally has a deterministic solution and is one of the few due date objective related problems that are solvable in polynomial time; namely with *Longest Remaining Processing Time first* (LRPT) [6]. The LRPT principle is simply to always prioritize the job that has the longest remaining processing time. When a job is processed enough that a different job has more processing time left, the machine switches to that job, which initially had the second longest remaining processing time. This goes on until no jobs have any processing time left.

However, the triplet given by Eq. 2 is not directly solvable by LRPT. For LRPT to be applicable to the problem of EV charge scheduling, the timeline must be reversed. This operation converts the due dates (d_j) of the jobs to release dates (r_j), and converts the zero-lateness objective ($L_{max}, z = 0$) to a maximum makespan (C_{max}) objective. Then the latest due date in the job set is considered the starting point, and the LRPT rule is applied backwards. If all the jobs can be completed between their respective release dates and time 0 following the LRPT principle, the schedule is feasible. If not, it would normally lead to lateness greater than zero, which in basic scheduling theory is solved by increasing the accepted lateness (z) until a feasible schedule is reached [6]. This approach is not possible for the charging problem, as it would violate the hard constraint that all EVs must be fully charged before their due dates. Nevertheless, since we model the number of machines as a soft constraint for the charging scheduling problem, the problem can instead be solved by increasing the number of machines until a feasible schedule is reached. One more machine means that the number of jobs that can be processed simultaneously increases by one. For the charging schedule, this means that the number of EVs allowed to charge simultaneously is increased by one. This way, it is ensured that the practical interests of the EV owners take priority over ideal charging patterns in terms of load shifting. If this is implemented in a real setting, a site-specific capacity related cap on number of machines could be added, triggering an expansion of the permitted charging time interval.

The triplet for the charging problem on a reversed timeline, which is solvable by LRPT, is thus given by Eq. 3:

$$P_m \mid prmp, r_j \mid C_{max} \tag{3}$$

Simulation of example schedules

A python-based program was developed [9] to solve the charging triplet (Eq. 3). The program takes information about a pool of parked EVs as input and simulates an example schedule based on the LRPT principle, with a few additional considerations.

Choice of objective to be minimized

The charging problem has two objectives to be minimized: maximum lateness (L_{max}) because the charging must be finished by the time the EV owner returns; and number of EVs that are charged simultaneously, for minimizing power peaks. The latter, which can be regarded as maximum idleness of the machines, is not a defined objective function in basic scheduling theory that can be set in for γ in the triplet (Eq. 1) [6]. It was therefore decided to solve it by adding a feature to the python program that minimizes the number of machines, the m in P_m in the triplet.

How the number of machines (m) is modelled

Instead of letting one machine represent one physical charger, the collection of chargers is modelled as a minimized number of "machines". The number of machines determines how many jobs can be processed simultaneously. Thus, minimizing the number of "machines" will minimize the amount of EVs charging at the same time.

In practice, this minimization starts by solving the problem as a single machine problem, setting m equal to 1. If the resulting schedule is proven feasible, it concludes that the collection of chargers can be modelled as one machine - meaning that all EVs can be fully charged by their due dates inside the defined permitted charging hours, while allowing only one EV to charge at a time. If the resulting schedule is not proven feasible, the program makes a new attempt with two machines modelled instead, and so on. It continues to add one machine until a feasible schedule can be found.

The theoretical maximum for the number of machines is the number of EVs parked. If this happens, it means that all the EVs need to be allowed to charge at the same time for all EVs to be ready by their due dates. Failing a feasible schedule with the maximum number of machines, the parameters for permitted charging hours (ideally set to the eight hours of the night with lowest demand and electricity price) must be altered in the program. If implemented in a real setting, a capacity related cap should be put on the permitted number of machines, if the electrical system is not dimensioned for all chargers to draw power simultaneously.

To account for the daily changes in the collections of parked EVs, it was concluded that each charging schedule should be regarded as a snapshot in time - a sensible charging plan based on the currently parked EVs. The schedule should further be updated once per day, considering the new EVs that arrived during the day. Since it makes sense both power peak wise and electricity price wise to only charge during night-time [8], if possible, the schedule only needs to be updated once per day, in the evening, before the nightly charging starts.

RESULTS AND DISCUSSION

The developed python-program gives a proof-of-concept simulation, where certain parameters are set by the user depending on the scenario to be explored. In this section, we simplify the input parameters for better visualization of the results for three example cases. The simulations are performed for a pool of six EVs, all with charging needs of six hours. The due dates (or rather, the number of days until due dates) are randomly generated numbers inside a specified interval. In this work, the interval is set between one and three, to avoid unnecessarily long example schedules. The generated numbers for the three example cases are shown in Table 1.

Table 1. The number of days until due dates for three example cases (randomly generated between one and three). All cases are simulated for a pool of six EVs, all with charging needs of six hours.

	Case 1	Case 2	Case 3
Due date EV-1	1	3	3
Due date EV-2	2	3	1
Due date EV-3	2	1	3
Due date EV-4	2	3	1
Due date EV-5	1	3	3
Due date EV-6	3	3	1

Charging is restricted to the eight-hour time span between 2200 and 0600 hours, because these are typically the hours with lowest demand and lowest electricity price [8]. However, users of the code can easily alter this parameter to fit their own circumstances.

The resulting example schedules are given in Figures 1 - 3. The row on top of the schedules represents each EV in the EV pool. The column to the far left represents time, in hours. Only the hours during the night are shown.

	Hour	EV-1	EV-2	EV-3	EV-4	EV-5	EV-6
Night 1	1						
	2			charge	charge		
	3	charge				charge	
	4	charge				charge	
	5	charge				charge	
	6	charge				charge	
	7	charge				charge	
	8	charge				charge	
Night 2	9		charge		charge		
	10		charge	charge			
	11		charge	charge			
	12		charge		charge		
	13			charge	charge		
	14			charge	charge		
	15		charge		charge		
	16		charge	charge			
Night 3	17						
	18						
	19						charge
	20						charge
	21						charge
	22						charge
	23						charge
	24						charge

Figure 1. Example schedule for charging EVs in case 1.

	Hour	EV-1	EV-2	EV-3	EV-4	EV-5	EV-6
Night 1	1						
	2						
	3			charge			
	4			charge			
	5			charge			
	6			charge			
	7			charge			
	8			charge			
Night 2	9						
	10	charge	charge				
	11					charge	charge
	12				charge		charge
	13				charge	charge	
	14	charge	charge				
	15	charge	charge				
	16				charge	charge	
Night 3	17				charge		charge
	18					charge	charge
	19	charge	charge				
	20	charge	charge				
	21					charge	charge
	22				charge		charge
	23				charge	charge	
	24	charge	charge				

Figure 2. Example schedule for charging EVs in case 2.

	Hour	EV-1	EV-2	EV-3	EV-4	EV-5	EV-6
Night 1	1						
	2						
	3		charge		charge		charge
	4		charge		charge		charge
	5		charge		charge		charge
	6		charge		charge		charge
	7		charge		charge		charge
	8		charge		charge		charge
Night 2	9						
	10						
	11						
	12						
	13						
	14						
	15						
	16						
Night 3	17						
	18						
	19	charge		charge		charge	
	20	charge		charge		charge	
	21	charge		charge		charge	
	22	charge		charge		charge	
	23	charge		charge		charge	
	24	charge		charge		charge	

Figure 3. Example schedule for charging EVs in case 3.

The example schedules demonstrate that no more EVs than necessary are charged simultaneously at any point. The number of machines modelled (i.e. the maximum number of EVs charging simultaneously) in case 1 and 2 is two, while for case 3 it is three. This is different every time, because it depends on the number of EVs, their due dates and their charging needs.

Furthermore, it can be seen that the schedules prioritize the EVs closest to their due dates first. It is also apparent that no charging starts before it needs to in order to reach its due date, within the constraint of the number of available machines, and the constraint of permitted charging hours. The interrupts that occur due to the LRPT principle are also well exemplified.

The schedules are based on the EV pool as it is any given moment in time. The idea is that an update would happen every day, where new EVs arrive and cause adjustments. Each EV will gradually be replaced by new ones. This means that none of the schedules will realistically be followed exactly as they are. It is likely that the adjustments to the original schedule will cause some EVs to require charging outside of the defined permitted charging hours, due to for instance unforeseen charging needs of new arrivals with a short due date.

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The demonstrated optimization measure is relatively simple and has a comparatively good ratio between how much it costs to implement, and how much there is to gain from it. Power peak wise, much is already achieved by delaying the charging until night-time, assuming that the power peaks occur during daytime [8]. If not, the method also works if there is an identifiable daily interval with low probability of power peaks occurring. Ensuring that no more EVs than necessary are charged at the same time fulfils the desire to distribute the demand as evenly over time as possible. Lastly, scheduling the charging such that no EVs charge before they must in order to complete by their due date, increases the chance of fitting all the charging hours into the hours with lowest demand and lowest electricity price. This makes charging schedules a worthwhile optimization measure. Furthermore, the charging schedule measure is a significant improvement from how it is done today, where the charging of a vehicle starts once it is connected to the charger.

CONCLUSIONS

Smarter charging of EVs parked at airports or other places offering long-term parking can be utilized as a measure for load shifting. Building on scheduling theory from industrial production, this work demonstrates a proof-of-concept for EV charging schedules. It proposes a system that schedules the charging of each EV in the EV pool such that all charging is restricted to night-time, if possible, on the assumption that power peaks rarely, if ever, occur during night-time. No EVs are charged before they must in order to finish in time, which increases the chance of fitting all charging hours into the defined interval. Provided that the EV owner knows when they will be back to collect their EV, this can be achieved without affecting the EV owners' interests. It is also ensured that no more EVs than necessary charge simultaneously, which will spread out the power demand used to charge the EVs and will therefore contribute to better grid utilization. For an existing parking facility, this optimization measure requires no additional equipment, and can be integrated into the existing systems at the parking houses.

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