

Coordinated charging strategies for plug-in electric vehicles to ensure a robust charging process

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ABSTRACT

Charging of plug-in electric vehicles is expected to heavily increase the load of the electric grid. Therefore coordinated charging strategies are proposed to facilitate a flexible charging process that may be delayed to a time when e.g. extra energy is available. The expected recurrence time of the client and the maximum speed of the charging process implicitly determine the latest possible time to start charging. This paper proposes a simple Hybrid Petri net (HPnG) model that implements a charging station based on a predicted recurrence time of the client. The impact of coordinated charging on the client is investigated by comparing three different charging strategies: (i) Immediate, (ii) Considerate and (iii) Just-in-time. Recent algorithms for model-checking HPnGs are used to compute the probability that the charging processes is finished upon the arrival of the client. This ensures that the client's charging requirements do not suffer from the created flexibility. We show that the proposed model may be used to identify system parameters for coordinated charging even though the recurrence time is not exactly known.

Keywords

Electric vehicles; Robust Coordinated charging; Hybrid Petri Nets; Stochastic Model Checking

1. INTRODUCTION

The power demand of plug-in electric vehicles (PEVs) is expected to have a huge impact on the stability of the power grid [8]. As shown in [5] PEVs cause a high power demand during their charging process. Therefore grid-coordinated charging may be used to relieve the grid. Hereby, the charging process can be delayed and started when the grid is less stressed. As motivated in [9] the available battery capacity may be used as a buffer for frequency regulation. Provided the right incentives are offered to the use, the battery may be charged from the grid (G2V) or discharged to the grid (V2G) to help maintain the appropriate frequency.

Recent work mainly focuses on the optimization of coordinated charging strategies. Refs. [10, 2] investigate the optimal charge profile by minimizing power losses. They use stochastic programming to incorporate the stochastic nature of load forecasts. Optimal schedules, based on time-varying prices and target profile, for charging PEVs are introduced in [11]. Ref. [7] presents optimal strategies w.r.t. the clients' requirements. The authors extend the so-called PowerMatcher to provide long-term demand and price predictions. They are able to formulate and solve an optimal short-term bidding strategy minimizing the clients costs. However, to the best of our knowledge, none of these papers take the stochastic nature of clients recurrence times into account. Ref. [12] considers a delay-optimal charging station with multiple charging points. The uncertainty of the arrival of the EV, the intermittence of the renewable energy and the variation of the grid power price are modeled as a Markov process. They aim at minimizing the mean waiting time under the long-term constraint on the power costs. A charging system comparable to the one proposed within this paper is presented in [6]. The authors present a real-time scheduling strategy that minimizes impacts on the power grid and guarantees the satisfaction of the client's charging requirements.

We use Hybrid Petri nets with a single general one-shot transition (HPnGs) [4] to model a charging station. Once a client arrives at the station he chooses (i) whether to charge the PEV immediately or (ii) whether to allow for coordinated charging. The recurrence time can either be specified by the client or estimated by the system, e.g. from the location of the charging system and known usage patterns. Nevertheless, the actual recurrence time may differ, hence a random variable is used to model the time until recurrence. In this paper we investigate the impact of coordinated charging strategies on the charging experience of the client, i.e. the *robustness* of the charging process. For now we do not take into account the load of the grid. Instead, the presented model can be used to investigate in how far the charging process can facilitate a coordinated use without affecting the robustness of the charging process. Moreover, we are able to obtain charging system parameters that satisfy clients' requirements even though the recurrence time may vary from the expected time.

The paper is further organized as follows: Section 2 introduces the charging station and explains the parameter choices. The initial Hybrid Petri net model is shown in Section 3. Section 4 recalls the measure of interest. Results are presented in Section 5 before Section 6 concludes the paper.

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VALUETOOLS 2016, October 25-28, Taormina, Italy
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DOI 10.4108/eai.25-10-2016.2266997

2. CHARGING STATION

Coordinated charging has recently been enabled by strongly increasing charging rates, which allow to delay the charging process until a time at which the grid is less stressed and to still charge the battery in time. We use data from Tesla¹ PEVs and charging infrastructure for the model parameter setup. As presented in [1] there are three different charging stations available that differ in the maximum charging rate: (i) *Home* charger, (ii) *Public* charger and (iii) *Supercharger*. The latter provides charging rates up to 120kW and hence is well-suited to be used for a charging strategy that allows a grid-coordinated use. A PEV's battery cannot be charged with maximum rate at all times, its rate depends on the current State-Of-Charge (SOC) and on external influences, e.g. heat. In this first approach we approximate the slope of the charging rate, based on the facts gathered from [1], with a granularity of 10 minutes.

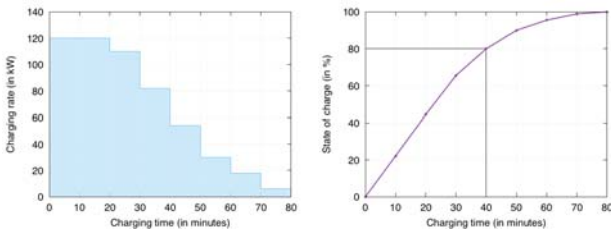


Figure 1: Charging rate

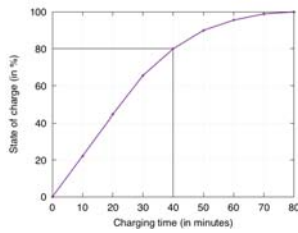


Figure 2: State of charge

Figure 1 shows the available charging rates for a Tesla Model S having a battery capacity of 90kWh. The maximum available charging rate decreases with increasing charging time due to external influences like heat, voltage level and state of charge (SOC). Figure 2 shows the resulting SOC of the PEV's battery. Note that it takes almost the same time to charge the last 20% and the first 80% of the battery.

Figure 3 presents a schematic overview of the components that are involved in the charging process. Once a *Plug-in Electric Vehicle* arrives at the *Charging Station* a client is able to select in the *GUI* whether or not coordinated strategies should be used. According to the chosen strategy, the *Charging Station Controller* determines the charging process and how to use the *Power Sources*. The client is able to choose three different strategies: (i) *Immediate* charging starts charging immediately with the highest possible charging rate. (ii) *Considerate* and (iii) *Just-in-time* facilitate coordinated charging. The process is delayed based on the predicted recurrence time. Just-in-time tries to maximize the flexibility within the charging process and aims at finishing exactly at the expected recurrence time. Since the robustness may suffer, Considerate charging includes a safety margin and finishes before the client is expected to return. Figure 4 illustrates the possible SOC for the three different charging strategies. The battery is always charged immediately up to a certain minimum state of charge (msoc) to expand battery lifetime and preserve power for frequency regulation. Note that since it can be difficult to specify the starting time for the Considerate strategy we use a model to identify system parameters that guarantee a robust charging process, i.e., the battery is charged up to the SOC that is expected by the customer upon its return.

¹<http://www.teslamotors.com>

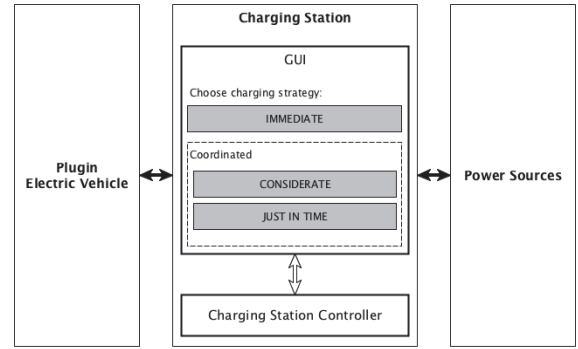


Figure 3: Schema of the charging station.

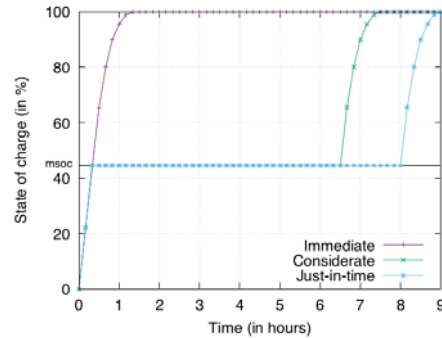


Figure 4: SOC of the three charging strategies.

3. MODEL OF THE CHARGING PROCESS

We use a Hybrid Petri Net with one general one shot transition, as introduced in [4], to model the *Charging Process*. The HPnG formalism is suitable, since we only need one general transition to model the recurrence of the client. Furthermore the system consists of a hybrid part to model the battery and a discrete part to control the system state. We approximated charging to a process with piece-wise deterministic rates to fit the HPnG formalism. Figure 5 shows an abstracted HPnG model of the charging process. The charging station is for example operated by a company and possibly powered with solar energy. We consider a setup in which a client charges the PEV during working hours, hence the general transition follows a normal distribution and is parametrized with mean $\mu = 9$ hours and varying standard deviations σ to model the variance in the duration of a working day. Charging is only possible as long as the client has not unplugged the vehicle from the charging station, i.e., the discrete place *loading* contains a token. *Battery Management* controls the flow of power, depending on the charging strategy. The model distinguishes three states of the battery, it can either be *full*, *good* or *empty*. In state *full*, G2V interaction is possible, since the battery is completely charged. The *Charging Station Controller* consists of the *G2V Controller* as well as the *V2G Controller* which are used to gather system information to regulate the charging and discharging process. Note that we focus on G2V within this paper, since adaptive V2G interaction would require a model that is able to reflect the state of the grid (e.g. voltage and frequency) to decide when the grid should be relieved.

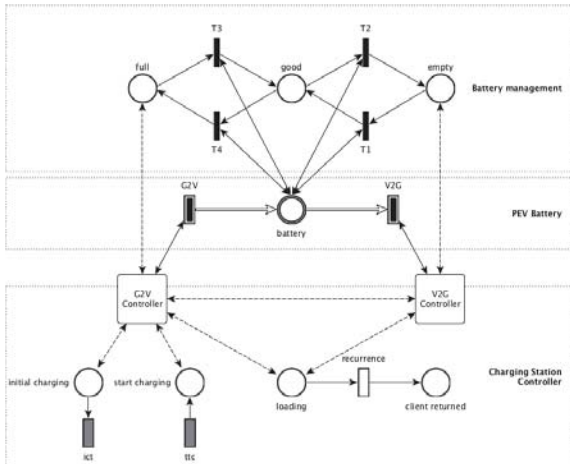


Figure 5: HPnG model of the Charging Station.

The deterministic transitions *immediate charging time* (*ict*) and *time to charge completely* (*ttc*) control the system in a time-based fashion. The *ict* is used to model the immediate charging up to the battery level *msoc*. The transition *ttc* determines the latest point in time at which the system has to start the remaining charging process.

4. MEASURE OF INTEREST

The presented charging strategies need to balance the interests of the grid-operator and the clients' interests. The first profits from a flexible battery use that is possible with coordinated charging whereas the latter requires the battery to be fully charged (if possible) when he returns. Note that the flexible battery use (*fbu*) that results from a delayed charging process with coordinated charging is a deterministic measure and can be obtained from simple computations or simulations and is not further investigated in this paper. In contrast we focus on the robustness of the charging process, which is a probabilistic measure that highly depends on the parametrization of the general transition. The robustness of the charging process describes the probability that the PEV is charged at least up to the expected SOC *esoc* when the client returns. This can be specified formally, using the so-called until operator of Stochastic Time Logic (STL) [3]:

$$\text{robustness} = \text{loading} \ U^{[0,t]} \ (\text{battery} \geq \text{esoc}). \quad (1)$$

This formula holds, when the battery is charged up to at least *esoc* within *t* time units until the client returned, i.e. place *loading* contains no token any longer. In this setting the time bound *t* corresponds to the maximum model execution time. We use $t = 14$ hours in our example setup hence we assume that employees are not allowed to stay longer than 14 hours at work.

5. RESULTS

This section presents results obtained from the analysis of the presented Hybrid Petri net model. We investigate (i) the impact of the Just-in-time strategy on the robustness and (ii) obtain the latest possible starting time for the Considerate strategy, which still ensures robustness.

Immediate charging and Just-in-time charging represent the best and worst case scenario, respectively. The first maximizes the robustness and does not facilitate grid-coordination, whereas the latter results in a very low robustness but is expected to provide a high flexibility for grid-coordination. Figure 6 compares the robustness probability of the Immediate and Just-in-time strategy for different standard deviations σ , i.e. expected inaccuracy of the predicted recurrence time. Due to its very early charging time the robustness of Immediate charging only suffers for very high values of σ . The robustness probability of Just-in-time charging drops to 0.5 very quickly. Hence it is not suitable in case of potentially imprecise recurrence time predictions.

As mentioned above Just-in-time charging performs worse when the distribution of the general transition shows a high standard deviation. The Considerate strategy may be used to obtain a better compromise between flexible battery use and robustness. We assess possible starting time parameters and compare Just-in-time with the chosen Considerate one. Figure 7 shows the robustness probability for Considerate charging with different completion times. The different graphs correspond to completion times $t \in [0, 120]$ minutes before the expected recurrence time, which increases the robustness of the considerate strategy. Especially for deviation values smaller than 30 minutes Considerate charging performs much better than the Just-in-time strategy.

Whenever a client chooses Considerate or Just-in-time charging it is likely that the battery is not charged completely in case the client returns early. However, he may be reimbursed for the use of the battery and therefore accept slight disadvantages. Figure 8 compares the probability that the battery is charged at least to a specified percentage for the Considerate and Just-in-time strategy. We use standard deviation values of 0, 30, 60 and 90 minutes to compare the two strategies. The Just-in-time strategy suffers largely for high deviation of 60 and 90 minutes. All other strategies have a probability larger than 0.9 that the battery is charged up to at least 90%. It can be seen that it is relatively expensive to ensure a completely charged battery in case any form of a delayed charging strategy is used.

6. CONCLUSION

This paper proposes a Hybrid Petri net model that implements a PEV Charging Station process. The case study shows that the model is suitable to investigate system parameters for charging stations that introduce delayed charging, based on a predicted recurrence time, to facilitate grid-coordination. We have investigated the robustness probability of three different strategies. (i) Immediate charging, (ii) Considerate charging and (iii) Just-in-time charging. The last two facilitate grid-coordination and therefore contribute to a more stable grid. We have seen that the Considerate strategy which finishes charging some time before the expected recurrence time offers a good trade-off between possible coordination and robustness. Its robustness (c.f. Eq.1) is larger than 0.95 for all standard deviations up to 60 minutes. Note that the Just-in-time strategy results in the lowest the robustness probabilities. In a real-world system the Just-in-time strategy would only be used in case the grid is highly loaded all the time the PEV should be charged. As soon as the grid is less stressed it would advise the charging station to charge the car according to the coordinated charging policy. This initial model does not take the grid's

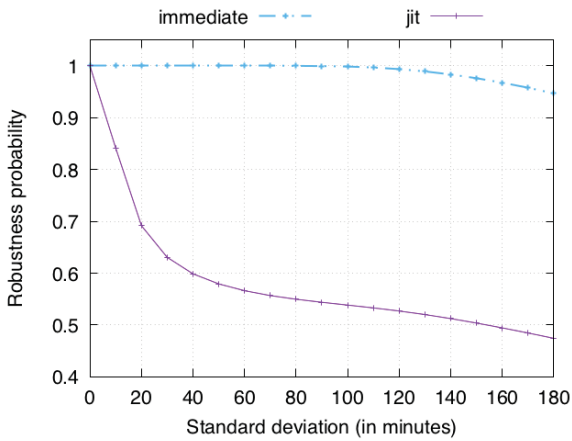


Figure 6: Probability that charging is robust for Immediate and Just-in-time and several standard deviations.

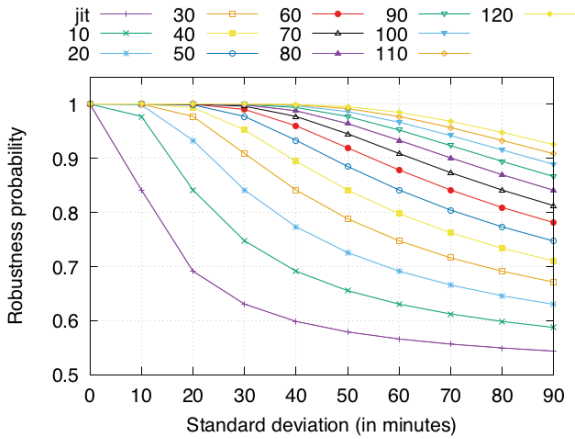


Figure 7: Probability that charging is robust for Considerate, several standard deviations and times to complete.

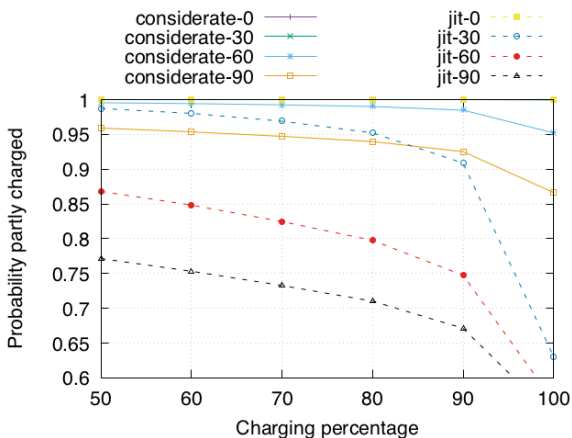


Figure 8: Probability that battery is charged up to a certain percentage for Considerate and Just-in-time.

load into account and while we are able to illustrate possible implementations of coordinated charging strategies, a more realistic model would include actual loading data. Then the static behavior of the presented model could be improved such that it adapts the chosen strategy based on the grids load. Furthermore we focused on charging (G2V) the PEV. Therefore another improvement would be to introduce the extension of discharging the PEV (V2G).

7. REFERENCES

- [1] Tesla supercharger: 2016. <https://www.teslamotors.com/supercharger>, 2016.
- [2] K. Clement, E. Haesen, and J. Driesen. Coordinated charging of multiple plug-in hybrid electric vehicles in residential distribution grids. In *Power Systems Conference and Exposition*, pages 1–7. IEEE, 2009.
- [3] H. Ghasemieh, A. Remke, and B. R. Haverkort. Survivability evaluation of fluid critical infrastructures using Hybrid Petri nets. In *Pacific Rim Int. Symp. on Dependable Computing (PRDC)*, pages 152–161. IEEE, 2013.
- [4] M. Gribaudo and A. Remke. Hybrid Petri nets with general one-shot transitions for dependability evaluation of fluid critical infrastructures. In *High-Assurance Systems Engineering (HASE)*, pages 84–93. IEEE, 2010.
- [5] G. Hoogsteen, A. Molderink, J. L. Hurink, G. J. Smit, F. Schuring, and B. K. Liandon. Impact of peak electricity demand in distribution grids: a stress test. In *PowerTech*, pages 1–6. IEEE, 2015.
- [6] J. Kang, S. J. Duncan, and D. N. Mavris. Real-time scheduling techniques for electric vehicle charging in support of frequency regulation. *Procedia Computer Science*, 16:767–775, 2013.
- [7] P. Kempker, N. v. Dijk, W. Scheinhardt, H. v. d. Berg, and J. Hurink. Optimization of charging strategies for electric vehicles in powermatcher-driven smart energy grids. In *Int. Conf. on Performance Evaluation Methodologies and Tools*, pages 242–249, 2016.
- [8] R. Liu, L. Dow, and E. Liu. A survey of PEV impacts on electric utilities. In *Innovative Smart Grid Technologies*, pages 1–8. IEEE, 2011.
- [9] N. Nigro. Plug-in electric vehicles could help the grid: Prospects with frequency regulation: 2010, howpublished=<https://goo.gl/d0hbmj>.
- [10] E. Sortomme, M. M. Hindi, S. J. MacPherson, and S. Venkata. Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. *IEEE Transactions on Smart Grid*, 2(1):198–205, 2011.
- [11] T. van der Klauw, M. E. Gerards, G. J. Smit, and J. L. Hurink. Optimal scheduling of electrical vehicle charging under two types of steering signals. In *Innovative Smart Grid Technologies, Europe*, pages 1–6. IEEE, 2014.
- [12] T. Zhang, W. Chen, Z. Han, and Z. Cao. Charging scheduling of electric vehicles with local renewable energy under uncertain electric vehicle arrival and grid power price. *IEEE Transactions on Vehicular Technology*, 63(6):2600–2612, 2014.