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Electric Vehicle Charge Management taking into account Grid State and Forecast Uncertainties of Photovoltaic Generation

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Summary

The increasing usage of electic vehicles (EVs) motivates the development of decentralized control strategies for EV charging stations. We present a predictive control scheme that can mitigate the stress on the distribution grids as well as increase photovoltaic (PV) self-consumption while catering for forecast uncertainties. Here, we demonstrate the performance of our approach through a simulation and a field test within a residential context. Results suggest a significant increase in PV self-consumption with our novel dynamic appoach compared to a previously static algorithm deployed in the same field environment.

Keywords: *demonstration, optimization, photovoltaic, smart charging, smart grid*

1 Introduction

In the light of the recent emissions scandal in Germany as well as the intensified awareness of climate change, it is expected that electric vehicles (EVs) will play an important role for individual mobility worldwide. There is a broad consensus that the market share of electric vehicles will increase strongly in the coming years [1, 2]. This transition entails a transformation in the refueling concepts. While gasoline is typically refueled in a short time at designated gas stations, battery recharging will be done in a much more decentralized manner using decentralized infrastructure such as private charging stations in residential buildings.
Nevertheless, decentralized charging processes are challenging for the residential distribution grids which are not designed for high powers. Especially if several charging processes happen simultaneously [2]. Currently, various market based mechanisms as well as direct control approaches are under discussion to deal with this problem. Market driven approaches aim at the flexibility of the charging process and try to avoid peak loads by providing incentives for load shifting. However, when grid congestion cannot be solved through incentives, the distribution system operator (DSO) must be able to limit the power supply to the individual customer. The actual form of such a measure is currently under discussion in the research project *C/sells* [3].
Within this project, households combining a private charging infrasture and PV system are considered. With these kinds of systems the possibility of EV charging through PV self-consumption arises. On the one hand, this strategy decreases the electricity bill of the end consumer. On the other hand, the anticipated savings in CO_2 emissions through electrification of individual mobility can only be achieved if EVs are charged with renewable energy.

These two goals - avoiding grid congestion and increasing the PV self-consumption - have been found to play an important role in consumer's decision to purchase private charging infrastructure [4]. Also, to meet these objectives, a smart control system taking into account a forecast of the residual PV generation available for EV charging is required.
Several such forecast based control schemes have been presented in the literature [5, 6, 7].
In this study, we present a two-stage control scheme to manage charging of electric vehicles in a residential setup. Our approach strives to maximize PV self-consumption while meeting all limits of the public infrastucture as communicated by the DSO.

2 Management of Charging Processes

The system we plan to control is a single-family house in a suburban neighbourhood. A schematic picture of our demonstrator is shown in Figure 1.

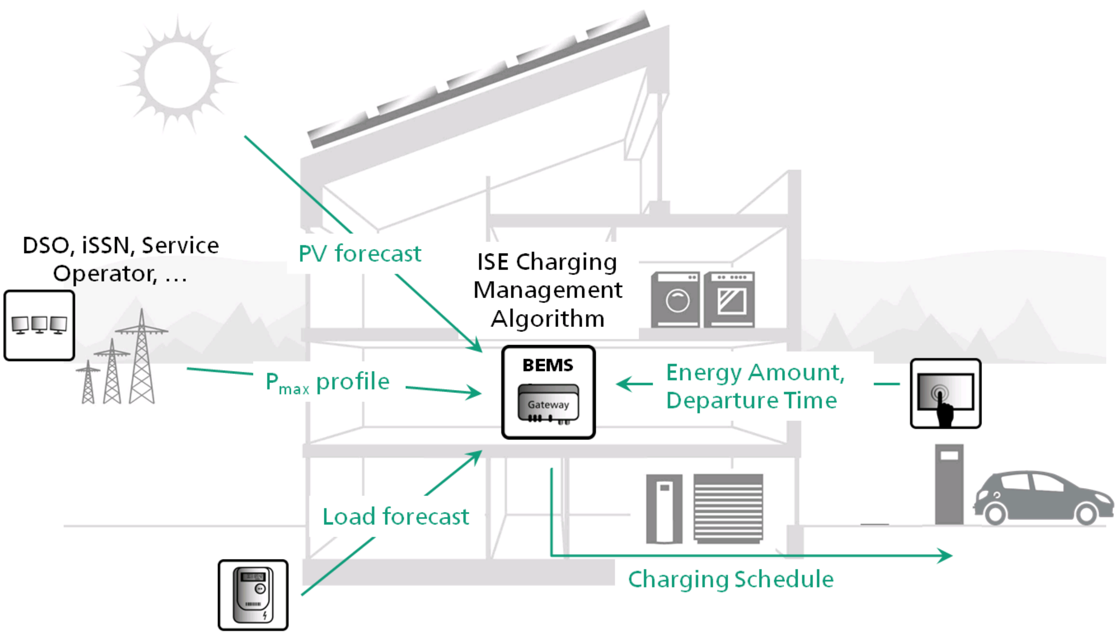

Figure 1: Architecture of the *C/sells* demonstrator.

In each house, a charging infrastructure compliant to IEC 61851 [8] is installed. The upper limit of the charging station power is 22 kW. Our setup and control concept is compliant with ISO 15118 [9]. Furthermore, a 10 kWp PV system and a German Federal Office for Information Security (BSI) compliant metering system were installed. The BSI designed a secure architecture for metering services and the controlling of decentralized consumers and producers. This architecture is about to be rolled out and will become mandatory for residential buildings over the next ten years [10, 11]. Thus, our approach meets national requirements, and at the same time we implemented international standardized communication protocols to ensure a wide applicability. Finally, the modular software design allows easy customization for similar use cases.

2.1 Energy management

All communication and control tasks are performed by the Building Energy Management System (BEMS). A connection between the BEMS and the DSO is sustained via the widely used IEC 61850 [12] communication standard. Indeed this direct communication channel aims to be used by the DSO in order to communicate a schedule of grid power limits. This can be applied in times of expected congestion of the local distribution grid in order to enforce grid usage of the individual user below a certain threshold.

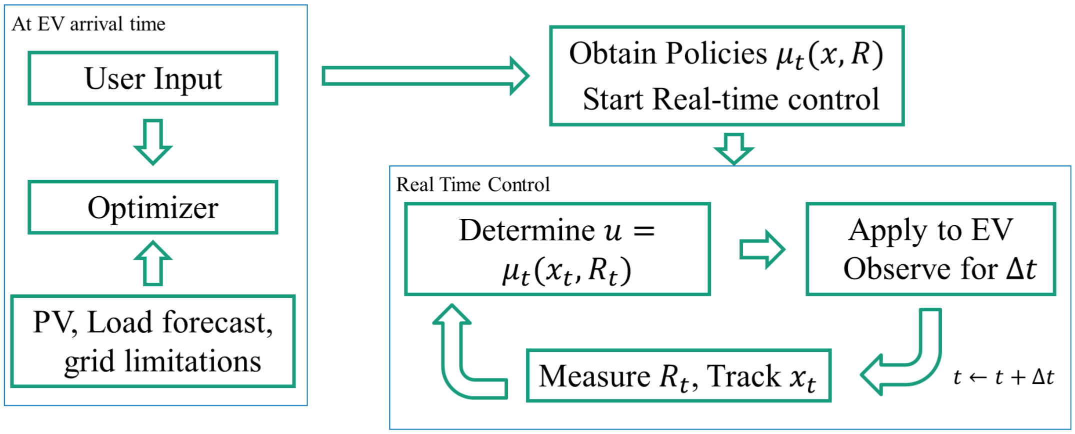

Figure 2: Control concept with real-time control unit. A schedule of charging policies μ is computed at an initiation of a charging process. In real-time measurement SoC x and residual generation R is measured periodically to determine the optimal charging power u.

When an electric vehicle is connected to the charging infrastructure a new charging process is initiated. The user can choose between an immediate uncontrolled and a controlled charging via a web user interface. If controlled charging is selected, the expected departure time and the current state of charge as displayed in the EV's user interface have to be supplied using a Web-UI of the BEMS. Then, an optimized charging schedule is computed by the BEMS based on an external PV forecast service and a household load forecast using a persistency approach.

2.2 Control Concept

In a previous research project [13], we implemented an open-loop controller based on a mixed integer optimization approach [5]. Within this previous implementation, an optimal charging trajectory is obtained based on the PV and the load forecast. Then, this power schedule is sent to the charging infrastructure. In order to mitigate model plant mismatch regarding the state of charge (SoC) at the end of the scheduled charging process, the EV is allowed to charge with the last power set value until fully charged.
In the current research project *C/Sells* [3], we extend this control scheme to include a real-time correction module. To this end, an optimizer based on lookup policies is implemented. When the user initiates a new charging process, a policy schedule is generated instead of a fixed charging schedule as in the open loop approach. The real-time control unit as shown in Figure 2 can use this policy schedule to determine and update the optimal charging power. Also, the policy for the respective time is used to determine the charging power given the currently measured residual generation and the current SoC. The protocol ISO 15118 will feature polling the SoC from the EV. For the field trial neither charging infrastructure nor an EV implementing this standard were available. Therefore, a fixed efficiency model as in (4) with an assumed efficiency of $\eta = 90\,\%$ is used to estimate the state of charge based on the measured charging power.

3 Policy Based Optimization

As opposed to the previous open loop control concept, the proposed optimization approach considers residual PV forecast uncertainty and the system's response to a realization of the PV and household load in the optimization procedure. We therefore perform an optimization in policy space. A policy in this sense is a mapping $\mu : (x, R) \mapsto p^{\text{charge}}$ from the measured state of charge x and the residual generation R to an optimal control action p^{charge}. The goal of the optimization algorithm is to find the optimal policy based on the current forecast for PV and load as well as the user's input of departure time.
For the optimization, we model our system as a household load, a PV generator and the battery of the electric vehicle. The subsystems are connected to the public distribution grid via the household bus system. Charging losses apply due to the limited efficiency of the charging station and the EV battery.

The grid connection can provide power up to a certain limit ensured by a fuse. As discussed, the form of a possible intervention of the grid operator is not yet clear. We chose to model this measure as a time series of power limits. This schedule is known prior to scheduling. An ad-hoc limit given by the grid operator without previous notice may be modeled statistically and can be included in the stochastic handling of the forecasted available power.

In this setup, a two-stage optimization scheme is developed. An optimization module described in the following is used to generate policies. These are then used in the real-time controller described in Section 2.2.

We discretize the time until the departure of the EV into N equidistant timesteps each with a length of Δt using the index k to denote a variable at the k-th timestep. When the EV is connected to the charger and the charging process is initiated by the user, for each timestep k, a policy μ_k is calculated. The policies can be used as a lookup table to determine the optimal charging power p^{charge} based on the realtime measurement of residual generation and SoC.

The policies are calculated using dynamic programming [14]. This algorithm starts at the end of the optimization horizon (at timestep N) and iterates backwards until the connection time is reached. In each iteration, a minimal cost-to-go is calculated for a discretized state space spanned by the residual household load and the state of charge of the battery in that respective timestep.

For this calculation, we start with terminal costs g_N for the SoC at the end of the optimization horizon x_N

$$g_N(x_N) = -x_N \cdot C_{\text{Bat}} \cdot c_N \tag{1}$$

with the terminal cost coefficient c_N and battery capacity C_{Bat}. The terminal cost penalizes uncomplete charging of the EV battery at the end of the horizon.

In addition to the terminal costs, we define transition costs that depend on the source of electricity used for charging (PV or grid). Power from photovoltaic generation p_{PV} is primarily used to cover the household load p_{Load}. We therefore define the residual generation $R = p_{\text{PV}} - p_{\text{Load}}$ as the power remaining for EV charging.

The power flow at the household grid connection point p_{G} can be determined from the residual generation and the charging power of the electric vehicle in the k-th timestep

$$p_{\text{G}}(p_k^{\text{charge}}, R_k) = p_k^{\text{charge}} - R_k \tag{2}$$

Note, that negative values for the grid power denote power fed into the grid (PV power generation exceeds the needs for household load and EV charging) and positive values denote grid supply. With this, the transition costs are determined by

$$g_k(p_k^{\text{charge}}, R_k) = \begin{cases} c_{\text{f}}\, p_{\text{G}}(p_k^{\text{charge}}, R_k)\Delta t & \text{if } p_{\text{G}}(p_k^{\text{charge}}, R_k) < 0 \\ c_{\text{s}}\, p_{\text{G}}(p_k^{\text{charge}}, R_k)\Delta t & \text{if } p_{\text{G}}(p_k^{\text{charge}}, R_k) > 0 \end{cases} \tag{3}$$

where c_{f} and c_{s} denote the reward for grid feed-in and the costs for additional electricity supply respectively.

The system state is modeled in terms of the SoC of the EV battery at timestep k denoted by x_k. For the purpose of our optimization, the evolution of x_k is modelled using a simple efficiency model

$$x_{k+1} = f^x(x_k, p_k^{\text{charge}}) \equiv x_k + \frac{\Delta t}{C_{\text{Bat}}} \eta\, p_k^{\text{charge}}, \tag{4}$$

where $\eta \in [0, 1]$ denotes a constant efficiency of the charging electronics.

The feasible set of the charging power is denoted by the symbol

$$\mathcal{P}_k(R_k) = \{p | p_{\min} \leq p \leq p_{\max} \wedge p_{\text{G}}(p, R_k) \leq P_k^{\text{Limit}}\} \cup \{0\} \tag{5}$$

where the charging power must stay between the upper and lower limit of the charging infrastructure and the technical limits of the EV. In addition, the limit of grid supply P^{Limit} may not be violated due to the charging of the EV.

Table 1: Simulation results

Method	Uncontrolled	Open Loop Controller	Real-time Controller	Real-time Controller w. Grid Limits
Σ	6.3 %	33.9 %	36.9 %	34.3 %

With these definitions, we can formulate an optimization problem for the charging process

$$\min_{\mathbf{x},\mu} \quad \mathop{\mathbb{E}}_{\mathbf{R}} \left(\sum_{k=0}^{N-1} g_k(p_k^{\text{charge}} = \mu_k(x_k, R_k), R_k) + g_N(x_N) \right) \tag{6}$$

subject to

$$\begin{aligned} x_{k+1} &= f^x(x_k, p_k^{\text{charge}}), && \forall k = 0...N-1 \\ 0 \le x_k \le 1 \quad & p_k^{\text{charge}} \in \mathcal{P}_k(R_k) && \forall k = 0...N \\ x_0 &= x_{\text{init}} \end{aligned}$$

where a boldface setting of a variable denotes the timeseries over the complete horizon. In (6), denote the expected value of the costs with the symbol $\mathbb{E}$. It is calculated based on the forecast for the residual generation $\mathbf{R}$ using a Markov chain model. For an in-depth discussion of this forcast model and the applied solution algorithm see [15].

4 Results

In order to study the scheduling approach on a broad database and obtain suitable parameter settings for the field test, we set up the following computer simulation.

4.1 Simulation of the Charging Management

We used profiles from previous field measurements for photovoltaic generation and household load of one year. The PV generation profile is scaled to 10 kW peak power, the household load stems from a 4 person family household. Using the model described in [16], a usage profile for the EV was simulated assuming the use of the EV by a commuting adult. As in the field test, an EV battery capacity of 41 kWh is simulated. The minimum and maximum charging power were 5 kW and 22 kW respectively. Both optimization based approaches rely on a forecast for load and PV generation. The former forecast was generated with a simple persistence approach using the load profile on the same day of the previous week as a forecast. A PV forecast for the used PV profile was developed at Fraunhofer ISE and available for the simulation.
The simulation procedure follows the procedure in the real system (see Section 2.2). Schedules are calculated at the arrival of the EV and subsequently processed by the real-time control.
For the evaluation of the simulation, we use the PV self-consumption ratio of a charging process

$$\Sigma = \frac{E_{\text{PV}\to\text{EV}}}{E_{\text{Charged}}} \tag{7}$$

which is defined as the ratio between the energy that is charged from the PV to the EV $E_{\text{PV}\to\text{EV}}$ and the energy charged to the EV overall E_{Charged}.
The results of our simulation study are shown in Table 1. The self-sufficiency of the charging process can be increased significantly by controlled charging. Even with the open loop controller, the Σ is increased. This is mainly due to shifting the charging periods to times of expected PV generation and reducing the average charging power compared to the uncontrolled case. The lower charging power leads to a longer duration of the charging process and therefore to potentially more PV-generation during that time period.

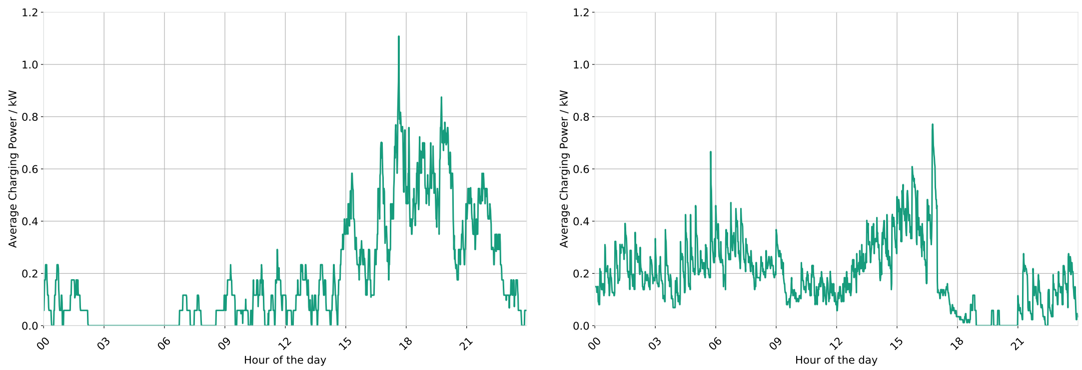

Figure 3: Charging power in simulation over the course of the day averaged over the year. In the uncontrolled case (left hand side), a high fraction of charging is done in the evening. Applying controlled charging and an off-period from 5 to 8 PM reduces the charging load during those times significantly without generating an additional peak demand. The overall charged energy remains the same for both approaches.

With the real-time controller, the self-sufficiency can be increased further. Here, the charging power is still decreased to allow PV energy in charging. Furthermore, through the real-time update, the charging is postponed when the residual generation is below a certain threshold determined by the optimization algorithm.
It is expected that the electrification of the transport sector together with uncoordinated charging behavior will lead to demand peaks in the late afternoon. Here, controlled charging as presented can be reasonable approach to mitigate these peaks without costly grid reinforcements. Currently, the option is discussed to allow the DSO to communicate off-periods to owners of charging infrastructures. During these off-periods no charging of electric vehicles from the grid would be possible. These off-periods do not exists in practice yet. In order to simulate the ramifications on our scheduling approach, we assume a daily off-period during the expected time of high demand between 5 and 8 PM. This period can be considered by the optimization generating policies that respect the limits. The results for the PV sel-consumption using this controller can be found in Table 1. During the off-period, charging can only be performed when the PV generation exceeds the minimum charging power. This leads to the small PV self-sufficiency losses as the PV generation below this threshold can not be used for EV-charging.
In Figure 3, the average charging power over the course of the day is shown for the uncontrolled case and with the state feedback controller with the off-period in effect between 17:00 and 20:00. It can be seen, that the charging processes are spread out over the night away from the off-period in the early evening. Furthermore, more charging is performed during day hours when power is generated from PV. However, due to the driving patterns, the potential is limited.

4.2 Preliminary Field Test Results

We deployed the system detailed in Sections 2 and 3 to a field test site located in a residential neighbourhood close to Stuttgart, Germany. Three houses are equipped with a charging station and a 10 kWp PV generator as well as a Reanault Zoe electric vehicle. Currently, the field test systems are controlled using the open loop controller presented in Section 2 and in a previous publication [13] during a test phase.
From the three field test sites, only household 2 regularly selected the option for controlled charging. Figure 4 shows the mean power of the charging infrastructure over the day. Compared to the other households, the charging processes in household 2 happen during the day more often. In general, more PV is available during those times. The charging power during the evening is lower in household 2. A higher load for the grid is expected especially in the early evening when commuters return and start charging simultaneously. This more grid-friendly behavior may be due to the usage of the open loop controller, shifting the charging processes to times with higher PV. An in-depth analysis considering the actual driving patterns of the residents will be performed.
From the household that regularly selected controlled charging, we show two charging profiles recorded in early 2020 in Figure 5. In the plot on the left hand side, the two main mechanisms of inceasing PV self-consumption can be seen. Compared to uncontrolled charging, the power used for charging is much lower close to the minimum charging power prolonging the charging process. In the left plot, over the duration of the charging process, the sun was partly covered by clouds. However, here the scheduled

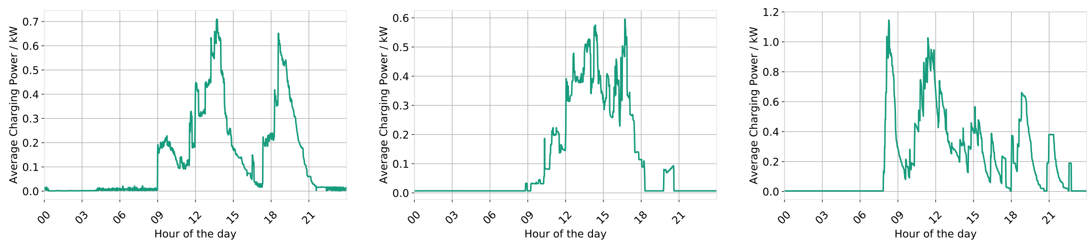

Figure 4: Measured charging power in field test. Plots show the average charging power over the course of the day. Household 1 (uncontrolled charging) on the left, household 2 (open loop controller) in the middle and household 3 (uncontrolled charging) in the right plot.

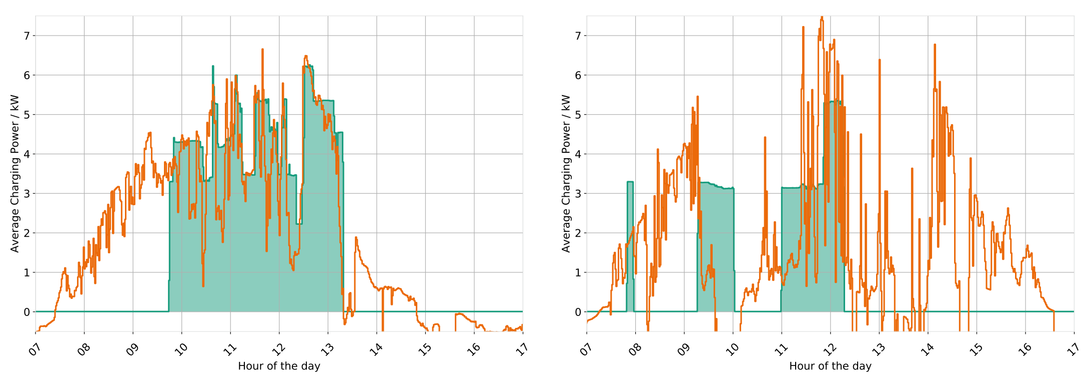

Figure 5: Measured charging profiles in the field test from February 2 (left plot) and March 3 2020 (right plot). The residual PV generation and charging power are plotted in orange and green respectively. A filled green area below the orange curve shows charging from PV while filled area above the orange curves symbolizes charging from grid. In the field setup, the open loop controller is deployed and was used to generate these charging profiles.

charging profile lined up with the alternations of the residual generation and the EV was charged with the available power from PV generation.
The shortcoming of the open loop algorithm can be seen between 10 and 11 AM in the plot on the right hand side. No charging happens when PV power is generated and charging starts although the residual generation drops to zero and below. With the open loop controller, the charging process is scheduled at the arrival time of the EV based on the forecasted residual generation. However, the actual residual generation may differ, especially on partly sunny days like shown.
Here, the proposed control approach using the real-time control module can increase the PV self-consumption. Based on the policies, the charging power is adapted to the actual measurement of the residual generation. This updated control method is currently deployed to the field test systems.

5 Conclusion and Outlook

With the increasing number of electric vehicles, charge management will become a more important tool to mitigate problems in the distribution grids. We developed and demonstrated a software framework that can be used to that end in a field implementation. It has been shown, that this approach is suitable to increase PV self-consumption while simultaneously adhering to grid limits of DSOs. An advantage of our approach using dynamic programming is the arbitrary form of system modelling. Therefore nonlinear effects can be modeled further. This will be used to improve the algorithm further with the findings from the ongoing field test. These findings could include a better understanding of battery behavior in different SoC ranges or proper penalizing of charging behavior that fosters battery aging.

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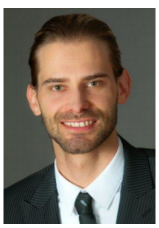

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