Evolutionary Computation Enabled Controlled Charging for E-Mobility Aggregators

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***Abstract*—Optimal integration of electric vehicles (EVs) into modern power grids plays a promising role in future operation of smart power systems. The role of aggregators as e-mobility service providers is getting investigated steadily in recent times and forms a fruitful ground for control of EV charging. Within this paper, a policy-based control approach is shown that applies an evolutionary simulation optimization procedure for learning valid charging policies offline, that lead to accurate charging decisions online during operation. This approach provides a trade-off between local and distributed control, since the centrally applied learning procedure ensures satisfaction of the operator's requirements during the learning phase, where final control is applied decentrally after distributing the learned policies to the agents. Since the needed information that the aggregator has to provide to the agents is crucial, further analysis on the achieved control policies concerning their data requirements are conducted.**

I. Introduction

Many investigations have been conducted in actual literature in order to find methods for computing optimal charging decisions of EVs [1] [2] for meeting objectives like peak-shaving, optimization of power quality metrics or maximal usage of power from renewable sources. Especially the interaction of renewable supply plants and electrified vehicles is seen as important concern. At the same time, both sides show strongly nondeterministic behavior, making their cooperation a challenging task. In this context, the approach of implementing additional service-suppliers between customers and the traditional distribution system operators (DSO) has lead to concepts of e.g. aggregators or e-mobility providers. These intermediate operators have to role of bundling numerous distributed appliances (like EVs) for making their services - like for instance demand side management - available to DSOs. On the other hand, they offer new services to the customers and enable a more comprehensive data-exchange between customers and DSO. For enabling such services making use of controllable EV charging loads, computational methods have to be developed that are capable of finding valid charging decisions which satisfy both stakeholders' interests. Therefore, a policy-based approach for optimal control will be demonstrated, that uses evolutionary algorithms for finding optimal charging policies of an electric car fleet within a given system. In order to overcome the high quantity of controllable devices (EVs) in the considered system, policy-based control is introduced as tradeoff between central and distributed optimization, making this approach suitable for large-scale applications using intermediate operators. This approach uses a simulation-based evolutionary offline learning procedure for finding performant charging policies, that lead to valid charging decisions during operation in real time.

The rest of the paper is organized as follows: section 2 introduces the general aim of controlled charging for EV fleets, where a literature overview is stated especially with respect to concepts of intermediate operators like aggregators. Section 3 continues by formulating controlled charging as optimization problem that can be solved using simulation-based evolution of charging policies with metaheuristic algorithms. The application of this approach to intermediate operators concepts is further discussed, enabling the control of EVs in a practical test scenario in section 4. Since the IT-architecture of such a system is crucial to its implementation, the evolved policy control is further analyzed in order to minimize the needed data exchange between customers, intermediate operators and DSOs in section 5. In the end, section 6 rounds up the paper with concluding remarks.

II. Electric Vehicle Charging Control

A. General Issue

Various researchers investigated the problem of integrating fleets of electric vehicles optimally into electric distribution grids, where direct control of charging power is considered as advantageous for reaching optimal load characteristics [3] [4] [5] [6]. Beside the optimization problem itself and its computation, the modeling and integration of the individual and probabilistic behavior that mainly characterizes electric vehicle charging load is of special interest. Especially for optimization in probabilistic systems, simulation-based optimization with heuristic algorithms has been applied to various

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practical areas and will be the main approach within this work, as already discussed in [7]. Here, with probabilistic simulation models, the uncertain system can be modeled holistically consisting of traffic simulation, probabilistic models of renewable supply as well as the power grid simulation model, resulting in an optimization approach that enables full integration of the system's uncertainty into the heuristic search process.

B. Aggregators and E-Mobility Providers

The idea of managing a huge amount of manifold load devices within an electric grid seems to be promising for different stakeholders within power systems and is a hot topic in smart electric grids research. For making the management of numerous distributed loads available, the concept of using aggregators has been introduced. Aggregators therefore operate between customers and the traditional DSO, building a new player in the grid or operating as part of the DSO. The application of aggregators has been proven to be suitable for enabling controlled electric vehicle charging [8] [9], where this additional player recruits controllable EVs and sells their services cumulated to higher-level stakeholders like power grid operators similarely to virtual power plants [10]. Beside aggregating services, additional tasks like billing or the monitoring of entire electric fleets can be performed by these new intermediate operators.

In addition to those in literature already established aggregator models, further software-as-a-service providers come into play at the same point, which try to build an intermediate player between EV customer and power grid operator. They all have in common that they provide ICT infrastructure for making EV-services available for both sides. For the rest of this paper, all these concepts including aggregators shall be adressed using the term "intermediate operator", which describes their common aim of creating a new interface between end-customers and traditional DSOs, while providing ICT infrastructure for enabling new services for both sides.

C. Control Architecture: Central vs. Distributed

The decision whether to implement a central or a distributed control architecture seems to be crucial for smart grid implementations [11]. A purely distributed control mechanism where for example local controllers could adapt charging power using local voltage and/or frequency measures would certainly be the easiest way for system-wide implementation. At the same time, with such an architecture the grid operator would have no direct influence on controllable loads for regulating the distribution system, which is shown to be necessary as stated above. But a purely central approach where decisions are computed for numerous distributed devices is hard to design from an ICT point of view, yielding computational decision problems that are barely tractable for being executed in real-time operation. Therefore, a computational approach is needed that builds a tradeoff between central and distributed decision making. From a communications point of view, it must be possible to integrate many hundreds or even thousands of EVs [10]. Here, intermediate operators build a convenient concept where suitable computational methods have to be implemented that are capable of final decision-making, where both interests of EV users as well as grid operators have to be satisfied appropriately.

III. Optimization Approach

For realizing the required tradeoff between centralized and distributed control, a policy-based optimization approach is applied. This approach has been discussed extensively considering its computational principles in [7] [12] and shall now be implemented to intermediate operators. In order to state its foundation, the respective optimization problem as well as the evolutionary computation approach for tackling it shall be discussed as follows.

A. Problem Statement

For an electrified fleet of vehicles within a given distribution grid, $Pc = [Pc_{1,1}, ..., Pc_{i,n}]$ gives the vector containing active charging power values of each EV n at time step i over a fixed time interval in advance considered for charging control. Each EV has to be provided with a defined amount of energy with respect to its daily demand $\sum_{i=1}^{24} P_{i,n} * \Delta t \geq E_{min}$ throughout the time interval. This constraint is sufficient assuming that batteries are big enough and the one-way distance of an EV does not lead to insufficient SOC (state of charge).

Electric load caused by charging processes may endanger power grid security, therefore, constraints are considered that ensure secure distribution grid operation within each time step i, satisfying the DSOs interests. Steady-state security constraints according to [13] are integrated for restricting power flows throughout the grid by: ensuring bounds for generator real and reactive power output $P_{G_j}^{min} \leq P_{G_j} \leq P_{G_j}^{max}$ and $Q_{G_j}^{min} \leq Q_{G_j} \leq Q_{G_j}^{max}$, over all buses $j = 1, ..., J$. Branches' power flows shall be restricted to $P_l \leq P_l^{max}$ as well as the voltage deviation that is constrained by $V_j^{min} \leq V_j \leq V_j^{max}$ for all power lines $l = 1, ..., L$.

Satisfying the defined constraints during optimization, the objective function is defined of minimizing financial costs of power supply: $min \sum_{j=1}^{J} C(Ps)$. Herein, Ps is implicitly given by adding Pc to the remaining base-load of the system as well as power losses, that aggregated build the total load which has to be supplied.

Finally, when achieving an appropriate solution Pc for controlled charging of all n EVs, both interests of users as well as the DSO are considered through satisfaction of the formulated constraints. The objective function of minimizing financial costs of power supply additionally can be advantageous for both stakeholders, depending on the finally applied business models which shall not be aim of this paper.

B. Policy-Based Approach

Considering related works on integrating fleets of EVs into distribution grids through direct control, the usual approach concerns implementing an optimization procedure for computing charging decisions based on forecasted system behavior in advance. Thus, the solution Pc is computed directly and represents a static vector, being distributed to the controllable EVs. However, in a stochastic and dynamic system such as an electric power grid faced with nondeterministic renewable supply, it is more appropriate to make decisions as they come up. Thus, reacting to dynamic situations very quickly, keeping full flexibility during runtime. This can be seen as the general aim of so called optimization over time.

P. Werbos investigated methods to perform this kind of control optimization in any engineering domain, namely Aproximate Dynamic Programming (ADP), a flexible and scalable technology which is stated as being suitable for future smart electric grid applications as well [2]. Based on ADP, the family of Adaptive Critic Designs (ACD) merges various approaches that learn neuro-controllers consisting of a set of artificial neural networks (ANN). Coming from Werbos' investigations, Venayagamoorthy [14] and Momoh [15] investigated extensions for handling optimal control problems in electric power system engineering.

Approaches related to ACD mainly come from optimal control theory, hence, aim at approximating the Hamilton-Jacobi-Bellman equation supported by computational intelligence techniques. Building an alternative approach for optimization over time, the evolution of flexible control policies using metaheuristic algorithms as demonstrated within this work shows validity for electric power engineering problems as demonstrated later. Applying a simulation-based evolutionary learning approach, policies of less-complex and interpretable mathematical structure are evolved, rather than neurocontrollers composed of several ANNs and their interconnections as in ACDs. These policies enable thorough analysis as discussed later on.

The applied policy-based approach has been discussed in its foundations in [7] and [12]. Here, each agent (EV) receives a flexible policy that provides valid actions for charging control, thus, makes it react to its environment individually and dynamically during operation, but in a globally optimal manner when deciding about the agent's charging. This policy is principally the same for all agents, but using individual data from agent's environment, it leads to agent-specific charging behavior. Thus, the decision-making process is executed locally in a distributed manner. But these flexible policies are designed and optimized offline using an evolutionary learning procedure for meeting global objectives, ensuring the satisfaction of grid-wide interests of the DSO respectively the intermediate operator at runtime.

The basic concept is indicated in Figure 1, where the policy evaluation is indicated for a given EV that arrives at an arbitrary location which is equipped with charging infrastructure. Principally, the optimized policy which finally decides the EV's charging power at a given time step is synthesized from atomic rules that consider agent-specific parameters from its environment. These rules are used to compute information for evaluating EVs power demand as well as the state of its environment. Here, three different parameter classes can be defined: global parameters are used to adress grid-wide interests considering for example total balance of demand and supply, while local parameters directly concern grid conditions in the neighbourhood area. Agent specific parameters finally ensure the EVs individual needs for guaranteeing user satisfaction.

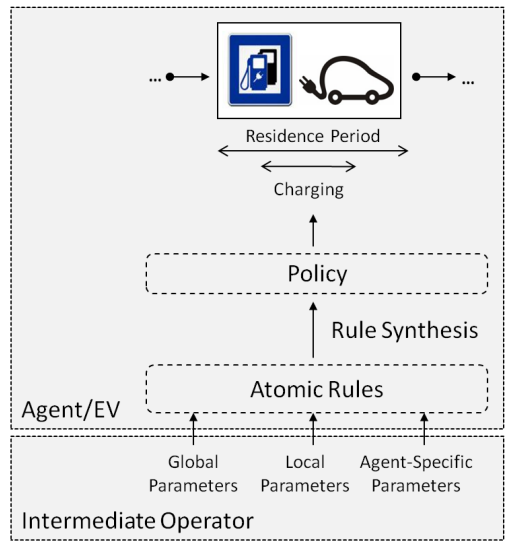

Fig. 1. Principles of Policy Control

For the design and optimization of policies, an evolutionary learning procedure is proposed, where the evaluation of a solution candidate is executed through simulation. The advantage of this approach is that it is possible to gather the whole complex system as well as its partly stochastic behavior within a simulation model, which would not be possible in form of any mathematical closed-form representation. This concept is shown in Figure 2.

As stated before, each policy is designed based on atomic rules that get synthesized to the final decision-making policy. The atomic rules therefore consider all relevant information through their parameters, that are needed for making valid charging decisions which satisfy both the EV user as well as the DSO. All applied atomic rules are listed in Table I.

Synthesizing these rules to a final policy according to [7] and [12], the final flexible policy is designed such that it ensures global optimal behavior of all EVs even if it is executed locally, making its application attractive to intermediate operators. For exemplary reasons, Figure 3 shows a simple synthesized policy, which would take the EV's estimated time to departure, the mean charging rate of all other EVs as well as the actual price signal in order to make the charging decision. The real-valued result of evaluating the policy for

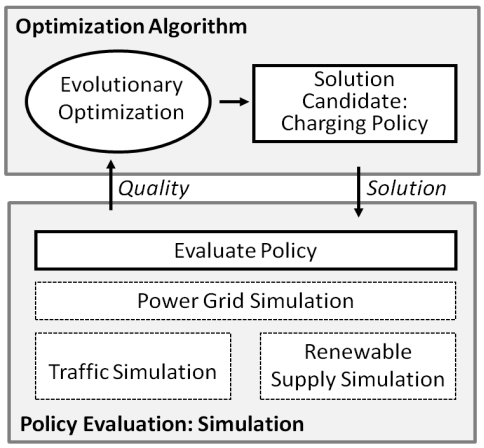

Fig. 2. Optimization Architecture

TABLE I
FORMULATION OF SIMPLE RULES

Rule	Acronym
Agent's Residence Time So Far	RT
Agent's Estimated Time to Departure	ETTD
Agent's Passed Residence Time	PRT
Actual Irradiance	AI
Past Irradiance	PI
Estimated Irradiance	EI
Actual Wind Speed	AWS
Past Wind Speed	PWS
Estimated Wind Speed	EWS
Actual Base Load	ABL
Past Base Load	PBL
Estimated Base Load	EBL
Actual Price	AP
Past Price	PP
Estimated Price	EP
Temporal Distance to Peak Load	DTP
Mean MVA Rating Connected Branches	MMVA
Number of EVs at Agent's Bus	NREVB
Mean Number EVs at Agent's Bus During PRT	MNREVB
Number of EVs Charging Globally	NREVC
Number of EVs Charging at Agent's Bus	NREVCB
Mean Charging Rate all EVs at Time $i-1$	MCR
Mean Charging Rate at Agent's Bus at Time $i-1$	MCRL
Agent's Already Charged Energy	ACE

agent n at time step i further describes the charging rate of the respective EV restricted by its maximum available charging power. In this case, the atomic rules "ETTD", "AP" and "MCR" are synthesized using a structured tree representation. Applying genetic programming [16] with HeuristicLab [17], policies represented by structured trees can be designed and optimized in an evolutionary process. A more thorough description of this concept of charging control can be obtained from the referenced literature and shall not be the scope of this paper. However, for subsequent comparisons a simpler learning approach is applied as well according to [7], where policies are synthesized using linear combination of rules rather than evolving a structured tree. Here, the evolutionary procedure optimizes weights of all rules within the linear combination.

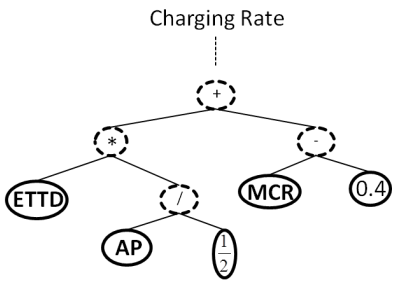

Fig. 3. Exemplary Policy

C. Holistic Consideration

This approach for optimized control of EV charging shall now be implemented to the concept of intermediate operators, stating its practical ability for large-scale applications.

1) Tradeoff Central vs. Distributed Control: The concept of using optimized policies offers a suitable tradeoff between centralized and distributed control: the policies are executed individually for each agent during runtime, enabling flexible and dynamic charging decisions tailored to the agent's local environment. On the other hand, the offline design- and optimization stage is executed centrally, considering the entire system's complex behavior within the simulation model. Thus, policy-enabled distributed decisions are guaranteed to fulfill globally optimized grid-wide behavior of the entire EV fleet with respect to the distribution grid. For better understanding, the timeline of policy-optimization and distributed control is highlighted in Figure 4.

This concept is further suitable for implementing it at any kind of intermediate operators. Since satisfaction of both end-user needs as well as electric power grid's operational requirements is guaranteed through the formulated constraints, an operation that fulfills both stakeholder's interests is enabled. In such a system, the central optimization of the policies could happen directly at the intermediate operator, or even at a higher stage comprehending multiple operators. During operation, the intermediate operator has to supply the needed data to the EVs for executing the policy. In this stage, no optimization has to be performed, since the learned policies provide optimal charging decisions to the EVs. In [7] the authors have verified, that this approach is capable of handling large-scale systems with thousands of EVs, where the problem size (i.e. number of controllable load devices like EVs) is less crucial concerning the computational effort for optimization.

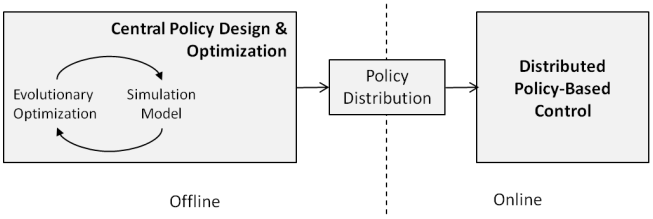

Fig. 4. Timeline of Policy Optimization and Control

2) Availability of Data: Since charging decisions are executed in a distributed manner, appropriate information needed for evaluating atomic rules is needed locally. Here, intermediate operators form suitable players for enabling these needed ICT abilities. In [18], researchers have already shown the sufficiency of existing IT infrastructures for the general aim of demand response. Using these infrastructures, the implementation of intermediate operators as software-as-a-service providers could offer this new kind of data exchange between traditional DSO and end-users, making policy-based distributed charging control attractive.
Further analysis on the needed data for enabling policy-based control will be discussed when applying it to a test scenario in the following section. Therefore, metrics computed based on the evolutionary learning procedure will be applied for thorough analysis of obtained policies.

IV. Application to a Practical Scenario

In order to guarantee generality of the approach as well as the final findings, a distribution feeder scenario is defined based on the IEEE 33-bus test feeder [19].

A. 33-Bus Radial Test Feeder

The 33-bus radial test feeder shows the application to primary distribution and is set-up as follows: the distribution network is modeled according to [19], where 1000 domestic customers are assumed to be served. As shown in the layout in Figure 5, eight photovoltaic power plants as well as two wind power plants are added to the grid in a distributed manner. The renewable generation capacity is assumed to be around 10% of the total supply. 300 EVs are modeled to exist within the system and get charged at different buses according to traffic patterns, the maximum charging load can come up to 10% of total supply. The black bar shows the slack bus, which is necessary for power flow calculation [13].

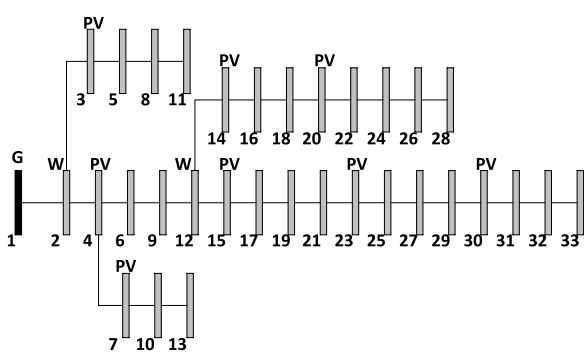

Fig. 5. Layout 33-Bus Testfeeder

1) Power Grid Simulation: Supply from renewable power plants is described by probabilistic models for sampling their estimated power supply during the considered time interval. Since supply from renewables is assumed to cause lower costs than from the remaining energy market, minimizing costs of energy supply as stated in the problem formulation causes a maximization of renewables' utilization. Additionally, it is assumed that all energy that has to be injected by the slack bus has to be imported from a higher power grid level and thus has to be bought at the spot market. Therefore, price data from the european electricity spot market is used for the cost function. Since prices tend to be high during peak hours, minimizing financial costs of power supply causes load-shifting to off-peak periods. All loads in the given grids follow common load profiles. The single loads satisfy these profiles with a normally distributed deviation of $N(1, 0.016)$, which is a common assumption in power flow studies.
For wind power modeling, the wind speed values at the plant sites are sampled from a probabilistic model in form of a Weibull-distribution as used in [20]. The sites' power curves are assumed such that each site reaches its maximum output at cut-off windspeed. With the sampled wind speed values, the resulting power output of the plant can be modeled using the plant's power curve. Photovoltaic-plants follow a typical daily generation profile that is randomized in each time step i with a standard deviation of 10%, being a common uncertainty in photovoltaic-supply forecasting.

2) EV Charging Model: Throughout the feeder, an EV fleet is modeled, where each single agent can produce a charging load of maximum 11kW, related to a three-phase charging process with 400V and 16A, as exemplarily possible when using a Mennekes VDE (Type 2) plug connector. Considering actual developments, this specification is seen to get a common standard throughout EV-manufacturers.
Representing individual electrified traffic of EVs from a power grid point of view, time interval and location of each EV is simulated when being parked to a charging station and thus being ready for charging. Therefore, a traffic simulation is added supported by real-world traffic data from an Austrian survey, where two central driving patterns are extracted for a week day: namely the pattern of full-time and half-time workers. For those patterns, different locations are considered for parking at home, at work and at any location in free time. Probabilities for the existence of a charging infrastructure are specified for each location, considered as a possible future infrastructure scenario from an actual point of view: each EV user has a domestic charging station. At work, with a probability of 50% an appropriate infrastructure is available. For locations where potential users remain in free time, this probability is assumed to be 25%.
For connecting the traffic simulation with the power grid simulation, the appropriate charging load at each location is than being correlated to a corresponding bus within the distribution grid model. In each simulation run, steady-state power flow computations are applied along a series of discrete time steps in order to verify the simulation's response (i.e. fitness of the policy) with respect to both the distribution feeder as well as the EV traffic simulation.

All parts of the model are realized as autonomous simulation components, building aggregated the problem

representation. The architecture of the model is illustrated in Figure 2 as discussed before. The simulation model itself consists of three components, including the distribution grid influenced by the probabilistic supply model as well as the traffic model which describes the behavior of EVs according to patterns [7]. $Emin$ is defined to be 8kWh over a period of $i = 24$ hours, which yields a mean driven distance of 40 kilometers per day for a common EV.

A more detailed description of the modeling approach can be obtained in [7] and would be too extensive at this point.

V. Analysis of Control Strategies

Finally, evolution strategies (ES) as well as genetic programming (GP) are chosen for learning valid policies based on the simulation model. Principally, two algorithmic approaches are applied for learning policies out of atomic rules: The first approach optimizes real valued weights for all atomic rules and combines them linearly [7]. While these weights are optimized by ES, the second approach uses GP for learning a structured tree that combines atomic rules with arbitrary mathematical operators as exemplarily shown in the previous section. A thorough description on the learning approaches as well as the algorithm configurations can be obtained from [7] [12].

For illustration of the functionality of the policy-based charging control, Figure 6 indicates the mean charging power over a simulated day that results from a learned policy which is distributed to all simulated agents. The dashed black line indicates the mean power over all EVs (300), while the bars show the charging power of two arbitrarily chosen agents out of this set. While one EV (black bars) obviously satisfies the pattern of a full-time worker, where charging is dispatched to the night hours, the other EV (white bars) uses attractive supply from photovoltaics for charging around midday. From this illustration it is clearly observable, that even if all EVs are controlled by the same policy, it allows inidivual charging behavior tailored to the agents' needs, where decisions are performed online in a volatile environment. Additionally, the resulting charging power is very low in each time step compared to the maximum power of 11kW, since the long remain times of EVs are used efficiently for low-power charging, making this kind of control attractive from a power grid operation point of view. The referred literature [7] [12] offers broad discussions on the achievable charging control with policies, deeper considerations shall now be performed concerning the structure of learned policies.

A. Impact of Single Rules

Since an evolutionary learning procedure is applied for building (synthesizing) the policies, analytics on this procedure can be taken for analysis. For the optimization of real-valued linear weights, these weights are shown in the second column of Table II. While atomic rules are normalized to a range [0,1], the appropriate achieved

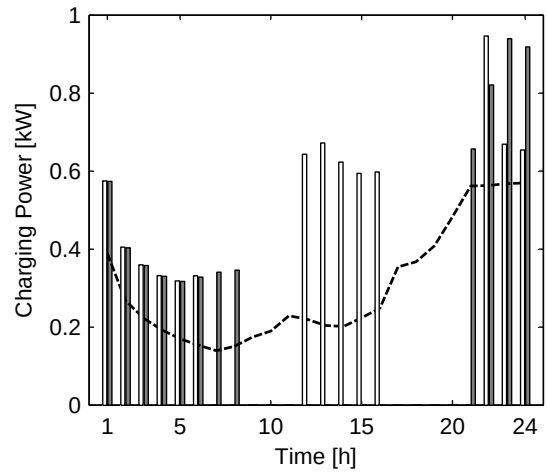

Fig. 6. Resulting Charging Power in Simulated Scenario

weight of each rule can roughly be interpreted as measure of "importance" to the charging decision. When learning policies with GP, an additional analysis is enabled: namely the so called variable impact [21]. This measure uses the frequency of used rules throughout the evolutionary optimization process, where rules of higher "importance" are assumed to be more successful during the evolution than others and thus occur more frequently.

For the herein analysis, the best found 10 policies are analyzed for each approach. In Table II, the second column shows the mean weight of each rule, while the third column lists the median variable impact rank of each rule throughout these 10 policies. The column "class" indicates to which kind of information this rule can be related. The class "Agent" comprises all information from the single EV itself, while "Other Agents" considers knowledge about the other agent's behavior. "Demand" addresses rules that describe the global load situation in the power grid, "Power Grid" addresses physical measures on the distribution equipment, while the "Supply" and "Price" classes describe the actual situation from the generation side.

Considering both the weights as well as the impact ranks, some observations can be derived: the most important information on the charging decision seems to stem from the agents' information, namely its remaining time (RT) or its already charged energy (ACE) - which seems to be reasonable since charging control has to satisfy the end-users' needs. Further, information on the base-load situation (like ABL) is ranked highly too for both metrics, which is necessary for the power grid operation for not violating power flow constraints. The general class of irradiance data is positioned quite in the middle of both ranking schemes, since it is directly coupled to the objective function of charging with lowest costs. Taking a look at Figure 6, a small peak in the middle of the dashed line indicates a clear tendency of charging with solar

TABLE II
RULE ANALYSIS

Rule	Linear Weights	Impact Rank	Class
RT	0.788	1	Agent
ACE	0.622	3	Agent
PRT	0.582	13	Agent
PBL	0.231	14	Demand
EBL	0.221	23	Demand
ABL	0.189	2	Demand
ETTD	0.121	15	Agent
MMVA	0.106	20	Power Grid
AI	0.096	4	Supply Solar
PI	0.094	12	Supply Solar
EI	0.052	21	Supply Solar
MCR	0.050	24	Other Agents
NREVC	0.049	17	Other Agents
PP	0.042	11	Price
AP	0.040	7	Price
NREVCB	0.038	10	Other Agents
AWS	0.034	9	Supply Wind
EWS	0.032	16	Supply Wind
MCRL	0.026	5	Other Agents
EP	0.026	18	Price
MNREVB	0.025	6	Other Agents
DTP	0.021	22	Demand
PWS	0.020	19	Supply Wind
NREVB	0.017	8	Other Agents

energy. However, for both ranking schemes, no class seems to concentrate at the lower ranks, making all information classes necessary for the charging decisions. Nevertheless, some single rules show both low weights and low variable rank (like PWS, DTP or EP), signifying that their information gets substituted by other rules and thus is of less importance.

B. Affected Data for Operators

The herein discussed policy-based control approach not only provides valid policies for charging control of EV fleets, but further allows the analysis of the needed information for applying them. With the above analysis, a clear statement is completed that shows which data are needed for making charging decisions from an intermediate operator's point of view, however, some data seem to be more important than others. Especially the top ranked classes concerning agents' information and demand data offer most important information and may be sufficient for simpler decision systems, while being able of both concerning EV users needs as well as power operation constraints.

VI. CONCLUSION

This paper showed a policy-based control approach suitable for operators like e-mobility aggregators. It unifies the advantages of centralized optimization with decentral decision making, where policies are learned offline through evolutionary simulation optimization that lead to valid charging decisions during online operation of individual EVs. These policies principally satisfy the EV user's needs, while considering power flow constraints for secure feeder operation. Since those policies are synthesized out of different information entities - so called atomic rules - variable impact analysis enabled by the evolutionary optimization was applied for verifying each rule's importance. This knowledge can further be used for building information systems for charging control of EV fleets.

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