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A Hierarchical Controller as an Alternative Multi-Objective EV Charging Manager

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***Abstract*—Smart electric vehicle (EV) charging typically requires the consideration of a multitude of objectives like (electricity) costs, carbon emissions, user request satisfaction, grid stabilization and other factors. These objectives are typically combined as a weighted sum over all individual objectives. While this is conceptually easy, finding proper weights and confirming that any specific set of weights correctly implements the decision maker's preferences is a great challenge, growing with every additional objective. This paper presents the implementation of an alternative approach, a hierarchical EV charging scheduler, which is utilized in a real-world setting to control the charging of EVs and a stationary battery at a company building. It employs a new scheduling approach where objectives are arranged in a hierarchy of priorities, providing a clear specification of the controller operation. The primary objectives of the scheduler are the maximization of the satisfaction of the EV's charging demands under load limit constraints and the maximization of the photovoltaics self-consumption. Additionally, the scheduler considers other practically relevant objectives, such as minimizing battery discharging. In experiments, it is demonstrated that the runtime of the scheduler scales well with an increasing number of considered EVs, and the working of the scheduler is illustrated on an exemplary use case.**

***Index Terms*—electric vehicles, charging control, linear programming, hierarchical optimization, multi-objective optimization**

I. Introduction

Controlled charging has been proposed as a way to reduce the cost and environmental impact of electric vehicle (EV) charging and to circumvent technical obstacles, such as transformer limits [1]. Various approaches for EV charging control can be found in the literature [2, 3], which consider different objectives including minimizing the peak load [4, 5], maximizing the satisfaction of EV charging demands under load limit constraints [6, 7], maximizing the self-consumption of photovoltaics (PV) production [8, 9], maximizing the provisioning of grid services [10, 11], and minimizing the electricity costs with help of trading on the electricity market [12, 13]. For a practical realization, it might be required to consider further objectives, like minimizing the amount of discharged energy to prevent unnecessary degradation of the EVs' batteries. Thus, a large number of objectives might be considered in the charging control. Since these objectives are typically conflicting, it is in general not possible to find a solution that optimizes all the objectives at the same time. It is only possible to find a solution that provides an optimal trade-off between the objectives. Moreover, it depends on the preferences of the system operator how the optimality of a trade-off is defined.

Expressing preferences in the objectives can be a difficult task for human decision-makers [14]. A common and simple technical approach to model preferences is to define a hierarchy of the objectives (i.e., following the notion that humans can state their preferences by ranking options [15]), where objectives at higher levels of the hierarchy are strictly prioritized over objectives at lower levels. In this case, a solution is optimal if it optimizes the objective at the highest level and if there is no other solution that improves one of the objectives at the lower levels without worsening one of the objectives at a higher level. This approach has been used to realize a linear programming (LP) based charging scheduler, which optimizes charging plans with respect to a variety of objectives and which is employed in a prototypical implementation of a charging control system at a company building in Germany [16]. The system controls multiple uni- and bi-directional charging stations used by employees, as well as a stationary battery. The present paper describes the concept and the implementation of this scheduler, which provides a practical solution for EV charging control.

The rest of the paper is organized as follows: In Section II we first analyze the problem of smart charging for multiple objectives from the end-user perspective. Section III then provides an overview of the scheduler and charging management system in which it is used. Section IV describes the LP model solved by the scheduler. Section V explains the hierarchical optimization approach. Section VI discusses experiments in which the runtime of the scheduler is evaluated and the working of the scheduler is demonstrated on an illustrative use case. Finally, Section VII provides a summary and conclusion.

II. Specifying a multi-objective controller

In most real-world settings in EV charging, several, often conflicting, objectives need to be considered. The operation of the controller is then strongly defined by the relative weighting of these objectives. The classic weighted sum approach uses a linear weighted sum of all objectives. Unfortunately, since the

different objectives are of different scales and might dynamically change over orders of magnitude, these weights are difficult to tune, and the proper operation of the system can only be verified in simulation. One approach to simplify this problem is to transform all objective values into the same range, for example, via a desirability function [17, 18]. Unfortunately, desirability functions also require a proper parameterization and might not be possible in all cases. Another approach was proposed in [19] where decision makers only have to provide rough importance scores (between 0% and 100%) for each objective. Here, a new approach is proposed that only requires a prioritization of objectives from the decision maker.

Figure 1 illustrates an abstracted controller definition problem. The control engineer (or operator) is trying to define the controller operation based on high-level instructions from the owner of the system (decision maker), who is often not familiar with the technical details. The conventional approach is to test the operation of the controller (typically, in simulation) for some combinations of weights until a (for the operator) satisfactory operation is reached. The resulting setting would then need to be communicated to and approved by the decision maker. Several problems arise in this approach, rooted either in the characteristics of human information processing, the complexities of the optimization process, or a combination of both (see also [20]).

1) Manual weight tuning requires time and cognitive effort, particularly with an increasing number of objectives. Hence, defining and understanding weight relations beyond a few objectives can potentially exceed human cognitive limits [21, 22].
2) Decision makers tend to rely too heavily on initial values (i.e., anchors), irrespective of real optimal values. This anchoring effect can distort the identification of the optimal solution [23].
3) The specification of weights could be subject to framing (i.e., how information is presented in terms of wording or order might affect decisions). For instance, the names of objectives might affect the choice of weights [24].
4) It is difficult to get a confirmation from the decision maker since the weights are barely interpretable.
5) There is no guarantee that the operation of the controller is as desired outside the tested conditions.
6) Any changes, like switching objective priorities, could require updating all weights.
7) Weighted sum approaches can also fail to observe essential requirements, for example, when lower performance in one objective shouldn't be balanced by higher performance in another objective.
8) Ultimately, there is a lack of transparency and interpretability in this approach, as specific features of any scheduler solution can hardly be mapped to specific weight settings, obfuscating the clear link between decision makers' choices and resulting charge schedules.

Therefore, this paper proposes a new approach, a hierarchical controller that strictly enforces a priority of objectives. This allows a clear translation of decision maker priorities and easy confirmation. Priorities can be changed easily, even while the system is active. The operation of the system is fully transparent leading to improved trust in the system.

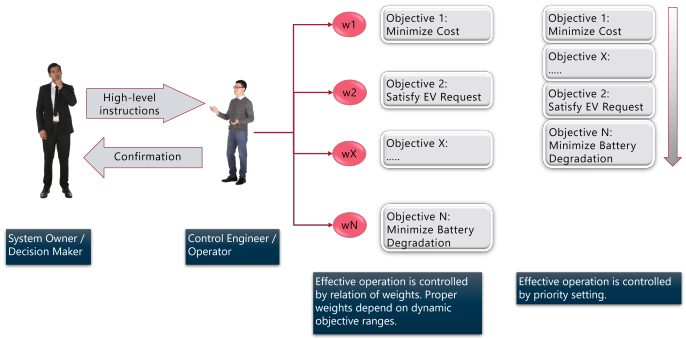

Fig. 1: Abstract view of the optimization setting. The operation of the charging controller is ultimately decided by the decision maker, but the specific implementation is done by an operator. For the standard weighted sum approach (middle), the operator has to specify a weight for every objective and get confirmation from the decision maker. For our proposed hierarchical control approach, the decision maker could directly specify the priority list of objectives.

III. Technical Overview

A charging management system (CMS) has been developed and deployed to control the charging at a company building in Germany equipped with a large photovoltaics (PV) system, a second-life stationary battery and multiple uni- and bi-directional EV charging stations [16]. At the point of writing, the CMS is still in operation and controls the charging at the building 24 hours a day, seven days a week. Figure 2 provides a rough overview of the CMS.

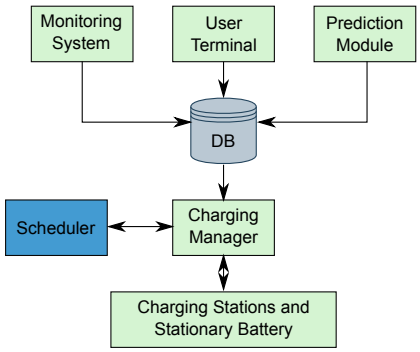

Fig. 2: Overview of the charging management system.

Its central component, called charging manager (CM), retrieves status information from the charging stations and the stationary battery. In particular, it retrieves information about connected EVs, such as their states-of-charge (SOCs) and maximum charging powers. A monitoring system stores records of the building's energy consumption and production in a database. A large part of the monitoring data recorded

between 2018 and 2023 has been made publicly available [25]. A prediction module predicts the future base load and PV production of the building and also stores the prediction in the database. Over a user terminal, EV drivers specify their departure times and target SOCs, which are stored in the database as well. Based on the information on the system's current state, the prediction of the future, and the users' charging requirements, the CM periodically formulates scheduling requests, sends them to the scheduler, and the scheduler returns a charging plan. The CM sends control signals to the charging stations and the stationary battery to control the charging according to the plan computed by the scheduler. The control signals are sent at a frequency of 10 seconds. The scheduler is called with a frequency of one minute. Thus, the charging plan is updated every minute to be able to react to unpredicted changes in the system's state.

The main goal of the control is to satisfy a predefined load limit (where the load consists of the base load of the company building and the charging load minus the PV production), while maximizing the satisfaction of the EVs' charging demands according to the specifications of the EV owners. More precisely, the 15-minute average load should be kept under the predefined limit because the company has to pay more than 200 Euro peak load charges per kW of the yearly 15-minute average peak load. The EVs or users are categorized into VIPs and non-VIPs[1], and the charging control should prefer VIPs over non-VIPs. A further goal of the control is to maximize the PV self-consumption (or to minimize the grid consumption, respectively) to reduce energy cost and carbon emissions. Unnecessary discharging of the EVs and stationary batteries should be prevented, and it is desired that the EVs and stationary batteries are charged as much as possible—even higher than their targeted SOCs—since it is assumed that this is in the interest of the users. Furthermore, EVs and stationary batteries should be charged as fast as possible to avoid that charging demands of EVs arriving in the future conflict with the charging plan for the currently plugged-in EVs and the stationary batteries. The stated requirements for the charging control result in several objectives for the scheduler. In total, there are the following seven objectives:

1) Maximize the satisfaction of target SOCs of VIP EVs
2) Maximize the satisfaction of target SOCs of non-VIP EVs
3) Minimize the grid consumption (to maximize the PV self-consumption)
4) Minimize the discharging of EVs
5) Minimize the discharging of stationary batteries
6) Charge EVs as fast and as much as possible
7) Charge stationary batteries as fast and as much as possible

The satisfaction of load limits and of target SOCs of stationary batteries are treated as hard constraints, and thus, they are not listed as objectives. The objectives of charging EVs as fast and as much as possible are combined into one objective since they do not conflict with each other. Analogously, the objectives of charging stationary batteries as much and as fast as possible are combined. Conflicts between objectives are handled with a hierarchical optimization approach. This requires the definition of a clear hierarchy of the objectives, where the first objective in the hierarchy has the highest priority, the second objective in the hierarchy has the second highest priority and so on. By default, a hierarchy analogous to the order in which the objectives are listed above is considered. Thus, per default, the satisfaction of the VIP EVs' requirements has the highest priority, followed by the satisfaction of the non-VIP EVs' requirements, and so on. However, the scheduler provides the flexibility to exchange objectives in the hierarchy or to remove objectives from the hierarchy.

The scheduler is implemented as a standalone service, which provides a REST (Representational State Transfer) interface over which a charging manager can send schedule requests and receive the resulting charging plans. This modular design would allow to use a single scheduler instance for the computation of charging plans for multiple charging managers at different sites. The frontend of the scheduler is implemented in Python. Initially, the backend for the actual calculation of schedules was implemented in C/C++. However, meanwhile, the backend has been ported to Python to achieve a better maintainability in exchange for a slight drop in performance. The problem of computing a charging plan with respect to the above-listed objectives subject to different constraints is formulated as a linear programming problem, which is solved with the free solver SCIP [26].

IV. Linear Programming Model

This section describes how the scheduler formulates the charging scheduling problem as a linear programming problem. Table I lists the decision variables, input variables and helper variables used in the model. The decision variables are the charging powers of the connected EVs and stationary batteries in the next T time intervals. The values of the input variables have to be provided by the charging manager over the REST interface when sending a schedule request. The number T of intervals to consider is one of these input variables. To improve readability of the problem formulation, it is assumed that for each time interval i, its length Δt_i in hours is provided, and for each EV n and time interval t, the fraction $F_{n,t}$ of the interval in which the EV is plugged-in is provided. In the practical implementation, only the length of the first time step, the length for the remaining time steps and the fractions the EVs are connected in the last interval before their departure have to be provided. This allows to align the charging schedule to the intervals on which the peak load charges are computed. As described, the peak load charges of the company building where the charging management system is deployed, is computed based on the 15-minute average peak load, and thus the charging plans are aligned to 15-minute

[1]Depending on business context VIPs could be EVs used for customer service, important employees, guests, or medical / firefighting vehicles.

TABLE I: Problem variables.

Variable Name	Unit	Description
		Decision Variables
$P_{n,t}^{\mathrm{EV}}$	kW	Charging power for EV n in interval t
$P_{b,t}^{\mathrm{Bat}}$	kW	Charging power for stationary battery b in interval t
		Input Variables
N	-	Number of (connected) EVs
B	-	Number of stationary batteries
T	-	Number of intervals
Δt_i	h	Length of interval i
Lim_t	kW	Load limit for interval t
P_t^{PV}	kW	PV power available in interval t
D_n	-	Departure interval of EV n
VIP_n	-	VIP status of EV n (1 for VIPs and otherwise 0)
C_n^{EV}	kWh	Battery capacity of EV n
$P_n^{\mathrm{EV_min}}$	kW	Minimum (possible negative) charging power of EV n
$P_n^{\mathrm{EV_max}}$	kW	Maximum charging power of EV n
$SOC_n^{\mathrm{EV_init}}$	-	Initial SOC of EV n between 0 and 1
$SOC_n^{\mathrm{EV_min}}$	-	Minimum SOC which should be satisfied all times for EV n between 0 and 1
$SOC_n^{\mathrm{EV_max}}$	-	Maximum SOC which should be satisfied all times for EV n between 0 and 1
$SOC_n^{\mathrm{EV_final_min}}$	-	Minimum final SOC for EV n between 0 and 1
$SOC_n^{\mathrm{EV_target}}$	-	Target SOC for EV n between 0 and 1
$F_{n,t}$	-	Fraction EV n is plugged-in in interval t
C_b^{Bat}	kWh	Capacity of stationary battery EV b
$P_b^{\mathrm{Bat_min}}$	kW	Minimum (negative) charging power of stationary battery b
$P_b^{\mathrm{Bat_max}}$	kW	Maximum charging power of stationary battery b
$SOC_b^{\mathrm{Bat_init}}$	-	Initial SOC of stationary battery b between 0 and 1
$SOC_b^{\mathrm{Bat_target}}$	-	Target SOC of stationary battery b between 0 and 1
		Helper Variables
$E_{n,t}^{\mathrm{EV}}$	kWh	Energy stored in battery of EV n after interval t
$E_{b,t}^{\mathrm{Bat}}$	kWh	Energy stored in stationary battery b after interval t
P_t^{total}	kW	Total charging power in interval t

intervals. Let the exemplary situation shown in Figure 3 be assumed: The current time is 10:10, and there is currently one EV connected with a planned departure time of 10:50. The

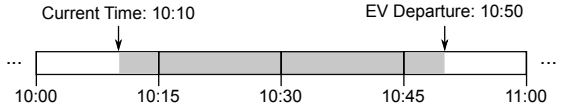

Fig. 3: Illustration of an exemplary situation.

charging manager would specify a length of 0.0833 hours (i.e., 5 minutes) for the first interval, since this is the time remaining in the current 15-minute interval. The length of the remaining intervals is always set to 0.25 hours (i.e., 15 minutes). Therefore, the departure interval of the EV is the fourth interval, and it is connected for a fraction of 5/15 = 1/3 of its departure interval. In the production system, the number T of intervals to consider is set to 40 by default, meaning that the charging is planned roughly 10 hours ahead.

In the LP model, the following constraints are considered:

$$P_n^{\mathrm{EV_min}} \leq P_{n,t}^{\mathrm{EV}} \leq P_n^{\mathrm{EV_max}} \qquad \forall n, \forall t, \tag{1}$$

$$P_{n,t}^{\mathrm{EV}} = 0 \qquad \forall n, \forall t > D_n, \tag{2}$$

$$P_b^{\mathrm{Bat_min}} \leq P_{b,t}^{\mathrm{Bat}} \leq P_b^{\mathrm{Bat_max}} \qquad \forall b, \forall t, \tag{3}$$

$$E_{n,t}^{\mathrm{EV}} = SOC_n^{\mathrm{EV_init}} \cdot C_n^{\mathrm{EV}} + \sum_{i=1}^{t} \Delta t_i \cdot F_{n,i} \cdot P_{n,t}^{\mathrm{EV}} \qquad \forall n, \forall t, \tag{4}$$

$$\min(SOC_n^{\mathrm{EV_min}}, SOC_n^{\mathrm{EV_init}}) \cdot C_n^{\mathrm{EV}} \leq E_{n,t}^{\mathrm{EV}} \qquad \forall n, \forall t, \tag{5}$$

$$E_{n,t}^{\mathrm{EV}} \leq SOC_n^{\mathrm{EV_max}} \cdot C_n^{\mathrm{EV}} \qquad \forall n, \forall t, \tag{6}$$

$$SOC_n^{\mathrm{EV_final_min}} \cdot C_n^{\mathrm{EV}} \leq E_{n,D_n}^{\mathrm{EV}} \qquad \forall n \tag{7}$$

$$E_{b,t}^{\mathrm{Bat}} = SOC_b^{\mathrm{Bat_init}} \cdot C_b^{\mathrm{Bat}} + \sum_{i=1}^{t} \Delta t_i \cdot P_{n,b}^{\mathrm{Bat}} \qquad \forall b, \forall t, \tag{8}$$

$$0 \leq E_{b,t}^{\mathrm{Bat}} \leq C_b^{\mathrm{Bat}} \qquad \forall b, \forall t, \tag{9}$$

$$SOC_b^{\mathrm{Bat_target}} \cdot C_b^{\mathrm{Bat}} \leq E_{b,T}^{\mathrm{Bat}} \qquad \forall b \tag{10}$$

$$P_t^{\mathrm{total}} = \sum_{b=1}^{B} P_{b,t}^{\mathrm{Bat}} + \sum_{n=1}^{N} F_{n,t} \cdot P_{n,t}^{\mathrm{EV}} \qquad \forall t \tag{11}$$

$$P_t^{\mathrm{total}} \leq Lim_t \qquad \forall t \tag{12}$$

Constraint 1 ensures that the minimum and maximum charging powers of the EVs (and charging stations) are satisfied. Note that the minimum charging power is negative if the EV and the charging station it is connected to support bi-directional charging. Constraint 2 prevents charging an EV after its departure. Constraint 3 ensures the minimum and maximum charging powers of the stationary batteries. Constraint 4 sets the battery levels of the EVs after each time

interval. Constraints 5 and 6 ensure that the SOC of an EV n does not fall below a certain minimum SOC $SOC_n^{\text{EV_min}}$ (or its initial SOC, if this is lower than $SOC_n^{\text{EV_min}}$) and that it does not exceed a certain maximum SOC $SOC_n^{\text{EV_max}}$. This is to ensure a minimum SOC in the case that a user departs earlier than planned. In practice, the maximum SOC is typically set to 1.0, but the scheduler provides the flexibility to specify a lower value since this might be beneficial for the battery health. Constraint 7 ensures certain minimum SOCs of the EVs at their departure times. Constraint 8 sets the battery levels of the stationary batteries after each interval, and constraint 9 ensures that they stay within the technically possible bounds. Constraint 10 guarantees that at the end of the planning horizon, the target SOCs of the stationary batteries are satisfied. Constraint 11 sets for each interval the total average charging power, and constraint 12 ensures that it stays below the specified limit. The limits for each interval are typically set based on the limit for the total load and the predictions of the base load and PV production.

The objectives of maximizing the satisfaction of the target SOCs of VIP and non-VIP EVs are formulated as follows:

$$\min f^{\text{sat_VIP}} = \sum_{n=1}^{N} VIP_n \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \quad (13)$$

$$\min f^{\text{sat_non-VIP}} = \sum_{n=1}^{N} (1 - VIP_n) \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}), \quad (14)$$

where the (nonlinear) maximum function is realized via a helper variable, which is not listed here for the sake of readability.

The objective of minimizing the grid consumption is formulated as

$$\min f^{\text{grid}} = \sum_{t=1}^{T} \max(0, P_t^{\text{total}} \cdot \Delta t_t - P_t^{\text{PV}} \cdot \Delta t_t), \quad (15)$$

where again, the maximum function is realized via a helper variable, which is not listed here. The input variable P_t^{PV} is the PV power available for charging in interval t. It is typically set to the (predicted) overproduction in interval t, i.e., by how much the predicted PV production exceeds the predicted base load. This overproduction can be used for charging the EVs and stationary batteries without having to consume the power/energy from the grid.

To reduce unnecessary discharging, which has a negative impact on battery life, the objectives for minimizing discharging of EVs and stationary batteries are formulated as follows:

$$\min f^{\text{dis_EV}} = -\sum_{n=1}^{N} \sum_{t=1}^{T} \frac{\Delta t_t}{\max_{0 \le i \le T} \Delta t_i} \cdot F_{n,t} \cdot \min(0, P_{n,t}^{\text{EV}}) \quad (16)$$

$$\min f^{\text{dis_Bat}} = -\sum_{b=1}^{B} \sum_{t=1}^{T} \frac{\Delta t_t}{\max_{0 \le i \le T} \Delta t_i} \cdot \min(0, P_{b,t}^{\text{Bat}}). \quad (17)$$

Note that the discharging power is multiplied by the normalized interval length to ensure that discharging in shorter intervals contributes less to the objective value than discharging in longer intervals. The minimum function is again realized with helper variables, which are not shown here.

The objectives of charging EV and stationary batteries as fast and as much as possible are formulated as

$$\min f^{\text{speed_EV}} = -\sum_{n=1}^{N} \sum_{t=1}^{T} \frac{1}{t+39} \cdot \frac{\Delta t_t}{\max_{1 \le i \le T} \Delta t_i} \cdot F_{n,t} \cdot P_{n,t}^{\text{EV}} \quad (18)$$

$$\min f^{\text{speed_Bat}} = -\sum_{n=1}^{N} \sum_{t=1}^{T} \frac{1}{t+39} \cdot \frac{\Delta t_t}{\max_{1 \le i \le T} \Delta t_i} \cdot P_{b,t}^{\text{Bat}}. \quad (19)$$

These objectives reward charging, and the reward is higher the higher the charging power and the earlier the charging takes place. Note that the "+39" in the denominator is theoretically not necessary, but it is used in the implementation of the scheduler since there were numerical issues in the solving process without it.

V. Hierarchical Optimization

There are multiple conflicting objectives (13)–(19). The traditional way to handle multiple objectives in LP is to combine them into one objective via a weighted sum. This is a simple approach, which is easy to understand and to implement. However, it is not obvious how to set the weights. Typically, it is assumed that a decision maker—in our case, the operator of the charging system—sets the weights according to their preferences. In practice, however, the operator is unlikely to be able to decide on a reasonable setting of the weights since it is not obvious how the setting of the weights impacts the charging schedules. It can be assumed that it is easier for an operator to specify a hierarchy of the objectives, which orders the objectives by how important they are for the operator. It might be possible to set the weights in a way that they reflect the hierarchy specified by the operator, but it is hard to find a weight setting that results in the intended behaviour for all possible inputs or optimization problems, respectively. Moreover, if the operator changes their mind and specifies a different hierarchy, the weights have to be adapted accordingly. To overcome these issues, the scheduler uses hierarchical (also termed lexicographic) optimization [27] to handle a hierarchy of objectives.

The concept of hierarchical optimization is illustrated in Figure 4 for three objectives. It requires solving multiple optimization problems—one for each objective. First, the original problem is solved with respect to the objective of the

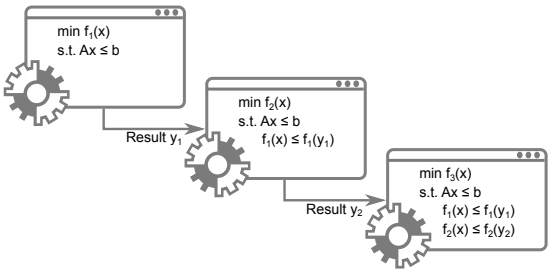

Fig. 4: Illustration of hierarchical optimization with three objectives.

highest priority. Then the problem is solved with respect to the objective of the second highest priority, with an additional constraint that the result should not be worse in the first objective than the result of the first optimization. Then the problem is solved with respect to the objective of the third highest priority, with a further constraint that the result should not be worse in the second objective than the result of the second optimization, and so on.

As an example, let an objective hierarchy with the following objectives in decreasing order of their priority be assumed: $f^{\text{sat_VIP}}$, $f^{\text{sat_non-VIP}}$, f^{grid}. With hierarchical optimization, one would first solve the problem considering only the objective of the highest priority:

$$\min f^{\text{sat_VIP}} = \sum_{n=1}^{N} VIP_n \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \quad (20)$$

subject to

$$(1) - (12). \quad (21)$$

Let y^1 be the optimal objective value of this problem. The second problem considers only the objective of the second highest priority, but an additional constraint ensures that the result will be optimal in the objective of the highest priority:

$$\min f^{\text{sat_non-VIP}} = \sum_{n=1}^{N} (1 - VIP_n) \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \quad (22)$$

subject to

$$(1) - (12), \quad (23)$$

$$\sum_{n=1}^{N} VIP_n \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \leq y^1. \quad (24)$$

Let y^2 denote the optimal objective value of this second problem. The third problem considers only the objective of the third highest priority, and a further constraint is added, ensuring that the objective of the second highest priority will not get worse than y^2:

$$\min f^{\text{grid}} = \sum_{t=1}^{T} \max(0, P_t^{\text{total}} \cdot \Delta t_t - P^{\text{PV}} \cdot \Delta t_t) \quad (25)$$

subject to

$$(1) - (12), \quad (26)$$

$$\sum_{n=1}^{N} VIP_n \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \leq y^1, \quad (27)$$

$$\sum_{n=1}^{N} (1 - VIP_n) \cdot \max(0, SOC_n^{\text{EV_target}} \cdot C_n^{\text{EV}} - E_{n,T}^{\text{EV}}) \leq y^2. \quad (28)$$

The charging plan resulting from this third problem will be used as the final solution.

The hierarchical optimization is implemented in the scheduler in a way that allows to dynamically adapt the considered hierarchy of objectives. More precisely, the hierarchy to consider can be sent as an additional input parameter of a schedule request. If no hierarchy is provided as input, the scheduler considers a prespecified default hierarchy. In the charging management system, the charging manager (cf. Figure 2) always specifies a hierarchy with each schedule request, and the operator can set the hierarchy as part of the configuration of the charging manager. Figure 5 shows a screenshot of the charging manager's configuration user interface. It allows to set which objectives are considered in the hierarchy and in which order they are considered. Thus, to summarize, the scheduler is designed in a way that makes it easy for operators to specify their preferences and to change them over time.

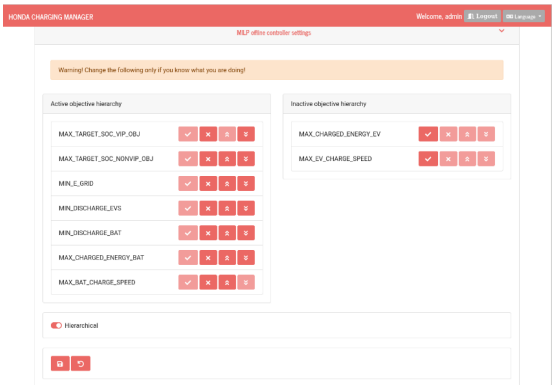

Fig. 5: Screenshot of the charging manager configuration user interface allowing the setting of the objective hierarchy.

VI. Simulation Experiments

In practice, the scheduler must react fast. Hence, in a first experiment, the runtime of the scheduler is measured, and it is evaluated how it scales to an increasing number of considered EVs. For this, scheduler requests are sent over the REST interface and the time between sending the request and receiving the result is measured. In the input parameters sent in the requests, the number of stationary batteries is set to one, the length T of the planning horizon is set to 40, and the objective hierarchy is set analogous to the list of objectives shown in Section III. The number of EVs is varied between 10 and 1000; the input variables for each EV, such as the initial SOC or the maximum charging power, are randomly sampled, and the power limit is set equal to the number of EVs for each interval. The scheduler and the client run on the same host equipped with an Intel Core i5-13400@4.6 GHz 16-core CPU. Version 9.02 of SCIP is used as LP solver. For each considered number of EVs, five requests are sent, and the runtimes are averaged over the five requests. The resulting runtimes are shown in Table II. Up to 500 EVs, the runtime is acceptable for the practical application, which should be sufficient for all practical applications now and in the near future. We found that our hierarchical approach takes roughly factor 5 more time than the plain weighted sum approach.

To demonstrate the workings of the scheduler, a further experiment on an illustrative use case is executed. In the use case, one stationary battery and two EVs are considered. The first EV is a VIP, and the second EV is not a VIP. The planning

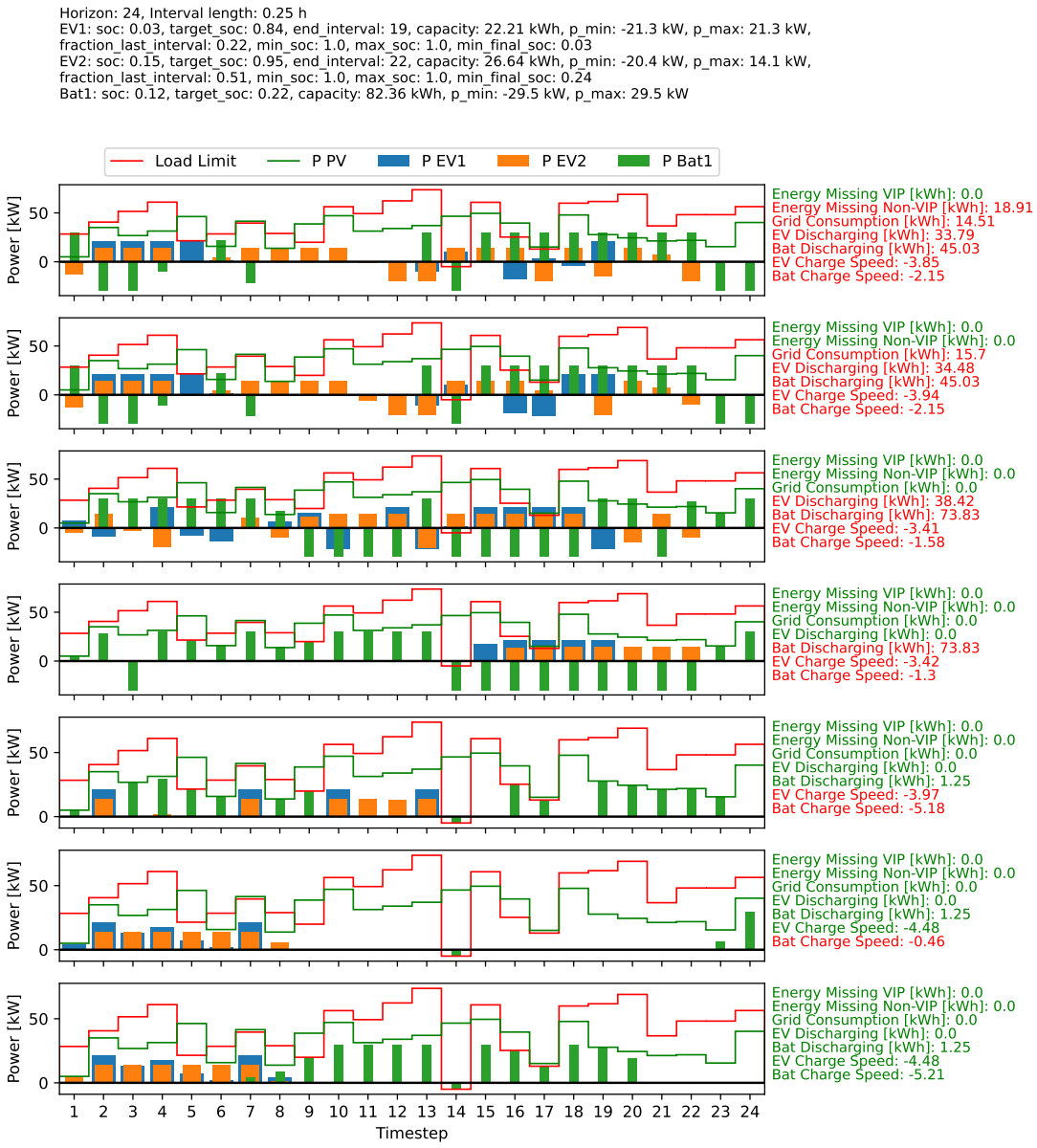

Fig. 6: Illustration of a use case showing inputs and schedules resulting from the optimizations with respect to the different objectives of the hierarchy. Objectives shown in green are considered (optimized), those in red not.

TABLE II: Runtimes of the scheduler for different numbers of considered EVs averaged over five runs.

Number of EVs	Runtime [s]
10	0.024
100	0.303
500	3.601
1000	14.520

horizon is set to 24 intervals of a length of 15 minutes each. In the experiment, the charging schedule resulting from each optimization of the hierarchical approach is recorded. Figure 6 shows the input parameters for the two EVs and the stationary battery at the top. The plots show the load limits and available PV powers together with the recorded charging schedules and the corresponding objective values. The top plot shows the schedule resulting from considering only the first objective of the hierarchy. The second plot shows the schedule resulting from considering the first two objectives of the hierarchy, and so on. Considering only the first objective results in the satisfaction of the target SOC of the VIP EV, but the target SOC of the non-VIP EV is not satisfied. Considering also the second objective, slightly changes the schedule, resulting in the satisfaction of the target SOC of also the non-VIP EV. The consideration of the third objective reduces the grid consumption from 15.7 kWh to zero by shifting the charging

to intervals with high available PV power. The fourth objective reduces the discharging of the EVs to zero, and the fifth objective reduces the discharging of the stationary battery to nearly zero. There has to be discharging since there is a negative power limit in one of the intervals. The stationary battery is used for discharging since the minimization of discharging of EVs has a higher priority than the minimization of discharging of the stationary batteries. The sixth objective increases the charging of EVs and shifts it to the first intervals. The seventh and last objective results in charging the stationary battery as much as possible after the EVs are fully charged.

VII. Summary and Conclusion

The present paper describes a scheduler used for the computation of charging plans in a real-world charging management system deployed at a company building. The scheduler considers multiple objectives, of which some are typically neglected in literature, although they are important for the practical application, such as preventing unnecessary discharging. The scheduler implements a hierarchical optimization approach to handle the objectives, and it allows to dynamically change the considered objective hierarchy. This makes it easy for operators to express and change their preferences. Furthermore, it eases the extension of the scheduler by further objectives. Although the hierarchical optimization induces computational overhead compared to the classical weighted-sum approach, the response times of the scheduler allow to handle a high number of EVs while, at the same time, respecting cognitive limits of human information processing, which might reduce the risk of biases in decision-making. Currently ongoing work focuses on a deeper understanding of the priority settings in terms of solution quality, specifically how higher priority objectives limit the potential for lower priority ones.

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