Smart Mobility Meets Industry: Enhancing Energy Flexibility Potentials by Combining Industrial Production & Electric Vehicle Charging

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Abstract

The increasing share of renewable energy sources poses the challenge of volatile energy generation, requiring demand side management (DSM) to manage such volatility. In view of the high industrial electricity demand and the increasing charging demand of electric vehicles (EVs), both industry and mobility represent relevant areas of DSM. However, the combination of EV charging and energy-intensive industrial processes still contains untapped synergy potentials. Thus, we present a mixed-integer linear program and quantify the economic and ecologic potential of combining energy flexibilities of industry and electric mobility within a case study. For our evaluation, we compare the results of our model to a benchmark case that separately manages industry and EV flexibilities. Our findings suggest that implementing our approach would yield both economic and ecological benefits, resulting in a reduction in anticipated costs and emissions, as well as a decrease in associated uncertainty.

Keywords

Energy-flexible Factory, Vehicle-to-Factory, Electric Vehicle Charging, Mixed-Integer Linear Programming

Introduction

As countries transition from fossil fuels to renewable energy sources (RES), they are confronted with considerable challenges. In nations with expansive territories and dispersed populations, such as Australia and Russia, the expansion of transmission infrastructure to cover vast distances poses a significant hurdle. In contrast, densely populated countries like Germany and Japan struggle with the integration of needed infrastructure within more limited space. Similarly, countries with rapidly growing suburban areas, such as India and Brazil, additionally need to address the challenge of balancing urban and rural energy demands. Despite these national differences, the variability inherent in RES-based electricity generation presents challenges for industrial sectors worldwide that traditionally require a continuous and high energy supply.

Additionally, the increasing use of electric vehicles (EVs) raises concerns that the existing distribution networks may become strained beyond their capacity (Godina et al., 2016). These concerns are due to physically infeasible power flows and corresponding demand peaks in the network, which can occur when EV charging and energy-intensive production processes coincide. Therefore, industrial companies must adapt their processes to be more energy-flexible (given volatile electricity generation of RES) and manage the rapid growth of EV fleets. This paper addresses these challenges and explores potential solutions that can significantly increase the energy flexibility of companies.

To become more energy-flexible and balance the growing time-disparity between RES generation and electricity demand, companies can use demand-side management (DSM) and electricity storages. DSM refers to a system's ability to modify its energy usage, allowing smart energy-flexible factories to adjust their load profile without negatively impacting production outcomes. In this context, the deployment of EV batteries as a means of intermittent electricity storage has become an increasingly appealing option, particularly as the number of available EVs continues to surge. Vehicle-to-X approaches, in particular vehicle-to-factory (V2F), involves utilizing EV batteries available in a company's EV charging park as cumulative energy storage units. Despite some studies investigating the V2F approach, a comprehensive analysis of the synergy potentials arising from actively combining energy flexibilities of industrial production processes and EV (dis-)charging is still lacking. To address this research gap, this paper aims to answer the following research questions:

- **RQ1:** How can the combination of industrial production processes and EV charging provide additional energy flexibility beyond the mere sum of the two flexibility potentials?
- **RQ2:** What are the economic and ecological potentials of the additional energy flexibility?

We address these research questions by first reviewing existing literature on V2F. On that basis, we develop a mixed integer linear programming (MILP) optimization model for the combined management of industrial and EV flexibility. In the following, we quantitatively evaluate our model in comparison to a benchmark case, where industrial energy flexibility and EV charging management are considered separately. Lastly, we conclude the results and provide an outlook for future research to advance the global energy landscape.

Related Research

We conducted a systematic literature review on V2F-related research, utilizing Scopus, ScienceDirect, and SpringerLink. We used a search query focused on EV charging and industrial energy flexibility, limited to title, abstract, and keywords. Our search was expanded through backward and forward snowballing, starting from our initial set of papers. In addition, we excluded all contributions published earlier than 2016 to ensure relevance. In the following sections, we provide a brief overview of the identified literature.

Vehicle-to-Factory

With the growing number of EVs, the availability of mobile battery storage is increasing, enabling different DSM techniques, for example, the optimization of self-consumption, minimization of peak loads, load shifting, and grid services (Roth et al., 2019). In the context of V2F, existing literature places significant emphasis on the optimization of self-consumption. In the context of company-owned EV fleets, several studies have demonstrated the potential of EV batteries to compensate for electricity demand/supply mismatches between variable RES generation and manufacturing systems (Beier et al., 2016; Betz & Lienkamp, 2016; Frendo et al., 2018). Beier et al. (2016) compared an in-house EV fleet with a stationary battery storage system, Frendo et al. explored EV charging strategies to examine effects on infrastructure utilization, and Betz & Lienkamp (2016) combined energy- and charging-management to achieve a higher self-consumption. Studies have also focused on cars that employees use for commuting to their workplace (Azimi et al., 2021; Casini et al., 2019; Guo et al., 2022; Jones et al., 2021; Roth et al., 2019; Yu et al., 2022). For example, Roth et al. (2019) demonstrated that targeted charging and discharging of employees' EVs can significantly increase the self-consumption rate. Additionally, alternative objectives of V2F technology have also been explored, such as the maximization of profits of the industrial microgrid (Azimi et al., 2021), the maximization of income of EV users (Guo et al., 2022), or an increase of network stability (Casini et al., 2019). However, a significant research gap remains regarding the ability of an EV fleet to balance a given production process profile. As highlighted by Roth et al. (2019), “the full potential of V2F requires a combination with energy-flexible production processes”. While the presented studies have demonstrated the feasibility of V2F approaches, research on the combination of EV charging and energy-flexible industrial production processes is still scarce.

Energy-Flexible Companies

The demand-oriented optimization of industrial energy flexibility potentials per se is a widely discussed topic in relevant literature (e.g., Angizeh et al. (2017), Keller et al. (2016), Roth et al. (2020), or Wanapinit et al. (2020)). Yet, many of the existing contributions are prone to certain limitations in terms of holism, interoperability, replicability, and transferability. Bahmani et al. (2022) developed an optimization model that supports industrial companies in selecting when (i.e. at which time) and how (i.e., the schedule) they should allow for flexibilities to optimize profit. They base their work on the Energy Flexibility Data Model (EFDM) of Schott et al. (2019), which allows for a generic description of energy flexibilities that abstracts from the specifics of the manufacturing infrastructure. Since the focus of our work is not on the physical design of manufacturing systems, but rather on the flexible adaptation of energy consumption and the interplay of bidirectional charging, we use the EFDM and parts of the profit-maximizing optimization proposed by Bahmani et al. (2022) to describe flexibilities. In more detail, we consider EVs to increase the flexibility of initially stationary load profiles of industrial processes. Overall, while previous studies have shown the feasibility of V2F, the need to evaluate how a combination of energy flexibilities of production processes and EVs provide additional energy flexibility remains omnipresent.

Methodology

In this section we provide an overview of our optimization model for the combined management of industrial and EV flexibility. First, we highlight the mathematical formulation of our model and present the constraints related to EV charging and flexible industrial loads (all sets, parameters, and variables are introduced in detail in the appendix). In addition, we provide further details of the case study conducted, i.e., focusing on the input data used and the implementation of the model itself (utilizing the *Gurobi* solver).

Formulation of the Optimization Problem

Objective Function

The core of the proposed MILP is the objective function, which quantifies the economic potential of a flexibility combination. The objective function (Eq. (1)) minimizes the net operational costs over the given time horizon *T*. The net operational costs are (1) electricity cost from the purchase of electricity from the grid p_t and (2) activation cost ac_f incurred due to the activation of the flexible loads F minus (3) revenues from the electricity fed into the grid r_t.

$$\min \quad \Delta t \cdot \sum_{t=1}^{|T|} (P_t^{grid,out} \cdot p_t - P_t^{grid,in} \cdot r_t + \sum_{f=1}^{|F|} ac_f \cdot start_{f,t}) \tag{1}$$

Constraints Related to the Power Balance and Grid Connection

To ensure that generation and consumption of electricity are equal in every time period, the total amount of electricity required for EV charging, flexible loads, and self-consumption must match the power drawn from the grid minus the power that is being fed into the grid (Eq. (2)). In addition, Eq. (3a) and (3b) ensure that the power fed into the grid is lower than the maximum power of the grid connection point and that withdrawing and injecting power simultaneously from/into the grid is not possible.

$$P_t^{grid,out} - P_t^{grid,in} = \sum_{c=1}^{|ChSt|} \sum_{v=1}^{|EVs|} P_{c,v,t}^{ch} + \sum_{f=1}^{|F|} P_{f,t}^{flex} + \left(P_t^{const} - P_t^{self}\right) \ \forall\, t \in T \tag{2}$$

$$0 \le P_t^{grid,in} \le P^{GCP,max} \cdot feedIn_t \ \forall\, t \in T \tag{3a}$$

$$0 \le P_t^{grid,out} \le (-P^{GCP,min}) \cdot (1 - feedIn_t) \ \forall\, t \in T \tag{3b}$$

Constraints Related to the Electric Vehicle Charging

Regarding relevant EV constraints, we base our work on Haupt et al. (2020), who implemented a MILP model for EV scheduling in charging hub microgrids. Eqs. (4a) - (4d) model the physical constraints of EV batteries (Haupt et al., 2020). Eq. (4a) and Eq. (4b) define the relationship between the SoC in t and the SoC in $t-1$. The SoC changes in one interval by the energy charged/discharged in relation to the nominal battery capacity of the EV. This change in SoC depends on both the (dis-)charging power of the charging station ($P_{c,v,t}^{dch}$) $P_{c,v,t}^{ch}$ as well as the (dis-)charging efficiency (η_v^{dis}) η_v^{ch} (Eq. (4b)).

$$SoC_{v,t} = SoC_{v,t-1} + \Delta SoC_{v,t-1} \; \forall \; t \in T \setminus \{1\}, v \in EVs \tag{4a}$$

$$\Delta SoC_{v,t} = \frac{\Delta t \cdot \left(\eta_v^{ch} \cdot \sum_{c=1}^{|ChSt|} P_{c,v,t}^{ch} - \frac{1}{\eta_v^{dis}} \cdot \sum_{c=1}^{|ChSt|} P_{c,v,t}^{dch} \right)}{C_v} \; \forall \; t \in T, v \in EVs \tag{4b}$$

In addition, according to Eq. (5a), the SoC of each EV must remain between a lower (SoC_v^{min}) and an upper limit (SoC_v^{max}) and we force the charging/discharging power used for charging to be between the minimum and maximum power value of the EV in Eq. (5b) and (5c).

$$SoC_v^{min} \leq SoC_{v,t} \leq SoC_v^{max} \; \forall \; t \in T, v \in EVs \tag{5a}$$

$$P_v^{ch,min} \cdot Ch_{c,v,t} \leq P_{c,v,t}^{ch} \leq P_v^{ch,max} \cdot Ch_{c,v,t} \; \forall \; t \in T, v \in EVs, c \in ChSt \tag{5b}$$

$$P_v^{dch,min} \cdot dCh_{c,v,t} \leq P_{c,v,t}^{dch} \leq P_v^{dch,max} \cdot dCh_{c,v,t} \; \forall \; t \in T, v \in EVs, c \in ChSt \tag{5c}$$

Based on Haupt et al. (2020), we model the interaction between EVs and charging stations using Eqs. (6a) - (7b). Eq. (6a), for example, requires that an EV can only be charged if it is on site in time t, indicated by the parameter $OnSite_{v,t}$. The allocation of the EVs to the charging stations is governed by Eqs. (6b) - (6d), ensuring equal distribution of EVs among the charging stations and guaranteeing that each station can accommodate only one EV for charging/discharging in every given time interval.

$$\sum_{c=1}^{|ChSt|} ChAssign_{c,v,t} = onSite_{v,t} \quad \forall \; t \in T, v \in EVs \tag{6a}$$

$$\sum_{v=1}^{|EVs|} ChAssign_{c,v,t} \leq 1 \quad \forall \; t \in T, c \in ChSt \tag{6b}$$

$$Ch_{c,v,t} + dCh_{c,v,t} \leq ChAssign_{c,v,t} \; \forall \; t \in T, v \in EVs, c \in ChSt \tag{6c}$$

$$ChAssign_{c,v,t-1} + onSite_{v,t} - 1 \leq ChAssign_{c,v,t} \; \forall \; t \in T \setminus \{1\}, v \in EVs, c \in ChSt \tag{6d}$$

Similar to the power limitations imposed on EVs (Eq. (5a) and (5b)), we force the charging/discharging power used for charging to be between a minimum and maximum power value (Eq. (7a) and (7b)).

$$P_c^{ch,min} \cdot Ch_{c,v,t} \leq P_{c,v,t}^{ch} \leq P_c^{ch,max} \cdot Ch_{c,v,t} \; \forall \; t \in T, v \in EVs, c \in ChSt \tag{7a}$$

$$P_c^{dch,min} \cdot dCh_{c,v,t} \leq P_{c,v,t}^{dch} \leq P_c^{dch,max} \cdot dCh_{c,v,t} \; \forall \; t \in T, v \in EVs, c \in ChSt \tag{7b}$$

Constraints Related to the Flexible Industrial Loads

Finally, for the constraints relating to the flexible loads (Eqs. (8) - (16)), we use the EFDM by Schott et al. (2019). Accordingly, deviations of flexible loads from a "normal" (i.e., ex-ante planned) operating point are depicted by power states, which describe the admissible power levels of the plateaus, i.e., during holding periods (Schott et al., 2019). Deviations of flexible loads are positive in the load increase type and negative in the load decrease type (Bahmani et al., 2022). More formally, Eq. (8a) ensures an operation under a lower and an upper power deviation, where $on_{f,t}$ is a binary variable indicating whether flexible load f is active in time t. Meanwhile, Eq. (8b) ensures that the residual industrial load, i.e., the constant base load adjusted by deployed flexible loads, remains a consumer of electricity at all times.

$$on_{f,t} \cdot P_f^{flex,min} \leq P_{f,t}^{flex} \leq P_f^{flex,max} \cdot on_{f,t} \quad \forall\, t \in T, f \in F \tag{8a}$$

$$P_t^{const} + \sum_{f=1}^{|F|} P_{f,t}^{flex} \geq 0 \;\forall\, t \in T \tag{8b}$$

For flexible loads that can freely operate under any power state, we only use Eq. (8a). However, some flexible loads might require to only operate at specific power states. In case discrete power states are required (Eq. (9a) and (9b)), $states_f$ accounts for the number of permissible power states between $P_f^{flex,min}$ and $P_f^{flex,max}$ and the integer variable $pState_{f,t}$ controls the actual power state value.

$$P_{f,t}^{flex} = on_{f,t} \cdot P_f^{flex,min} + \frac{P_f^{flex,max} - P_f^{flex,min}}{states_f + 1} \cdot pState_{f,t} \;\forall\, t \in T, f \in F \tag{9a}$$

$$0 \leq pState_{f,t} \leq \left(states_f + 1\right) \cdot on_{f,t} \;\forall\, t \in T, f \in F \tag{9b}$$

In case unique power states are required, i.e., the flexible loads can only operate in one unique power state, Eq. (10a) and Eq. (10b) allow for only one increase and one decrease in the power in the flexibility's start-up and shut-down time, resulting in a single power state during flexibility activation.

$$P_{f,t}^{flex} - P_{f,t-1}^{flex} \leq P_f^{flex,max} start_{f,t} \quad \forall\, t \in T, f \in F \tag{10a}$$

$$P_{f,t-1}^{flex} - P_{f,t}^{flex} \leq P_f^{flex,max} end_{f,t} \quad \forall\, t \in T, f \in F \tag{10b}$$

Additional constraints (Eqs. (11) - (15)) define the validity, holding duration, regeneration duration, and usage of flexible loads. The validity constraint, represented by Eq. (11), requires flexible load f to only be active at time t, if it is within the bounds of validity. This is important because some processes may not be disrupted, for example, since certain delivery obligations take priority over load utilization (Schott et al., 2019). We impede the flexible load activation and deactivation at the same time using Eq. (12). The holding duration constraint (Eq. (13)) imposes limits on the duration for which the flexible loads operate at specified power levels, with minimum and maximum bounds represented by hd_f^{min} and hd_f^{max}. The regeneration duration constraint (Eq. (14)) describes the time limitation rd_f to activate a load after deactivation. Furthermore, the number of activations of each flexible load is limited through the usage constraint (Eq. (15)), where $usage_f^{min}$ and $usage_f^{max}$ define the usage limits for flexible load f over the planning horizon.

$$on_{f,t} \leq validity_{f,t} \;\forall\, t \in T, f \in F \tag{11}$$

$$start_{f,t} + end_{f,t} \leq 1 \;\forall\, t \in T, f \in F \tag{12}$$

$$start_{f,t} \leq \sum_{s=hd_f^{min}}^{\min\{|T|, hd_f^{max}\}} end_{f,t+s} \quad \forall\, t \in T: \left|t + hd_f^{min}\right| \leq |T|, f \in F \tag{13}$$

$$\sum_{s=t}^{\min\{|T|, t+rd_f-1\}} \left(1 - on_{f,s}\right) \geq rd_f \cdot end_{f,t} \quad \forall\, t \in T, f \in F \tag{14}$$

$$usage_f^{min} \leq \sum_{t=1}^{|T|} start_{f,t} \leq usage_f^{max} \;\forall\, f \in F \tag{15}$$

Finally, the relationship between the binary variables $on_{f,t}$, $start_{f,t}$, and $end_{f,t}$, which indicate the status, starting time, and ending time of the flexible load, respectively, is described by Eq. (16).

$$on_{f,t} - on_{f,t-1} = start_{f,t} - end_{f,t} \;\forall\, t \in T, f \in F \tag{16}$$

Description of the Conducted Case Study

In the following, we present the setup and input parameters for the evaluation of our approach. The simulation environment consists of two central modules, specifically a planning module and an execution module. The planning module determines a portfolio of control signals for each future period of the current planning horizon for both the charging infrastructure and the energy flexibilities of the industrial processes. The execution module operates based on the outputs of the planning module and performs state changes to the simulation environment in each period of the planning horizon according to the control signals formulated for that period in the current version of the execution plan. The implementation of the planning module resorts to the formulated MILP. We assume complete knowledge concerning two areas: On the one hand, complete knowledge of the realizations of electricity prices and electricity generation of photovoltaic (PV) plants is assumed. While this assumption leads to a necessary further development of the model, including forecasts of electricity prices and generation, it significantly reduces the complexity of the optimization model and the required computational effort. On the other hand, the planning module has complete knowledge of the distributions, given by the respective probability density functions, of the occurrence of charging-related events such as the arrival or departure time of the EVs. Due to the stochastic nature of some parameters, deviations between the expected and actual realization of random variables are inherent. To incorporate stochasticity, we follow the approach of dynamic programming. While the execution module is active in every period, a run of the planning module occurs exclusively in periods in which a change in the planning-relevant parameters of the simulation environment compared to the previous period can be observed. Such a change can be triggered by the arrival and connection of an EV to the charging infrastructure. If no change is observed, the execution plan used in the previous period is still valid in the current period and remains optimal.

In our case study, the simulation environment describes a medium-sized industrial company that has a base consumption $P_{base}(t)$ of its various industrial manufacturing activities. The characteristics of the internal energy-intensive processes allow the use of various energy flexibility measures, which lead to a deviation of the actual load of the manufacturing activities from the base consumption by $P_{flex}(t)$. In addition, the company operates its own PV plant (which generates an output of $P_{pv}(t)$) and a charging infrastructure, where EVs can be charged and discharged both unidirectionally and bidirectionally. The residual load of the charging park is denoted as $P_{ch}(t)$. In more detail, we consider the following input data for the optimization. To quantify the electricity price p_t, we used actual market data from the European power exchange (*EPEX SPOT*) for the German day-ahead market of the year 2022. For the emission factors that are used for an ecological evaluation of our results, we apply hourly data on the specific GHG emissions of the German electricity mix (Forschungsstelle für Energiewirtschaft (FfE), 2022). Furthermore, we model the power generation of the PV plant based on a real-world dataset from a German medium-sized company (energy and building technology industry) for October 2022. For the simulation, we consider a time frame of five working days, beginning on Monday, October 10th, 2022. Thereby, each day is handled separately and acts as a self-contained planning horizon. The MILP within the planning module considers discrete periods of 15-minute intervals between the moment of planning and the end of the respective day / planning horizon. To model the base load of the manufacturing company, we assume production to take place between 9:00 a.m. and 6:00 p.m. We also assume a constant (ex-ante) demand of $P_{base}(t) = 500\ kW$ for all production-related processes in this period (9 a.m. < t < 6 p.m.). Furthermore, we consider five different flexible loads as depicted in *Table 1* and assume the execution of flexible loads to be valid, i.e., $validity_{f,t} = 1$ during the daily time of production.

	Deviation Type	Power	Usage Number	Holding Duration	Regeneration	Activation Cost
Unit	-	kW	-	15min	15min	€
Flexible Load 1	Decrease	[0,125]	[0,3]	[4,12]	0	0
Flexible Load 2	Decrease	[250,250]	[0,2]	[4,8]	12	0
Flexible Load 3	Decrease	[350,475]	[0,1]	[4,4]	0	0
Flexible Load 4	Decrease	[62.5,187.5]	[0,1]	[8,8]	0	15
Flexible Load 5	Increase	[62.5,125]	[0,3]	[4,12]	0	0

Table 1. Flexible Loads Used in the Simulation (adapted from Bahmani et al. (2022))

For the modeled EVs, we assume a fleet of ten privately-owned and ten company-owned EVs. We distinguish the two types of EVs in terms of their ability to be charged bidirectionally. Privately-owned vehicles can only be charged unidirectionally, as we assume employees to not want the capacity or the lifespan of their private EV batteries to suffer from possible negative effects of bidirectional charging. Company-owned vehicles, on the other hand, can be charged bidirectionally. The individual vehicles' battery capacity and (dis)charging power is quantified in *Table 2* for all EVs.

	Charging Power	Battery Capacity	Unidirectional	Bidirectional
Unit	kW	kWh	-	-
Tesla Model S	[0,250]	100	2	4
VW ID.3	[0,120]	58	4	4
Renault Zoe Z.E	[0,50]	52	4	2

Table 2. Types of EVs Used in the Simulation

We model the arrival (departure) time of each EV as a gamma distribution with a shape parameter $\alpha = 2$ and a scale parameter $\beta = 1$ within a given time range from 7:00 a.m. to 11:00 a.m. (4:00 p.m. to 8:00 p.m.). The arrival SoC is normally distributed with a mean $\mu = 0.5$ and standard deviation $\sigma = 0.13$ within the interval [0, 1], while the target SoC at the expected period of departure is triangularly distributed between the respective arrival SoC and fully charged state of 100% with a mode of $\bar{x}_M = 1$. Concerning the charging infrastructure, we consider 10 unidirectional and 10 bidirectional charging stations with a respective charging/discharging power of 11kW (2 stations), 22kW (4 stations) and 150kW (4 stations). Furthermore, across all possible combinations of EVs and charging stations, we assume the charging/discharging efficiency to be equal to the industry reference value of $\eta_v^{ch} = \eta_v^{dis} = 90\%$ (Roth et al., 2019). Finally, we also consider consumption and feed-in limitations at the grid connection point of $P_t^{GCP,max} = 1000kW$ and $P_t^{GCP,min} = -1000kW$ as well as a constant remuneration for feed-in of $r_t = \frac{0.08€}{kWh}$ (Bayerische Landesanstalt für Landwirtschaft, 2022). To ensure a certain degree of explanatory power considering the stochastic properties of the model, we conducted *n=10* runs over the aforementioned 5-day period.

Results

To quantify the additional flexibility realized under our approach, we define an appropriate point of comparison based on the status quo in research and practice. In particular, our benchmark assumes a separate consideration of smart charging and industrial load management, i.e., a sequential approach was adopted: Given the particular impact of flexible load management on industrial processes, our benchmark initially optimizes industrial flexible load usage. Subsequently, these results provide input parameters for the optimal charging and discharging operations of the fleet of EVs. Note that our proposed MILP can be divided into two sets of constraints that intersect only in Constraints (3), (4a), and (4b). Consequently, the resulting two separate MILPs constitute the basis for the sequential approach, which aims to quantify the benchmark used. In the following, we will refer to the approach presented in the penultimate section as the "combined approach", while our benchmark will be named "sequential approach". These two approaches were tested in the same simulation environment as outlined in the previous section. Corresponding results are summarized in *Table 3*.

	Combined Approach	Sequential Approach	Difference
$E[cost]$	980.23 €	1,094.79 €	11.69%
$\sigma[cost]$	95.22€	68.37 €	−28.21%
$E[emission]$	2,738.33 kg	2,947.75 kg	7.65%
$\sigma[emission]$	196.53 kg	158.98 kg	−19.11%

Table 3. Results of 10 Runs of the Simulation Model for Both Planning Approaches

Compared to the sequential approach (benchmark), costs can be reduced significantly by 11.69% when using the combined approach. At the same time, a significant reduction in emissions by an average of 7.65% can be realized. Especially for energy-intensive companies, whose energy costs account for up to 40% of their total production costs (Sauer et al., 2019, p. 109), such cost reduction can have a significant impact on profit margins and overall competitiveness. Considering the ongoing electrification of the energy sector and reduction of the dependence on fossil fuels, the ecologic perspective will gain even more importance in the coming years: The fact that a reduction in costs is accompanied by a decrease in emissions is an important aspect when jointly increasing economic competitiveness and fighting against climate change at the same time. Here, especially the degree of self-consumption and the CO_2 footprint of the external electricity supply plays a major role. Since an emission factor of zero kg CO_2-eq per kWh was assumed for the installed PV system, and direct GHG emissions resulting from the manufacturing processes were assumed to be immutable, the purchase of electricity on the day-ahead spot market (external electricity supply) represents the only source of emissions. The time-varying emissions per kWh depend on the current electricity mix and the specific emissions of the different energy sources. Differences in costs and emissions of both approaches can attributed to two aspects: First, the ability to shift the grid-effective electricity consumption can be utilized to exploit significant changes in spot market prices, e.g., due to volatile supply of RES, and, consequently, reduce procurement costs. Those distinct changes in prices result from fluctuating power generation as RES, such as wind turbines and PV, are limited in their ability to adjust to current electricity demand (Bank et al., 2021). Therefore, this is a characteristic of electricity markets with a relatively high share of RES in the electricity mix (Sauer et al., 2019). Secondly, utilizing flexible loads and storage capacity of electric vehicles, the corporate electricity demand can be adjusted to self-generation to increase self-consumption and thereby reduce the power demand to the grid. Overall, a combined consideration of flexible industrial electricity consumption and company-owned EV charging infrastructure can enhance the competitiveness of companies and contribute to emission reduction and climate neutrality goals. Consequently, entrepreneurial efforts are fostered in two main dimensions.

Discussion and Conclusion

Lastly, we want to critically reflect our study's findings regarding the combination of energy flexibilities from industrial processes and EV charging. Our approach allows to quantify the flexibility benefits, with our findings in fact supporting the expected increase in economic and ecological flexibility potentials. However, it is essential to acknowledge the need for suitable metrics to quantify the potential of combined solutions. Future research should, therefore, focus on developing precise evaluation methods, such as diverse ecological metrics, and investigate the optimal planning for various sectors to assess the generalizability of our findings. Our model for EV charging involves several assumptions to reduce complexity. One such assumption is the constant maximum charging power, which has limitations, particularly if one were to consider local temperature variations in Germany, as the ideal temperature range for maximum charging power efficiency, proposed by Lindgren et al. (2016), is near 20 °C. Furthermore, our research was not based on real-world arrival and departure data, but gamma distributions were used instead. Moreover, in practice, a flexible reduction in load is often accompanied by a compensatory increase in load (Bahmani et al., 2022). However, due to problem complexity, no dependencies between flexible loads were considered in our research, thus making it possible to obtain results in a reasonable time span. Additionally, we assumed a certain level of EV penetration, which is above the current international level (Xue et al., 2021). This particular assumption may impact the applicability of our findings to real-world scenarios with different EV adoption rates. However, considering the rapid adoption of EVs, we anticipate that our assumption will soon align with the actual market situation.

We also want to discuss the ex-ante information of energy prices in energy planning and decision-making. For a real-world implementation, incorporating information uncertainty in future research can significantly improve transferability to and applicability in practice. This enables stakeholders to make more informed decisions on optimizing energy consumption and reducing costs. Additionally, our paper does not delve into the costs of integrating our findings, monitoring their function, or determining the thresholds that would make the adoption of our findings desirable for companies. From a policy perspective, incentivizing the adoption of combined approaches could encourage companies to reduce energy costs and carbon emissions. It is vital to analyze policy measures that support synergetic planning and remove regulatory barriers to facilitate the uptake of such strategies. In conclusion, our study, despite its limitations, contributes to a better understanding of untapped flexibility potentials in electrified mobility and energy-intensive industries as we transition to a sustainable energy landscape. By critically examining our findings and addressing shortcomings, we hope to inspire further research and policy development in this area.

Appendix

Sets and Indices		η_v^{ch}	$\in [0,1]$	Charging efficiency of the EV battery
t	Index of time from $1,\dots,\lvert T\rvert$	η_v^{dis}	$\in [0,1]$	Discharging efficiency of the EV battery
v	Index of EVs from $1,\dots,\lvert EVs\rvert$	C_v	$\in \mathbb{R}_0^+$	Battery capacity of EV v $[MWh]$
c	Index of charging stations from $1,\dots,\lvert ChSt\rvert$	$SoC_{v,t}^{min}$	$\in [0,1]$	Minimum State-of-Charge of EV v in time t

f_{pos}		Index of flexible loads representing a load increase from $1, \dots, \lvert F_{pos} \rvert$
f_{neg}		Index of flexible loads representing a load decrease from $1, \dots, \lvert F_{neg} \rvert$
f		Index of flexible loads from $1, \dots, \lvert F \rvert$ where $F = F_{neg} \cup F_{pos}$
Variables Related to EV Charging		
$P^{ch}_{c,v,t}$	$\in \mathbb{R}^+_0$	Charging power of charging station c in time t $[MW]$
$P^{dch}_{c,v,t}$	$\in \mathbb{R}^+_0$	Discharging power of charging station c in time t $[MW]$
$SoC_{v,t}$	$\in [0,1]$	State-of-Charge of EV v in time t
$Ch_{c,v,t}$	$\in \{0; 1\}$	Indicates if EV v is charged at charging station c in time t
$dCh_{c,v,t}$	$\in \{0; 1\}$	Indicates if EV v is discharged at charging station c in time t
$ChAssign_{c,v,t}$	$\in \{0; 1\}$	Indicates if EV v is assigned to charging station c in time t
Variables Related to Flexible Industrial Loads		
$P^{flex}_{f,t}$	$\in \mathbb{R}$	Load of flexible load f in time t $[MW]$
$start_{f,t}$	$\in \{0; 1\}$	Indicates if flexible load f is activated/started in time t
$end_{f,t}$	$\in \{0; 1\}$	Indicates if flexible load f is shut down/ended in time t
$on_{f,t}$	$\in \{0; 1\}$	Indicates if flexible load f is active in time t
$pState_{f,t}$	$\in \mathbb{N}$	Number of power state of flexible load f at time t
Variables Related to Power Balance & Grid Connection		
$P^{grid,in}_t$	$\in \mathbb{R}^+_0$	Power into the grid in time t $[MW]$
$P^{grid,out}_t$	$\in \mathbb{R}^+_0$	Power out of the grid in time t $[MW]$
$feedIn_t$	$\in \{0; 1\}$	Indicates if power is feed-in in time t
Parameters Related to EV Charging		
$P^{ch,max}_v$	$\in \mathbb{R}^+_0$	Maximum charging power of EV v $[MW]$
$P^{ch,min}_v$	$\in \mathbb{R}^+_0$	Minimum charging power of EV v $[MW]$
$P^{dch,max}_v$	$\in \mathbb{R}^+_0$	Maximum discharging power of EV v $[MW]$
$P^{dch,min}_v$	$\in \mathbb{R}^+_0$	Minimum discharging power of EV v $[MW]$
SoC^{max}_v	$\in [0,1]$	Maximum State-of-Charge of EV v
SoC^{min}_v	$\in [0,1]$	Minimum State-of-Charge of EV v
$P^{ch,max}_c$	$\in \mathbb{R}^+_0$	Maximum charging power of charging station c $[MW]$
$P^{ch,min}_c$	$\in \mathbb{R}^+_0$	Minimum charging power of charging station c $[MW]$
$P^{dch,max}_c$	$\in \mathbb{R}^+_0$	Maximum discharging power of charging station c $[MW]$
$P^{dch,min}_c$	$\in \mathbb{R}^+_0$	Minimum discharging power of charging station c $[MW]$
$OnSite_{v,t}$	$\in \{0; 1\}$	Indicates if EV v is expected to be on site in time t
Parameters Related to the Flexible Industrial Loads		
ac_f	$\in \mathbb{R}^+_0$	Activation cost of flexible load f [€]
hd^{max}_f	$\in \mathbb{N}$	Maximum holding duration of flexible load f [h]
hd^{min}_f	$\in \mathbb{N}$	Minimum holding duration of flexible load f [h]
$P^{flex,max}_f$	$\in \mathbb{R}$	Maximum power deviation of flexible load f $[MW]$
$P^{flex,min}_f$	$\in \mathbb{R}$	Minimum power deviation of flexible load f $[MW]$
rd^{min}_f	$\in \mathbb{N}_0$	Minimum regeneration duration of flexible load f [h]
$states_f$	$\in \mathbb{N}$	Number of permissible power states of flexible load f
$usage^{max}_f$	$\in \mathbb{N}$	Maximum number of usages in time t
$usage^{min}_f$	$\in \mathbb{N}_0$	Minimum number of usages in time t
$validity_{f,t}$	$\in \{0; 1\}$	Indicates if usage of flexible load f is valid in time t
Parameters Related to the Power Balance & Grid Connection		
$P^{GCP,max}_t$	$\in \mathbb{R}^+_0$	Maximum power at grid connection point in time t $[MW]$
$P^{GCP,min}_t$	$\in \mathbb{R}^-_0$	Minimum power at grid connection point in time t $[MW]$
P^{const}_t	$\in \mathbb{R}^+_0$	Constant demand in time t $[MW]$
P^{self}_t	$\in \mathbb{R}^+_0$	Self-generation in time t $[MW]$
General Parameters		
Δt	$\in \mathbb{R}^+$	Length of time interval $[t_i; t_{i+1}]$
e^{grid}_t	$\in \mathbb{R}^+_0$	Emission factor of grid power in time t $[kgCO_2eq/MWh]$
e^{self}_t	$\in \mathbb{R}^+_0$	Emission factor of self-generation in time t $[kgCO_2eq/MWh]$
p_t	$\in \mathbb{R}$	Dynamic electricity price in time t $[€/MWh]$
r_t	$\in \mathbb{R}^+_0$	Feed-in remuneration in time t $[€/MWh]$

Table 4. Nomenclature

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