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OrtsNetz

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Zusammenfassung

Der steigende Einsatz dezentraler erneuerbarer Energiequellen sowie die Elektrifizierung des Transport- und Wärmesektors stellen grosse Anforderungen an das Verteilnetz. Zur Bewältigung der entstehenden Herausforderungen untersucht das Pilotprojekt OrtsNetz den Einsatz von zeitabhängigen Netznutzungstarifen, welche helfen sollen, Leistungsspitzen im Niederspannungsnetz zu vermeiden und dezentrale Quellen zu integrieren. In diesem Kontext ermittelt und vergleicht das Projekt (i) Verhaltensänderungen von Kundinnen und Kunden durch Tarifsignale, (ii) eine automatisierte lokale Laststeuerung wichtiger Verbraucher (Boiler, Wärmepumpen und Elektrofahrzeuge) und (iii) eine direkte Ansteuerung flexibler Lasten durch den Verteilnetzbetreiber, die auf einer zentralen Optimierung basiert.

Das Projekt ist in vier Arbeitspakete unterteilt. Das erste Arbeitspaket befasst sich mit der Kundeninteraktion sowie mit dem Tarif- und Studiendesign. In den Arbeitspaketen 2 und 3 werden die Algorithmen zur Ermittlung der genauen Tarifwerte und der Schaltbefehle entwickelt. Der Fokus des vierten Arbeitspakets liegt auf dem Systemdesign und den Komponenten, die für eine erfolgreiche Implementierung während der Pilotphase benötigt werden.

In Arbeitspaket 1 wurde das Tarifdesign finalisiert. Basierend auf historischen Energiemessungen aus dem Projektgebiet wurde ein Time-of-Use Tarifprofil evaluiert und auf Kostenneutralität skaliert. Diese Skalierung bestimmt auch die Spanne eines Echtzeittarifs. Die verschiedenen Studiengruppen des Projekts wurden definiert und den insgesamt 630 Teilnehmenden zugeordnet. Erste Ergebnisse zeigen eine Opt-out-Rate von unter 4 %.

Das Arbeitspaket 2 analysiert die Wechselwirkung zwischen den Tarifwerten und dem Verbrauchsverhalten unter idealisierten Bedingungen. Sowohl die Perspektive des Verteilnetzbetreibers als auch die der Kundinnen und Kunden wurden modelliert, und ihre hierarchische Interaktion wurde als Bilevel-Optimierungsproblem formuliert. Die Lösung des Problems hat wertvolle Erkenntnisse für den Time-of-Use Tarif geliefert. Aufgrund des hohen Rechenaufwands bei der Betrachtung eines dynamischen Tarifs wurden alternative Methoden angewandt, welche in Arbeitspaket 3 beschrieben sind.

In Arbeitspaket 3 werden Unsicherheiten und begrenzte Informationen, d.h. reale Bedingungen, berücksichtigt. Für die Bestimmung der Preise des Echtzeittarifs haben wir eine proportionale Preismethode entwickelt und arbeiten an einem Reinforcement Learning basierten Ansatz. Darüber hinaus wurde das automatische Lastmanagement auf Haushaltsebene mit Hilfe eines Reinforcement Learning Agenten zur Steuerung von Boilern und Wärmepumpen sowie zur Optimierung der Steuerung des Ladevorgangs von Elektrofahrzeugen fertiggestellt. Letztlich haben wir einen Algorithmus zur Berechnung der Schaltbefehle für die direkte Laststeuerung entwickelt.

Im Arbeitspaket 4 wurde die Hardware und Infrastruktur für die Testphase entwickelt und fast vollständig installiert. Dies beinhaltet die Entwicklung der bei den Kunden installierten Lastschaltgeräte, die Einrichtung der Cloud-Infrastruktur, die Installation der Kommunikationsinfrastruktur und die Entwicklung der OrtsNetz-Plattform. Die Infrastruktur befindet sich noch nicht im Endzustand, aber die Steuerung der Lasten von Kunden hat bereits begonnen.

Summary

The increasing deployment of decentralized renewable energy sources and the electrification of the transport and heating sectors place great demands on the distribution grid. To meet these challenges, the OrtsNetz pilot project is investigating the use of time-dependent grid usage tariffs, which are intended to help avoid power peaks in the low-voltage grid and ease the integration of decentralized sources. In this context, the project is investigating and comparing (i) changes in customer behavior through tariff signals, (ii) automated local load control of important consumers (boilers, heat pumps, and electric vehicles) and (iii) direct control of flexible loads by the distribution grid operator based on central optimization.

The project is structured into four work packages. Work package 1 focuses on customer interaction, as well as the tariff and experiment design. The algorithms to determine the exact tariff values and the switching commands are developed in work packages 2 and 3. Work package 4 focuses on the system design and the components that are needed for a successful pilot implementation.

In work package 1, the tariff design was finalized. Based on historic energy measurements from the project area, a time-of-use tariff profile was evaluated and scaled for cost recovery. The same scaling determines the range of a real-time tariff. The different study groups of the project were defined and applied to a total of 630 participants. First results show an opt-out rate below 4 %.

Work package 2 analyzes the interplay between tariff values and consumption behavior under idealized conditions. Both the perspective of the distribution system operator and the customers have been modeled, and their hierarchical interaction has been formulated as a bilevel programming problem. Solving the problem gave relevant insights for the time-of-use tariff scheme. Due to the computational complexity when considering a dynamic tariff, alternative methods were applied, as described in work package 3.

In work package 3, uncertainties and limited information, i.e., real-world conditions are considered. For determining the real-time price values in the dynamic tariff scheme, we developed a proportional pricing method and are working on a reinforcement learning-based approach. Furthermore, the automatic load management at the household level has been finalized, using a reinforcement learning agent to control electric water heaters and heat pumps, and optimization for controlling electric vehicle charging. Third, we developed an algorithm to compute the switching commands in the direct load control setting.

Finally, in work package 4, the hardware and infrastructure for the test phase has been developed and almost completely been installed. This includes the development of the load control devices installed at the customers, setting up the cloud infrastructure, installing the infrastructure necessary for power line communication and developing the OrtsNetz platform. The infrastructure is not in its final state but control of customers' loads has already started.

Contents

Abbreviations

API	Application Programming Interface
DLC	Direct Load Controller
DSM	Demand Side Management
DSO	Distribution System Operator
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EWH	Electric Water Heater
FEDRO	Federal Roads Office
HES	Head End System
HP	Heat Pump
KKT	Karush-Kuhn-Tucker
LCD	Load Control Device
LCMA	Load Control Master Agent
LCSA	Load Control Service Agent
MAE	Mean Absolute Error
MILP	Mixed Integer Linear Programming
MIQP	Mixed Integer Quadratic Programming
PLC	Power Line Communication
PV	Photovoltaic
P2P	Peer-to-Peer
RL	Reinforcement Learning
SFH	Single Family Home
SoC	State of Charge
TECA	Total Energy Correctly Assigned
TS	Transformer Station
ToU	Time-of-Use
WP	Work Package

1 Introduction

1.1 Background information and current situation

Current efforts towards decarbonization and increased sustainability are fundamentally reshaping the electricity sector. Conventional power plants running on fossil fuels are replaced with distributed, renewable energy sources, which are much more volatile and intermittent. These changes challenge traditional supply-side approaches to balancing supply and demand. Simultaneously, the electrification of transport and heating increases electricity demand, putting extra stress on the distribution grid during peak times and necessitating costly grid expansions [1].

Enabled by the progressing digitalization, Demand Side Management (DSM) is a means to address these challenges. Instead of adapting supply to a given demand, the flexibility present in many devices is used to adapt their demand to available supply, shifting peaks in demand to those in supply or flattening demand curves in general. In particular, the heating and transportation sectors exhibit considerable flexibility. Heating systems can use thermal inertia to store energy, and batteries in Electric Vehicles (EVs) are typically connected to the grid for longer periods than they require for charging, allowing flexibility during the charging process. Due to these beneficial properties, demand-side flexibility has been incorporated in the revision of the StromVG [2] and is already grounded in the “NOVA” concept for grid planning.

1.2 Purpose and objectives of the project

The overall goal of OrtsNetz is to define and evaluate approaches that facilitate the integration of renewable energy sources into the future’s low-voltage grid by using appropriate tariff schemes and flexible loads. To this end, the project aims to reduce power peaks in the low-voltage grid, considering system costs, practicability, and the fair distribution of costs and benefits.

The project studies different DSM approaches and evaluates their effectiveness in promoting grid-friendly behavior of the consumers. Two main strategies are compared (Figure 1): In a direct load control setting (strategy 1), the Distribution System Operator (DSO) directly controls devices based on a centralized optimization. The control is limited to allowing or blocking power consumption by a particular device, and customers receive in return a reduced constant grid-usage tariff for providing flexibility to the DSO. In the second approach, indirect load control scheme (strategy 2), the tariff is time-dependent. Here, two different tariff schemes are compared, a pre-planned Time-of-Use (ToU) tariff that extends existing high/low tariff rates, and a fully dynamic real-time tariff that adapts to newly developing grid situations. Part of the customers are equipped with a device on which a intelligent local agent can control Heat Pumps (HPs) and Electric Water Heaters (EWHs) based on the current tariff value, while EV charging is controlled via an Application Programming Interface (API) over the internet. Customers can also react manually to price changes to minimize their electricity cost.

OrtsNetz consists of three key components, which also form the basis for the different work packages: Firstly, it studies customer acceptance of dynamic tariffs and automated control of devices, as well as manual intervention of participants. Secondly, it explores and develops algorithms to determine the tariff values and the switching commands for the automatic load control. Finally, it provides important insights regarding the required infrastructure and hardware for a successful implementation of DSM schemes.

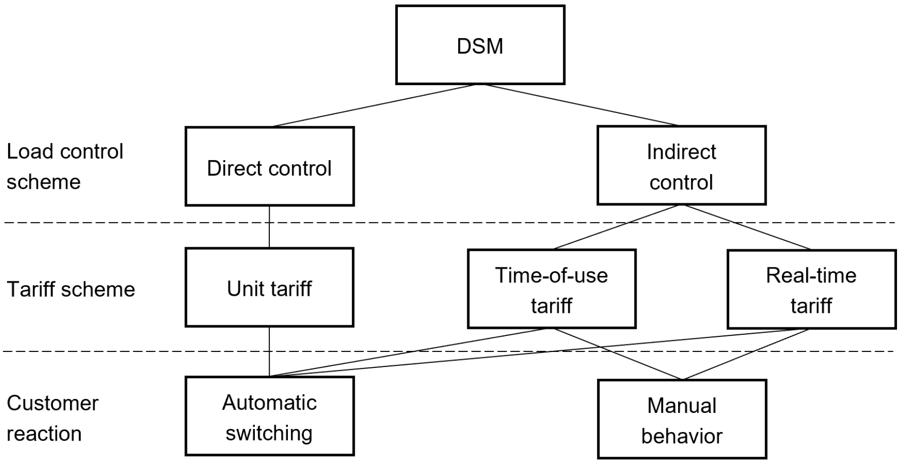


Figure 1: Overview of demand side management schemes studied in the project.

2 Description of facility

The pilot project is set in the municipality of Winkel, located in the canton of Zurich. Winkel has a population of 4,855 persons living in 2,198 private households (as of 2022) [3]. All inhabitants are supplied by the local electricity supply company EKZ.

The households are equipped with a smart electricity meter that measures active and reactive energy consumption (and possibly feed-in) at intervals of 15 minutes. The measurements are communicated once a day to EKZ via Power Line Communication (PLC). In some cases, a household can have more than one smart meter for separately monitoring the consumption of appliances like HPs.

Due to the rapidly increasing share of EV sales, the number of vehicles registered in Winkel have significantly changed since the last report. According to data by the canton of Zurich, there are 130 privately owned EVs (4.1 % of all registered vehicles) and 288 hybrid vehicles (8.8 %) in Winkel [3], which is a relatively high share of EVs compared to the rest of Switzerland (3.3 % and 7.6 %, respectively) [4].

Customers' residences are connected to one of 16 Transformer Stations (TSs) with a total power rating of 10 MVA. Three TSs are equipped with fiber networked equipment that allows near real-time monitoring of power and voltage levels. Each of the DSM schemes described in chapter 1 is assigned to one of these TSs. A battery storage system will be installed at a fourth TS that will also be equipped with network equipment.

For automatic switching of EWHs and HPs, nearly 53 Load Control Service Agents (LCSAs) and Load Control Devices (LCDs) were installed in households, where a potential of 11 installtions is left. The LCSA is an intelligent control device that can compute switching commands based on a price signal, while the LCD is a simple device implementing the switching commands computed by the LCSA or the central system. Since the project focuses on using existing infrastructure, the LCSAs are not networked and only communicate through PLC with the central system. Furthermore, LCDs act as simple on/off switches and do not receive any information on the state of the device they control, e.g., the water temperature. LCDs can only block devices from running but not actively turn them on.

Currently, 37 customers registered their EVs to be used as a flexible load in the pilot project. EV charging is controlled via an API that directly communicates with the vehicles. This allows retrieving information on a vehicle's current status, e.g., its State of Charge (SoC) and whether it is plugged in. The charging process can be started and stopped via the API, while the vehicle controls the power.

Automatized load control is used either for direct load control (following a command issued by the central system) or for indirect load control via price signals (Figure 2). In the former case, the DSO communicates a switching profile to the LCDs every 15 minutes for the next 96 15-minute intervals (24 hours) or in case of EVs potentially starts or stops the charging process. In the latter case, the LCD receives switching commands from the LCSA, which computes them based on the time-variable tariff. This price profile is either known in advance (ToU tariff) or dynamically calculated by the DSO and communicated every 15 minutes to the households (real-time tariff). The algorithm determining the EV charging schedules in the indirect load control setting is implemented centrally but acts in the interest of each individual customer.

The existing PLC infrastructure has a direct impact on the kind of data that is available at each location and time. In the decentralized scheme, local LCSAs have immediate access to the 15-minute interval smart meter readings of their given household. On the other hand, the smart meter data of each household is collected only once a day by the central location. Furthermore, communication errors can lead to data sometimes being available later or not at all.

In order to ensure comparability among the different settings that will be evaluated, the basis for the switching decision must be the same in all approaches. Therefore, the assessment of the grid situation (Fig. 2) is based on the same information from the TS in all scenarios.

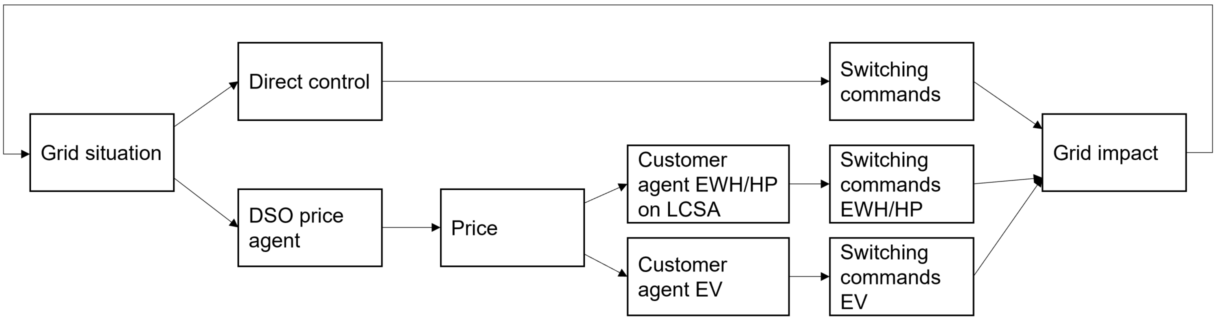


Figure 2: Influence of the grid situation on automatic switching through a variable tariff or direct control.

3 Activities and results

OrtsNetz is a collaboration of two labs at ETH Zurich and EKZ, the electricity utility company of the canton of Zurich. OrtsNetz is organized in Work Packages (WPs) that are distributed across the partners, each having distinct milestones. Exchange between partners and collaboration in WPs happens in weekly meetings on a technical level and quarterly steering meetings on an organizational, strategic, and administrative level. The activities conducted in the various WPs and their results are presented in the following sections.

3.1 WP 1: Customer interaction, market and tariff design

Work package WP1 deals with the design of the tariff schemes as well as the evaluation of customer behavior and overall impact. Over the course of the last year, the tariff schemes and customer groups presented in the previous report were developed in detail and implemented. Letters with tariff sheets were sent to customers over the summer and at this point in time all participants have been successfully recruited. Most milestones due in WP1 have already been reached last year. Regarding the final evaluation (WP1.4_MS3 & WP1.5_MS36), we present initial results on participant recruiting.

The next subsection presents the grouping of study participants. This is followed by a detailed explanation of the tariff structure and design decisions in regard to cost recovery and fairness. The final subsections features a preliminary evaluation of recruiting efforts.

3.1.1 Study groups

Participation in the OrtsNetz study is differentiated along three dimensions. Firstly, OrtsNetz features three distinct grid usage tariffs (OrtsNetz Tariffs) that are different from the standard tariff (EKZ Tariff):

- A Time-of-Use tariff
- A dynamic real-time tariff
- A unit tariff for participants with directly controlled devices

Each tariff is matched to one of the three selected Transformer Stations (TSs). TSs have been chosen from within the project area to optimize the number of single family households with EWHs and HPs, which are the customers eligible for installation of an LCD.

Since the direct control approach is most assured to reduce peaks and avoid rebounds effectively, it is applied to the TS with the lowest power rating, while the real-time and ToU tariff settings are matched to the two remaining TS. Secondly, two classes of participants are discerned: the ones with automatically controlled devices and those without (Fig. 3). Automatically controlled devices are HPs, EWHs and EVs. As HPs and EWHs are controlled via PLC, they are distributed among the three selected TSs equipped with the required gateways (Section 3.4.2). These participants receive a Load Control Device (LCD) that is installed in their electrical panel. EVs are instead distributed across the whole project area as they are controlled via the internet. As detailed in the next subsection, customers with automatically controlled devices may receive a modified energy tariff in addition to their OrtsNetz grid tariff to provide further compensation. Additionally, customers with EVs can decide for every charging session if they want to deactivate the intelligent control and opt out of the associated energy tariff for the following 12 hours.

Thirdly, participants are either recruited in an opt-in or an opt-out scheme. The initial announcement of the project encouraged proactive registrations by the customers. In summer 2023, an additional group of customers was selected and informed by letter about their respective new OrtsNetz tariff, with the possibility to opt out. All participants are subject to the best-accounting policy, such that no one will pay more than they would under the normal EKZ Tariff. After the first billing period (January 2024), the revenue of the OrtsNetz Tariffs and the standard EKZ tariff will be calculated. The differences will give valuable insight into the cost of load-shifting within the project.

This design allows for three major studies:

- The effect of different DSM approaches can be studied by comparing the efficiency of automatic control between direct control, agents reacting to ToU prices, and agents reacting to real-time prices.
- The behavior of participants in response to dynamic prices can be compared between the ToU and real-time tariffs.
- The results of opt-in recruiting and opt-out recruiting can be compared to unveil the impact of selection biases on observed participant behavior.

These participation schemes have been implemented in the project area of Winkel as described in Subsection 3.1.3.

3.1.2 Tariff design

Automatic devices Participants with automatic devices are compensated for the inconvenience of having an LCD installed, as well as giving up some flexibility in when they can use their device. This is implemented by billing them a lower energy component of the electricity tariff. Specifically, they receive the low-tariff component of the normal EKZ Tariff, which is usually only valid during night times and weekends, for all points in time (10.35 Rp./kWh in 2023 and 17.50 Rp./kWh in 2024[1]). This change in the tariff has the benefit that it is easy to communicate to customers. Assuming the H4 standard

[1] Unless stated otherwise, all tariff values are without taxes.

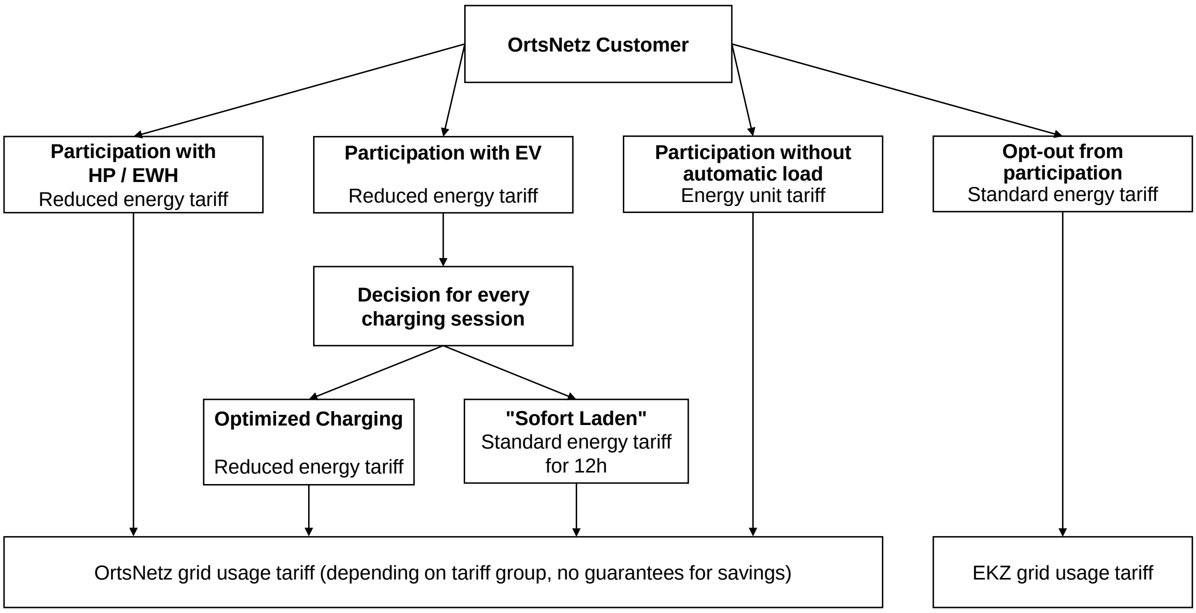


Figure 3: Overview of ways to participate in the OrtsNetz project. When taking part with an EV, participants still have the chance to opt-out of intelligent charging of their vehicle for individual charging sessions.

profile published by ElCom [5] with additional demand of 2000 kWh/year for an EV, the reduction in the energy component results in savings of 33 CHF over one year. The exact savings for the participants however strongly depends on their heating and driving demand and can be far greater. On top of this compensation, participants are subject to the grid usage OrtsNetz Tariff at their respective TS which enable additional savings.

Time-of-Use tariff The ToU grid usage price profile is determined based on a bilevel programming problem that optimizes grid utilization and customer costs simultaneously (Section 3.2.3). While the optimization selects the best times for the price switches, the exact values of the profile need to be scaled for cost recovery and fair distribution of costs.

Cost recovery is implemented by calculating the revenue from non-responding customers without flexible loads to the baseline EKZ Tariff. Calculations for a specific season are based on historic demand in the equivalent period from 2022–2023. Specifically, we use the total demand of residential households at a selected TS without devices that could be controlled automatically and calculate the revenue for Winter 2023 (October–December), Winter 2024 (January–April), and Summer 2024 (May–September). This implementation reflects the understanding of fair cost distribution in the project that is also compatible with the best-accounting policy. Customers without the ability to majorly shift demand will pay the same, whereas customers with large loads are encouraged to shift their operation to times of cheaper prices which are the ones with lower grid utilization.

Before selecting the final grid usage tariff values, we take another consideration into account. The current EKZ Tariff already includes a ToU profile, not only for the grid usage component, but also for the electricity price. The two components have the same profile (high tariff on weekdays from 7:00–20:00), resulting in a price jump between only two levels that is convenient for customers to memorize. However, the ToU profile that is selected by the bilevel optimization (Section 3.2.3) has up to three price levels at different times (Fig. 4). Overlaying this with the existing time profile of the energy component of the EKZ Tariff would result in an undesirably complicated profile. Instead, we calculate a single energy tariff component from the low and high tariffs. We use the average weighted by the energy demand of the selected subgroup of inflexible load customers to ensure cost recovery.

The preceding considerations allow to determine the specific tariff values for the ToU grid tariff. For a tariff

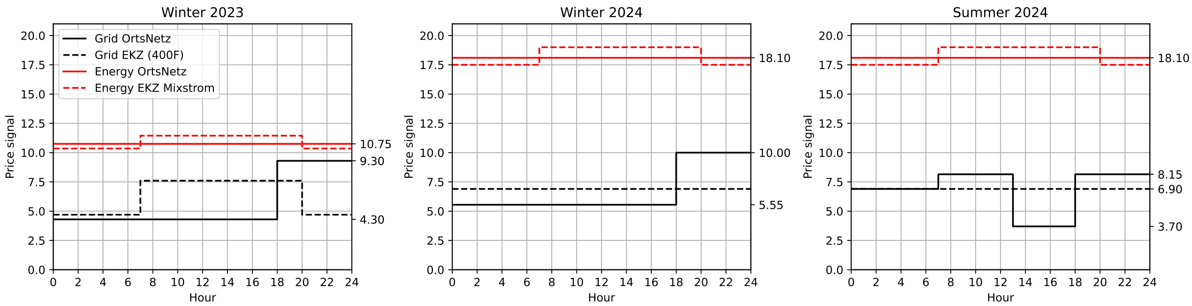


Figure 4: Final ToU tariff profiles selected for the project. Exact values are annotated on the right y-axis of each plot.

with two price levels, selecting one level determines the other one to achieve cost recovery. For a three component tariff there is another degree of freedom that needs to be decided. As the grid component of the EKZ Tariff 2024 will be a unit tariff, we decided to fix the mid value of the summer profile of the OrtsNetz 2024 tariff to the same value. This reduces one degree of freedom and cost recovery enforces a direct relation between the high and low tariff components. To analyze the effect of this relation we developed a tool that allows to dynamically visualize the tariff profiles, ratios, and cost impacts. The final selection of the tariff values was conducted together with the tariff department of EKZ and aimed to increase the span between high and low tariff components while keeping them at reasonable levels (Fig. 4).

Real-time tariff The real-time grid usage tariff can vary from the high to low tariff range (4.30–9.30 Rp./kWh for 2023 and 3.70–10.00 Rp./kWh for 2024) and must fulfill the same cost recovery constraints as the ToU tariff. Cost neutrality is applied per day, using the monthly mean daily revenue with a corresponding cost-neutral unit tariff for reference. Section 3.3.2 provides more details on the algorithm choice and the current implementation of the real-time tariff.

Direct control Finally, as the direct control setting is not price-based, participants receive a unit tariff for grid usage. This allows the direct control system to optimize based on the grid situation alone, without taking potential cost (dis-)advantages for customers due to time-varying prices into account. The grid component of the 2024 EKZ Tariff is a unit tariff anyways (6.90 Rp./kWh). For 2023 the value is determined based on the same calculations as above, as the demand weighted average of the low and high tariff, using the demand profile of customers without flexibility for costs recovery (5.80 Rp./kWh).

3.1.3 Customer recruiting

While the final project evaluation and derivation of recommendations can only be conducted once the trial phase is complete, here we present initial findings regarding customer recruiting.

The study grouping described in Subsection 3.1.1 was applied to a total of 630 participants in Winkel, of which 35 opted out of the OrtsNetz tariff. The three automatic control settings are distributed across three selected TSs. Table 1 lists the number of customers that were approached for installation of an LCD, as well as the additional customers with an EV that are part of the same control scheme but not located at the same TS. While the direct control and real-time price schemes have the same number of LCDs, the ToU scheme only has half as many due to the size of the respective TS. Furthermore, since the control of EVs does not depend on the PLC infrastructure, they can be matched to any tariff. Each TS only has one customer with an EV, which have to be matched to the respective DSM scheme. The other EV participants reside elsewhere in Winkel and are randomly distributed across the direct control and real-time price settings. Due to the limited number of EV participants, we decided to leave out the ToU tariff here. The customers without an automatically controlled device are distributed across the two time-varying tariffs only. The direct control setting brings no insights for customers without automatic loads (only 35 customers without an LCD that reside at the TS with the ToU scheme receive this tariff).

	LCD	EV	No automatic device Opt-in	Not opt-out
Direct control	21	20	17	18
Time-of-Use	10	1	108	149
Real-time	21	16	111	138

Table 1: Participant numbers

Of the 257 customers with the ToU tariff, 42 % had already opted into the project by signing up on the platform. For the real-time tariff, 45 % of 249 customers had already opted in.

Participation in the project is generally high. Only 21 customers (3.7 %) without automatic control opted out. For the installation of an LCD, 14 customers (21 %) opted out. Furthermore, 12 devices could not be installed because of space constraints. More potential candidates are currently being approached to install the last LCDs.

Recruiting of EV participants started in March 2023. The Federal Roads Office (FEDRO) provided a list of all plugin vehicles (battery electric vehicles and plugin hybrid electric vehicles) registered by inhabitants of Winkel. Out of a total of 206 vehicles, 143 are fully supported by the provider of the API interface that allows to control the charging process (exactly 100 of which are battery electric vehicles). Recruiting was done by letter, which provided project information and a link to a website through which vehicles can be connected to the OrtsNetz system. To incentivize participation, the letter advertised savings of around 100 CHF/year on average. This amount corresponds to average driving demand and shifting of all charging to the lowest tariff times. Naturally, the exact savings highly depend on driving demand and general household electricity consumption. To protect residents' privacy, the letter was sent by FEDRO in the name of EKZ to all inhabitants of Winkel that own a plugin vehicle.

Overall interest in the EV study has been high. In the first two weeks, 221 page visits were registered and 50 unique email addresses were entered into the system. This resulted in 32 successful sign-ups of users that connected at least one vehicle. Over the course of the following half year more customers signed up, whereas some participants had to deregister for various reasons (not charging at home, not residing in Winkel, sold vehicle). Currently there are 37 users (26% if possible vehicles) registered in the OrtsNetz system.

3.2 WP 2: Idealized analysis of interactions and tariff design

A key component of the project is determining the tariff values for indirect load control via time-varying grid-usage tariffs. The tariff values influence customer behavior as the customers aim to minimize their electricity costs while meeting their demand needs. On the other hand, the resulting consumption profiles affect the power flows in the grid. Therefore, there is a mutual impact between the tariff values and the consumption behavior. Thus, the DSO must take the customers' reactions into account when computing the tariff values, which results in a problem structure that is rather complex to describe and solve mathematically. As a first step, idealized conditions are assumed in WP 2. It is assumed that the inflexible consumption and production profiles, as well as the load behavior, are known. Furthermore, the customers behave rationally with respect to the cost minimization. Lastly, there is complete transparency, i.e., the DSO has the same information as the customers.

3.2.1 Problem formulation

The above-mentioned interdependency between the DSO's and customers' actions is modeled as a bilevel programming problem. Thereby, the hierarchy between the DSO (upper-level problem) and the customers (lower-level problems) can be represented. As described in [6] and [7], the customer problem is a mixed-integer problem when the control is modeled according to the given infrastructure in the project, i.e., blocking a device or not. Several solution approaches were evaluated in [6], but none of the investigated approaches showed satisfactory results. Therefore, the focus of WP 2 in this report is on a simplified problem formulation with continuous variables for the device power. Further, it is limited to the ToU tariff scheme to reduce the upper-level search space, only considers EWHs as flexible loads, and does not take self-consumption optimization into account.

Customer's perspective (lower level) Each customer aims to minimize the electricity costs by shifting EWH consumption to low-price periods:

$$\min_{\mathbf{P}_c^{\text{EWH}}} \quad \sum_{d=0}^{D-1} \sum_{t=0}^{K-1} \left(\pi_t^{\text{buy}} \cdot \Delta t + \beta_c \cdot t \right) \cdot P_{c,d,t}^{\text{EWH}} \tag{1a}$$

$$\text{s.t.} \quad \sum_{t=0}^{K-1} P_{c,d,t}^{\text{EWH}} \cdot \Delta t = E_{c,d}^{\text{EWH}}, \qquad \forall d \tag{1b}$$

$$0 \leq P_{c,d,t}^{\text{EWH}} \leq P_{c,\text{nom}}^{\text{EWH}}, \qquad \forall d, t \tag{1c}$$

where D denotes the number of considered days, K is the number of time steps within one day (96 for 15-minute resolution), Δt is the duration of one time step, and π_t^{buy} denotes the electricity price in time step t (the price profile is the same for all days). The variable $P_{c,d,t}^{\text{EWH}}$ describes the EWH demand for customer c in time step t on day d and is limited by the nominal power $P_{c,\text{nom}}^{\text{EWH}}$, while $E_{c,d}^{\text{EWH}}$ is the energy that must be delivered by the EWH on day d. Finally, β_c specifies the customer preference for running the EWH as early (positive value) or late (negative value) as possible. This preference is included to ensure the uniqueness of the lower-level solution, as explained in [6]. β_c is set to a small value such that the second summand in (1a) does not shift consumption to a different tariff level, but only shifts consumption among times with the same price.

DSO's perspective (upper level) The DSO aims to determine the tariff values for drawing electricity from the grid such that the maximum aggregated active power of all customers P^{max}, i.e., the peak absolute power observed within the analyzed time horizon, is minimized. The constraints of the DSO are the following:

$$P^{\text{max}} \geq P_{d,t}^{\text{inf}} + \sum_{c=1}^{N_{\text{customers}}} P_{c,d,t}^{\text{EWH}}, \qquad \forall d, t \tag{2a}$$

$$P^{\text{max}} \geq -\left(P_{d,t}^{\text{inf}} + \sum_{c=1}^{N_{\text{customers}}} P_{c,d,t}^{\text{EWH}} \right), \qquad \forall d, t \tag{2b}$$

$$\pi^{\text{buy,min}} \leq \pi_t^{\text{buy}} \leq \pi^{\text{buy,max}}, \qquad \forall t \tag{2c}$$

$$\pi_{t+1}^{\text{buy}} = \pi_t^{\text{buy}}, \qquad \forall t \in [t_p^{\text{start}}, t_p^{\text{end}}), \quad \forall p \tag{2d}$$

Constraints (2a) and (2b) define the lower bound for P^{max}, given by the sum of the inflexible load $P_{d,t}^{\text{inf}}$ and the EWH load in each time step. Constraint (2c) puts bounds on the tariff values, while constraint (2d) specifies that the price must be constant within each pre-specified period p. If there should not be a change in the tariff value at midnight, this is enforced by an additional constraint $\pi_{K-1}^{\text{buy}} = \pi_0^{\text{buy}}$.

DSO - customer interaction The interaction between the DSO and the customers is expressed in a bilevel programming problem:

$$\min_{\pi^{\text{buy}}, P^{\text{max}}, \mathbf{P}^{\text{EWH}}} \quad P^{\text{max}} \tag{3a}$$

$$\text{s.t.} \quad (2a) - (2d) \tag{3b}$$

$$(1a) - (1c), \quad \forall c \tag{3c}$$

Note that the customer problems can be combined into one problem with the sum of the individual customer's objectives as the overall objective function, subject to all the individual constraints.

3.2.2 Solution approach

The bilevel programming problem presented is a pricing problem with linear upper-level and lower-level constraints, a linear upper-level objective function, and a bilinear lower-level objective function as it contains products of upper- and lower-level variables. However, the lower-level objective function is linear for fixed upper-level variables, and therefore, the lower-level problem can be replaced by its Karush-Kuhn-Tucker (KKT) conditions or by optimality conditions based on the strong duality theorem [8].

We chose the second approach to transform (3) into a single-level problem, i.e., the lower-level problem is replaced by its primal constraints, its dual constraints, and the strong duality condition, which states that the primal and dual objective function values must be equal. The only non-linearities in the resulting problem are the products $\pi_t^{\text{buy}} \cdot P_{d,t}^{\text{EWH}}$ in the primal objective function ($P_{d,t}^{\text{EWH}} = \sum_{c=1}^{N_{\text{customers}}} P_{c,d,t}^{\text{EWH}}$). These bilinear terms are linearized by discretizing π_t^{buy} using a binary expansion, and linearizing the resulting products of a binary and a continuous variable, as proposed, e.g., in [9], and described in the following. The price variable π_t^{buy} is rewritten as $\pi_t^{\text{buy}} = \pi_t^{\text{buy,min}} + \Delta\pi^{\text{buy}} \sum_{w=0}^{W-1} 2^w b_{t,w}$, where $b_{t,w}$ is a binary variable, $\pi_t^{\text{buy,min}}$ is the lower price bound, $\Delta\pi^{\text{buy}}$ describes the discretization interval, and the parameter W determines the number of considered different price values 2^W. Then, the bilinear terms $\pi_t^{\text{buy}} \cdot P_{d,t}^{\text{EWH}}$ can be replaced by $\pi_t^{\text{buy,min}} P_{d,t}^{\text{EWH}} + \Delta\pi^{\text{buy}} \sum_{w=0}^{W-1} 2^w z_{d,t,w}$, where the continuous variable $z_{d,t,w}$ is defined by the following two constraints:

$$0 \leq z_{d,t,w} \leq G \cdot b_{t,w}, \qquad \forall d, t, w \tag{4a}$$

$$0 \leq P_{d,t}^{\text{EWH}} - z_{d,t,w} \leq G \cdot (1 - b_{t,w}) \qquad \forall d, t, w \tag{4b}$$

G is a sufficiently large positive constant. A valid value for G is given by $\sum_{c=1}^{N_{\text{customers}}} P_{c,\text{nom}}^{\text{EWH}}$. The resulting model is a Mixed Integer Linear Programming (MILP) and is solved using Gurobi [10].

3.2.3 Case study

Setup The optimization is applied to one of the TSs in Winkel. According to EKZ's records, 45 households at this TS have an EWH. For each of these households, the energy consumption $E_{c,d}^{\text{EWH}}$ is determined by disaggregating the EWH load from the smart meter data using the approach described in section 3.3.1. The nominal device power $P_{c,\text{nom}}^{\text{EWH}}$ is specified according to EKZ's records, and the inflexible load $P_{d,t}^{\text{inf}}$ at the TS is estimated by subtracting the EWH load from the total TS load. Note that HPs and EVs are considered inflexible in this analysis, while they are flexible in the pilot implementation. The constant β_c is set to a small positive value, such that all EWHs operate as early as possible, which is reasonable assuming that devices are unblocked for the entire low-price period. The analysis focuses on one week in summer and one week in winter. More specifically, we analyze the week for which the grid load in Winkel most closely resembles the average over eight weeks in July and August for summer and January and February for winter [11]. The duration of one time step Δt is 15 minutes.

The project partners agreed that the price can change every full hour (enforced by constraint (2d)), but there can be at most three different price levels and four price changes. As the model does not consider price sensitivities, only the shape of the price profile matters and not the actual price values, i.e., the customers' response is the same for any linear transformation of the price profile obtained from the bilevel solution [12]. Therefore, we enforce $\pi_t^{\text{buy}} \in \{1, 2, 3\}, \forall t$ to reduce the search space and transform the profile ex-post to meet the cost neutrality condition. The number of price changes is enforced by adding a binary variable per time step that takes a value of 1 if the price differs from the previous time step and 0 otherwise. The sum of these binaries over the entire day must be smaller than or equal to four.

Results Figures 5 and 6 show the results for summer and winter, respectively. From Fig. 5, it is visible that the disaggregation captures a major share of the nightly peaks (original $P^{\text{tot}} - P^{\text{inf}}$), which are caused by the current ripple control of EWHs. However, the remaining peaks in P^{inf}, e.g., at 3:00 on the first day, indicate that the actual EWH load is potentially higher than considered in this analysis. For summer, the

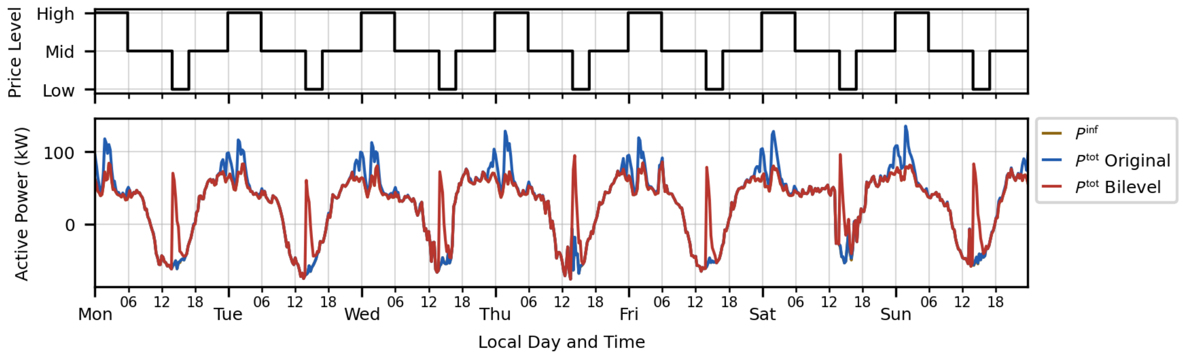


Figure 5: Original TS load and bilevel results for the week from 18.07.2022 to 24.07.2022.

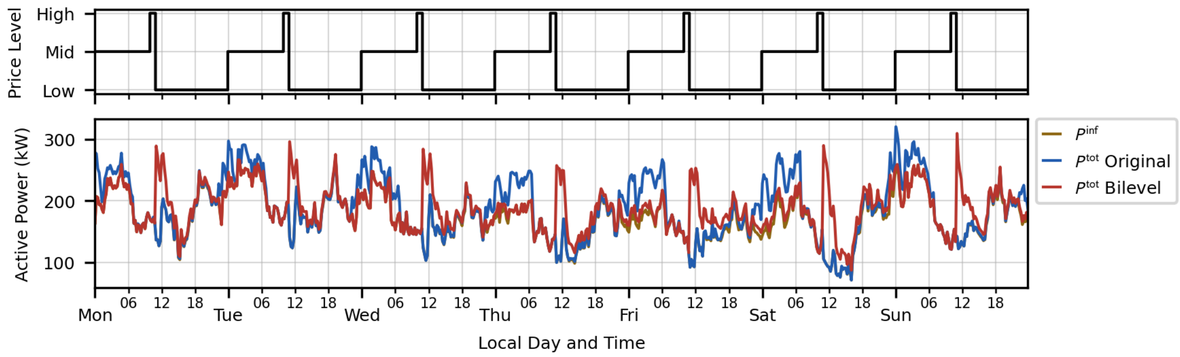


Figure 6: Original TS load and bilevel results for the week from 31.01.2022 to 06.02.2022.

optimization chooses a low price value starting from 14:00 and thereby shifts the peak EWH load to this time. It does not operate the EWHs at an earlier hour with excess Photovoltaic (PV) power, e.g., 10:00, because this would lead to a higher maximum load P^{max}. Note that several other tariff profiles lead to the same customer response. What is most relevant is the start of the lowest price period. In winter, the overall consumption is higher and there is no excess PV power. A main contributor to the high load during the night are electric storage heaters, which are currently unblocked from 23:00 to 7:00. The dip in original demand before noon stems from HP blocking during weekdays. The optimization chooses a low price value starting from 11:00, which results in a peak load that is 39 kW higher than the highest "inflexible load" in the analyzed time window. If HPs and electric storage heaters were also considered flexible, this would further increase the peak in total load. This indicates that synchronized operation of devices is not desirable in winter.

3.2.4 Discussion and pilot time-of-use tariff

Two limitations of the above analysis are that only EWHs are considered as flexible loads, and that the disaggregation could potentially be improved (e.g., by improving the data quality with respect to EWH presence, unblocked time windows and nominal device power), which impacts the shiftable energy and inflexible load. Even though these could be addressed in future work, the results already give important insights into the tariff design and were leveraged for determining the ToU tariffs in the OrtsNetz pilot. As discussed by many studies in the literature and observed above, time-variable prices can cause power rebounds. In summer, the DSO can exploit these rebounds to reduce injection peaks. For this, it is important to "schedule" the flexible devices to run during the hours with the highest PV power. Solar noon in Zurich in summer occurs at around 13:30 local time, so we choose 13:00 as the start of the low-price period. Most EVs are only connected to the charging station from evening to morning. To reduce the coincidence between EV charging and inflexible load peaks in the morning and the evening, a mid-price period is applied from midnight to 7:00, which incentivizes shifting charging to these hours. Note that we intentionally chose the medium price for this period and not the low price, such that EWHs, which are always available, do not shift to the same time. In winter, the results show that synchronized operation of devices should be avoided, as there is less PV power and the spread between the minimum and the maximum inflexible load is not high enough to schedule a power rebound effectively. To increase randomness in EWH operation, the price is low for most of the day, and there is only a high-price period from 18:00 to midnight to avoid coincidence between the evening inflexible load peak and EV charging. The resulting price profiles are visualized in Fig. 7 and were scaled according to section 3.1 before they were communicated to the customers. The summer tariff is applied from the beginning of May until the end of September, and the winter tariff is applied in the remaining months.

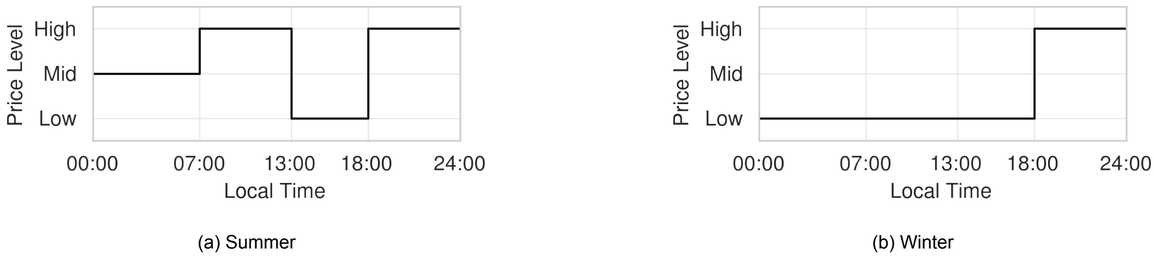


Figure 7: ToU tariff OrtsNetz pilot.

3.3 WP 3: Automatized load management and tariff design

3.3.1 Inflexible load forecast

Overview Forecasting the inflexible load is required for direct load control and the proposed proportional pricing scheme. The most similar historical day to the one being forecasted is identified to forecast this load. Then, the inflexible load estimated for that historical day is used as a forecast. The method is split into two steps:

1. Load disaggregation: This step disaggregates past smart meter data to create a database of historical flexible demand.
2. Most similar day matching: This step involves leveraging weather data to match the day to be forecasted to a similar historical day. Then, the inflexible load for that historical day is computed using the historical TS load measurements and flexible demand.

In the following paragraphs, these two steps are described in detail.

Load disaggregation Disaggregating the total TS load into its flexible and inflexible components is the first step toward forecasting the inflexible load. The flexible load at a TS level is the sum of the load of every EWH, HP, and EV managed through a control scheme. While the demand of EVs is known via the API, EWHs and HPs are not measured separately. Therefore, this paragraph describes how the load profiles of EWHs and HPs can be estimated given the smart meter data at a household level, i.e., the active and reactive energy withdrawn from the grid in each 15-minute interval. First, the smart meter data are converted from energy to active power. Then, the load disaggregation is split into two sub-components:

1. HP load detection: this component estimates the average active power of the HP given measurements of active and reactive power withdrawn from the grid at a household level (with a 15-minute resolution) minus the EV consumption (if present), the nominal power of the HP installed, and a list of switching commands. Each switching command $u_t^{\text{HP}} \in \{0, 1\}$ determines whether the HP can run in time step t for a specific customer/household.

2. EWH load detection: this component estimates the active power of the EWH given the active power measurements at a household level where the HP and EV consumption (if present) has been already extracted, the nominal power of the EWH installed, and a list of switching commands. Each switching command (u_t^{EWH}) is in $\{0,1\}$ and determines whether the EWH can run.

The HP load detection component uses the smart meter measurements converted to power values (without the EV consumption) to estimate the time steps when the HP is running. The heuristic algorithm defines a variable $hp_t^{\text{ON}} \in \{0,1\}$ that represents whether the HP is running at time step t or not ($hp_t^{\text{ON}} = 1$ represents a running HP at time step t). At every time step t, hp_t^{ON} is computed as follow:

$$hp_t^{\text{ON}} = \mathbf{1}_{\{P_t > \gamma \cdot P_{\text{nom}}^{\text{HP}}\}} \cdot \mathbf{1}_{\{Q_t > Q_{\text{AVG24h}}\}} \cdot u_t^{\text{HP}} \tag{5}$$

The first indicator function $\mathbf{1}_{\{P_t > \gamma \cdot P_{\text{nom}}^{\text{HP}}\}}$ is 1 if the active power measurement from the smart meter data is greater than the discounted nominal power of the HP: $\gamma \cdot P_{\text{nom}}^{\text{HP}}$. The discount factor γ is heuristically determined to be 0.3. The second indicator function evaluates to 1 if the reactive power measurement is greater than the average reactive power of the measurements in the 24-hour window that is being disaggregated. If both indicator functions evaluate to 1 and the switching command (u_t^{HP}) is 1 the HP is considered to be running. In a second step, the heuristic algorithm computes an approximation of the magnitude of the HP demand. To that end, the average active power when the HP cannot run $P_{\text{AVG24h}}^{\text{noHP}}$ (i.e., during the time steps in the 24-hour window when the switching command is 0) is computed based on the smart meter measurement. Then the HP active power at time step t is estimated as follow:

$$P_t^{\text{HP}} = \mathbf{1}_{\{hp_t^{\text{ON}}=1\}} \cdot \max(\min(P_t - P_{\text{AVG24h}}^{\text{noHP}}, P_{\text{nom}}^{\text{HP}}), 0) \tag{6}$$

If the HP is estimated to be running $hp_t^{\text{ON}} = 1$, its active power is obtained by subtracting $P_{\text{AVG24h}}^{\text{noHP}}$ from the active power measured via the smart meter P_t and taking the minimum between the result and the nominal power of the HP ($P_{\text{nom}}^{\text{HP}}$). The outer $\max$ operator ensures that the HP active power is non-negative.

The EWH load detection component leverages the active power P_t^{noHP} from the smart meter measurements where the HP load (and if present, the EV load) has already been subtracted. The heuristic algorithm defines a variable $ewh_t^{\text{ON}} \in \{0,1\}$ that represents whether the EWH is running at time step t or not. At every time step t, ewh_t^{ON} is computed as follow:

$$ewh_t^{\text{ON}} = \mathbf{1}_{\{P_t^{\text{noHP}} > \zeta(P_{\text{nom}}^{\text{EWH}}) \cdot P_{\text{AVG24h}}^{\text{noHPnoEWH}}\}} \tag{7}$$

The EWH is estimated to be running if the active power measured without the HP load exceeds the average active power without the HP when the EWH cannot run, i.e. $P_{\text{AVG24h}}^{\text{noHPnoEWH}}$, by $\zeta(P_{\text{nom}}^{\text{EWH}})$ times. $\zeta(P_{\text{nom}}^{\text{EWH}})$ is heuristically determined as follow:

$$\zeta(P_{\text{nom}}^{\text{EWH}}) = \begin{cases} 2 & if \quad P_{\text{nom}}^{\text{EWH}} < 3 \\ 3 & if \quad 3 \leq P_{\text{nom}}^{\text{EWH}} \leq 7 \\ 4 & if \quad P_{\text{nom}}^{\text{EWH}} > 7 \end{cases} \tag{8}$$

Once ewh_t^{ON} has been computed for the entire 24-hour window, all the groups of $1s$ that are not fully included in an unblocked window (i.e., where the switching commands allow the EWH to run) are discarded. The new obtained variable is called $\overline{ewh_t}^{\text{ON}}$. Finally, the EWH active power at time step t is estimated as follow:

$$P_t^{\text{EWH}} = \mathbf{1}_{\{\overline{ewh_t}^{\text{ON}}=1\}} \cdot \max(P_t^{\text{noHP}} - P_{\text{AVG24h}}^{\text{noHPnoEWH}}, 0) \tag{9}$$

If the EWH is estimated to be running, its active power is obtained by subtracting $P_{\text{AVG24h}}^{\text{noHPnoEWH}}$ from the active power measured via the smart meter P_t^{noHP} without the HP (and if present, without the EV). The outer $\max$ operator ensures that the EWH active power is non-negative. In this case, the power is not capped at the nominal value because it is unlikely that another large load is running at the same time (given the narrow unblocking window for EWHs, 3-8 hours) and because the records of the nominal EWH power are not always accurate.

Table 2: Assessment of load disaggregation accuracy. AP refers to active power.

Test Case	TECA	MAE AP (kW)	Mean AP (kW)	Std. AP (kW)
1	0.82	0.52	1.44	2.43
2	0.94	0.10	0.84	1.76

To assess the accuracy of the disaggregation approach, the algorithm is applied to two households in Winkel for which the EWH and HP consumptions are measured with a separate meter from the rest of the households' load. Table 2 presents the results for applying the algorithm to the two households on the historical data over one year (from June 2022 to June 2023). The table shows the Total Energy Correctly Assigned (TECA), the Mean Absolute Error (MAE), the mean active power, and its standard deviation for the two test cases. TECA is introduced in [13] and is a dimensionless metric evaluating the degree to which energy is correctly assigned (and not assigned) in relation to the total energy. The analytical formulation of TECA is given by:

$$TECA = 1 - \frac{\sum_{t=1}^{T} |y_t - \hat{y}_t|}{2\sum_{t=1}^{T} y_t} \tag{10}$$

In the above equation, y is the ground truth, while $\hat{y}$ is the prediction. Interpreting the results for test cases 1 and 2, it is noticed that in both cases, TECA is high (above 0.8). In test case 2, the metric even exceeds the 0.9 mark. To further understand the accuracy of the disaggregation algorithm, a few results for both test cases are plotted.

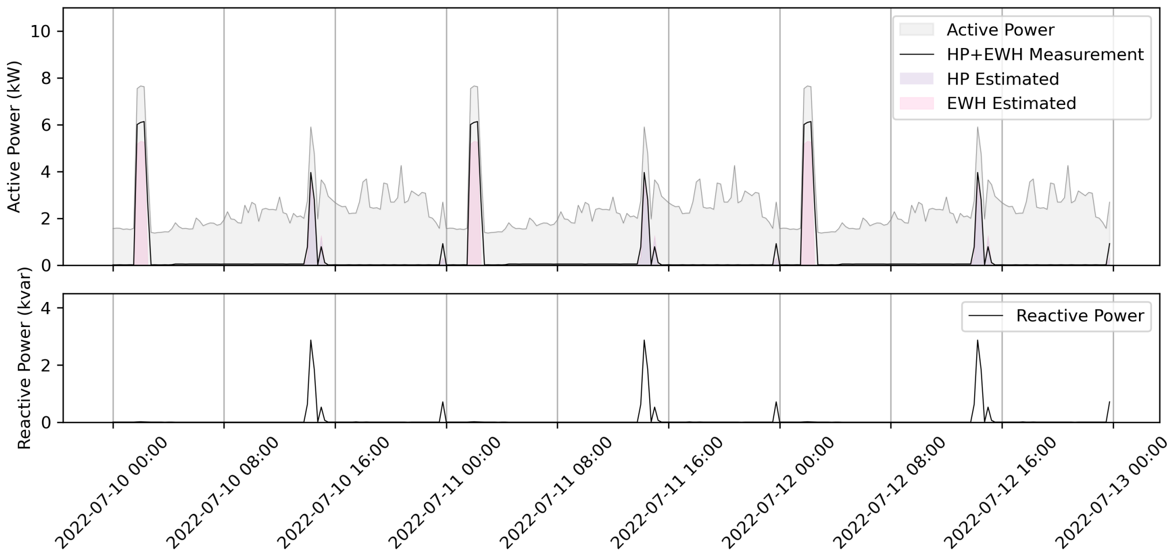


Figure 8: Load disaggregation results versus ground truth for test case 1 from 10.07.2022 to 13.07.2022.

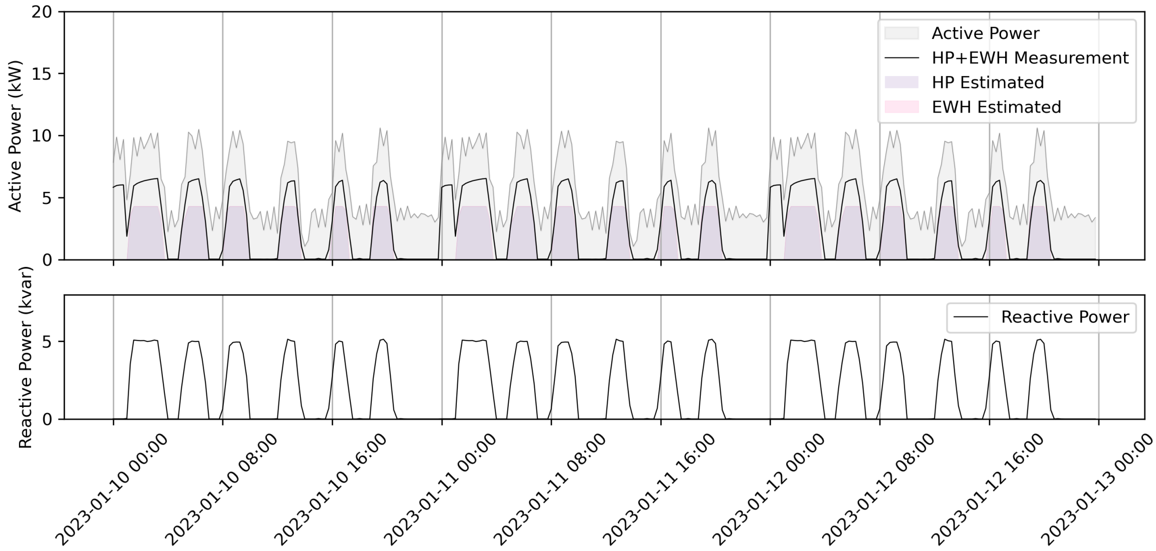


Figure 9: Load disaggregation results versus ground truth for test case 1 from 10.01.2023 to 13.01.2023.

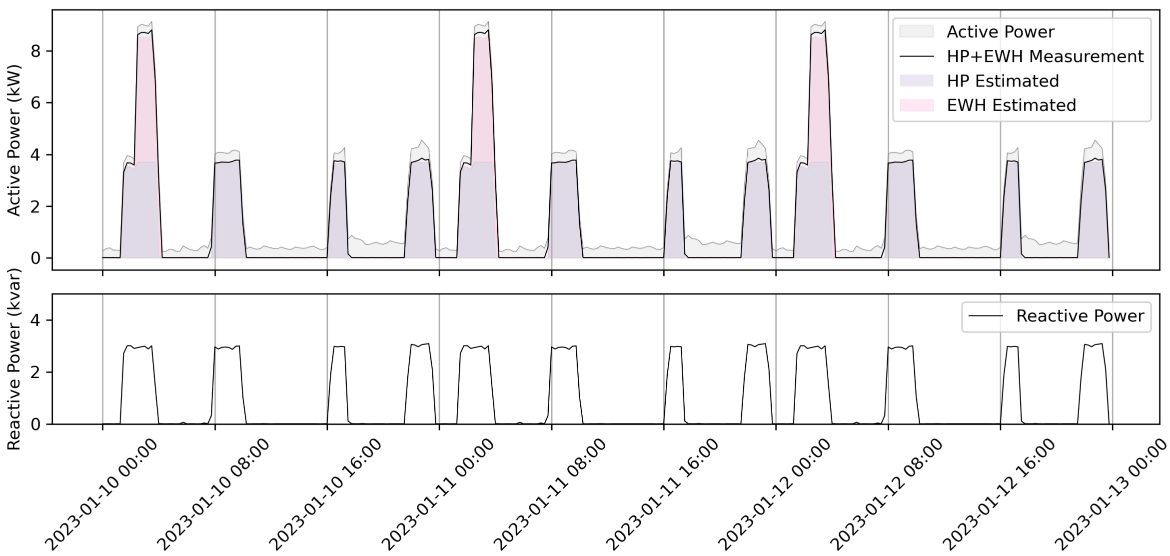


Figure 10: Load disaggregation results versus ground truth for test case 2 from 10.01.2023 to 13.01.2023.

The results displayed in Figs. 8, 9, and 10 show that the heuristic algorithm can estimate fairly accurately the HP and EWH loads. The major challenge for the algorithm lies in identifying the correct magnitude of the loads. In particular, it can be seen in Fig. 9 that the algorithm underestimates the HP load. This is because the estimation of the HP load is capped at its nominal power. However, in some instances, the HP shows a higher load than its nominal power. Load magnitude estimation is a possible future improvement to the proposed method.

Most similar day matching Most similar day matching is the second step toward forecasting the inflexible load. After having populated a database with flexible loads (EWH and HP) for every household, there is the need to identify the most similar day to the one being forecasted. Similarity between days is measured by leveraging weather data. In particular, temperature (T) and solar irradiation (S) are considered. Given two different days $d1, d2$ and two lists for each day $T^{di}, S^{di}, i \in \{1, 2\}$ that contain measurements or forecasts of the temperature and solar irradiation values at a fixed frequency, the similarity score can be defined as follow:

$$SIM^{d12} = \frac{\sqrt{\sum_{t=1}^{T}(T_t^{d1} - T_t^{d2})^2} + \sqrt{\sum_{t=1}^{T}(S_t^{d1} - S_t^{d2})^2}}{2} \tag{11}$$

The above equation computes the similarity score SIM^{d12} between $d1$ and $d2$ as a simple average of the Euclidean distance between the temperature lists and the solar irradiation lists. In practice, before computing the Euclidean distance, the lists are normalized from 0 to 1 to ensure comparability.

To forecast the inflexible load, the following approach is used:

1. For each day in the database where historical flexible load profiles are present, a similarity score SIM^{dif} is computed based on available weather data, TS load measurements, and flexible load profiles.
2. The day with the highest similarity score is identified.
3. The inflexible load estimate for this day is then calculated by subtracting the flexible load profiles (EWH, HP, and EV, the latter obtained through direct measurement) from the total TS load.

It is important to note that days are clustered in types (weekdays, Saturdays, Sundays and holidays), and the similarity score is computed only between days of the same type. In the actual implementation of the component the temperature and solar irradiation measurements and forecasts have a 15-minute frequency. A future improvement for this method could be to return an average inflexible load from the X most similar days (e.g., X=5) instead of exclusively returning the inflexible load from the most similar day. This could prevent outliers and reduce the variance of the load.

3.3.2 Real-time tariff setting

Overview This chapter presents the algorithms that were developed for the indirect load control scheme with real-time prices. Figure 11 provides an overview of the different components.

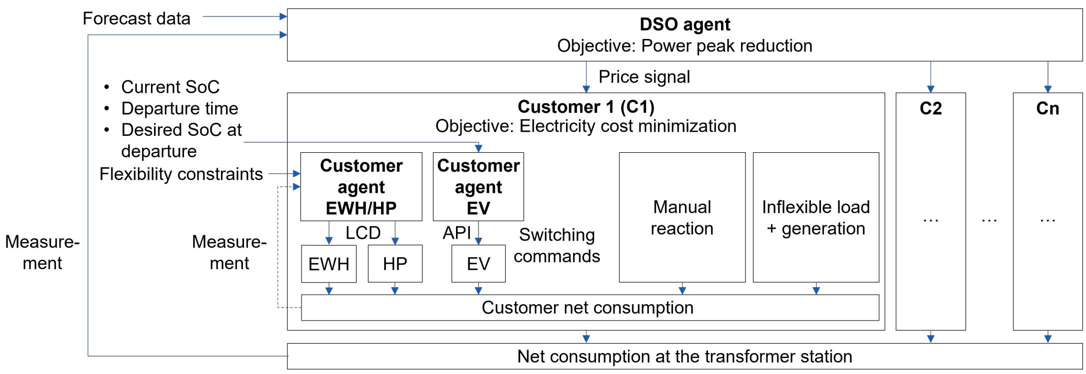


Figure 11: Interactions of the DSO agent and the customer agents.

On the DSO level (DSO agent), the price values need to be determined taking the uncertainties in customer behavior and consumption and generation forecasts into account. However, the DSO's knowledge of the customers' load models and device states, such as temperatures and charging states, is limited. On the one hand, this is due to technical limits. On the other hand, customers might also have privacy concerns when sharing their data with the DSO. Additionally, WP 2 showed that already under the assumption of idealized conditions, the bilevel problem is hard to solve. This is especially the case for the real-time tariff, which can take a different price value in each time step. Modeling the uncertainty in the bilevel programming problem would increase the computational complexity further. Therefore, we apply a proportional pricing scheme in the first step and are developing an Reinforcement Learning (RL)-based approach to determine the price in each 15-minute interval.

On the customer level, the optimal commands for the EWH, HP, and EV charging need to be determined. For the EWH and the HP (Customer agent EWH/HP), the LCSA receives a new price value via PLC every 15 minutes and takes the blocking decision locally at the household. A key challenge is the limited information on the devices and customer behavior. Besides the current electricity price, only the smart meter measurements and the rated power of the devices are known. To overcome this challenge, again an RL-based solution approach is applied in the project. The arrow for the measurement is dashed because this information is not used in the current implementation. For the EV (Customer agent EV), information on the current SoC and whether the EV is plugged in at home is available via the API. Additionally, customers specify their desired SoC and a departure time. The commands are determined by solving an optimization problem that chooses the time intervals with the lowest price while ensuring that all the constraints are met. The following subsections provide more details on the formulation and the results for the different agents.

DSO agent At this project stage, the real-time price is proportional to the estimated inflexible load. Shortly before midnight on each day, the inflexible load for the next day is forecasted using the approach explained in section 3.3.1. The resulting profile is scaled to meet the cost neutrality condition defined in section 3.1. For this, the following equation is solved to compute $\pi^{\text{buy,max}}$ given $\pi^{\text{buy,min}}$:

$$\sum_{t=0}^{K-1} \left(\pi_t^{\text{buy}} \cdot P_t^{\text{inf,cons}} \right) = \sum_{t=0}^{K-1} \left(\pi_t^{\text{buy,ref}} \cdot P_t^{\text{inf,cons}} \right), \tag{12}$$

where the price in time step t is defined as:

$$\pi_t^{\text{buy}} = \pi^{\text{buy,min}} + \frac{P_t^{\text{inf}} - P^{\text{inf,min}}}{P^{\text{inf,max}} - P^{\text{inf,min}}} \cdot \left(\pi^{\text{buy,max}} - \pi^{\text{buy,min}} \right). \tag{13}$$

K denotes the number of time steps within one day, and $P_t^{\text{inf,cons}}$ describes the mean demand of inflexible consumers for the given type of day (weekday, Saturday, Sunday) and month, while P_t^{inf} is the forecasted inflexible net load at the TS, with minimum and maximum values $P^{\text{inf,min}}$ and $P^{\text{inf,max}}$. The reference price $\pi_t^{\text{buy,ref}}$ is a flat tariff, which is cost-neutral with respect to the monthly demand of inflexible consumers and the EKZ standard tariff. The EKZ standard tariff has a high-price window from 7:00 to 20:00 on weekdays and low prices at all other times [14]. Therefore, directly using it as $\pi_t^{\text{buy,ref}}$ in (12) would lead to considerably lower prices on weekends. To ensure comparable savings for flexible loads, $\pi^{\text{buy,min}}$ is set to the lowest price of the ToU tariff. If a price π_t^{buy} exceeds the maximum price specified in the dynamic tariff sheet, it is replaced by the corresponding value.

The proportional pricing scheme can shift flexible loads to times when the inflexible load is low. However, it cannot leverage different device characteristics (e.g., EWHs are always connected while EVs are not), and in reality, the DSO would not know at which time steps an EWH or HP was blocked, which is leveraged for the disaggregation. Therefore, we are working on an RL agent. The inputs to the agent are the current timestamp, past TS load measurements, past electricity price values, and past and forecasted values for solar irradiation. The agent's action is the price for the next 15-minute interval.

Customer agent EWH/HP The customer agents are implemented according to the second approach described in [15], i.e., using a hypothetical energy consumption instead of the actual smart meter measurement as feedback to the agent. The agent takes the current timestamp, the electricity price for the next 15-minute interval, as well as the 95 latest price values and the 95 latest applied blocking actions as inputs and outputs whether the EWH and/or HP should be blocked in the next 15-minute interval. A key difference between [15] and the final implementation is that EV charging is not considered anymore, as the control of EVs is implemented via the API and not, as initially planned, via the LCSA and the charging station. This reduces the number of possible actions to four if the household has both an EWH and HP and two if only one of the devices is present. Furthermore, PV generation is not considered as LCSAs are only installed in households without an energy management system. Therefore, the selling price and its history are removed from the state vector. Finally, the agent is trained not to violate the constraints concerning the maximum number of blocked time intervals in each 24-hour window instead of per calendar day. The settings for the blocking constraints are based on the current ripple control scheme.

Customer agent EV This agent computes the switching (blocking/unblocking) commands to the EV by solving a MILP. The objective is to minimize the cost of EV charging, subject to a) reaching the desired SoC (namely $\text{SoC}^{\text{goal}}_{c,\text{EV}}$) at the departure time defined by the user, b) the EV can be blocked only after it has reached a minimum SoC, and c) no more than $N^{\text{max,24h}}_{c,\text{EV}}$ OFF-to-ON switchings are allowed in any 24-hour window. The optimization model is coded in Python, and the problem is solved by Gurobi [10]. As depicted in Fig. 11, the customer agent EV uses as input the electricity price signal, the current SoC and the desired SoC at the departure time, as defined by the EV owner. The price signal is a prediction for the next 24 hours; only the price for the next time step is known.

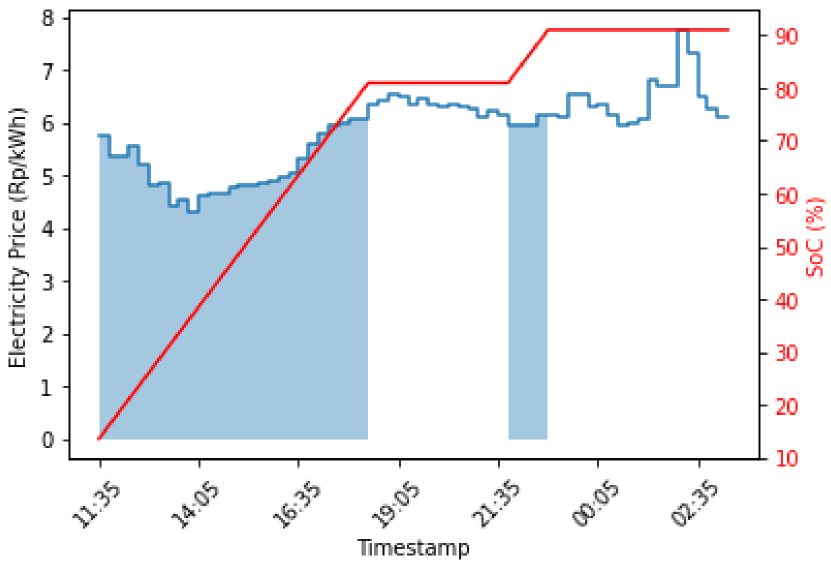


Figure 12: Optimal EV charging based on the price forecast.

Figure 12 illustrates an optimal EV charging based on this optimization problem for the predicted electricity price shown in the plot. It is assumed that the EV owner wants to charge the almost-empty battery to $\text{SoC}^{\text{goal}}_{c,\text{EV}} = 90\%$. In this case, the owner did not define any departure time, but $N^{\text{max,24h}}_{c,\text{EV}}$ was set to 3.

The charging session starts at 11:35 hours and is interrupted at about 18:30 hours when the electricity prices are high. The charging is restarted at the end of the night and continues until the desired SoC is reached.

3.3.3 Automatized load management in the Time-of-Use tariff setting

The same optimization as in the real-time tariff setting (cf. section 3.3.2) is applied for the EV. The only difference is that the optimization takes the price values of the ToU tariff for the next 24 hours as an input instead of a price prediction. Figure 13 presents the optimal charging for a second EV for the price values of the ToU tariff. The charging session starts at 12:50 hours and is interrupted before 18:00 hours when the electricity prices for the ToU tariff are higher. The charging is restarted at midnight until the desired SoC is reached.

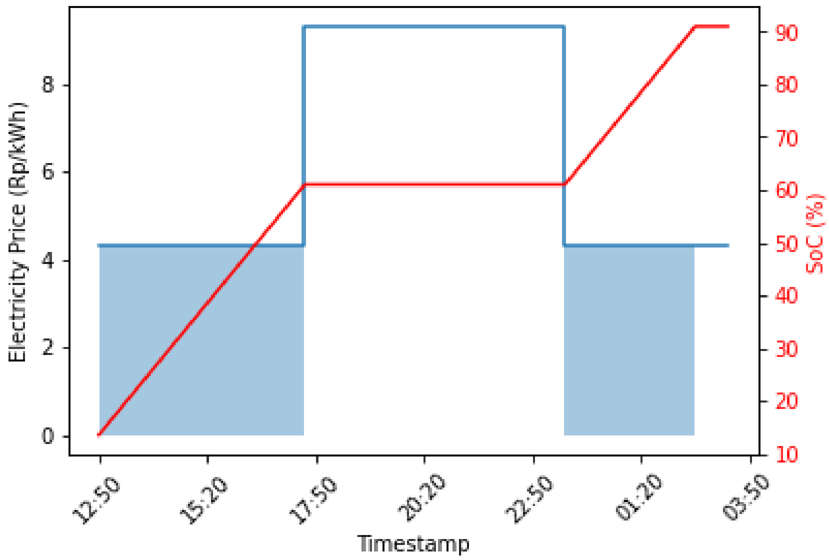
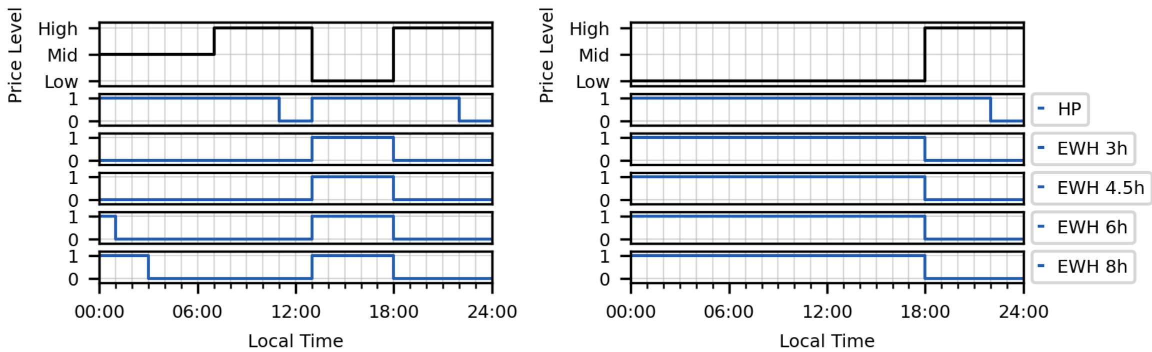


Figure 13: Optimal EV charging based on ToU-price signal in winter.

EWHs are unblocked for the entire low-price period. Additionally, if the minimum number of hours, for which the device must be unblocked in each 24-hour window exceeds five hours (duration of low-price period in summer), the earliest hours of the mid-price period are unblocked, as shown in Fig. 14.

HPs can be blocked for up to four hours in each 24-hour window and up to two hours per blocking instance. Therefore, they are blocked for two hours at the end of each high-price period, such that the rebound falls into the following lower-price period.



(a) Summer

(b) Winter

Figure 14: EWH and HP control based on ToU-price signal; 1 means a device can operate, while 0 means it is blocked; the number of hours indicates how long an EWH needs to be unblocked according to the current ripple control scheme.

3.3.4 Direct load control

The proposed Direct Load Controller (DLC) consists of a centralized optimization-based scheme that sends optimal switching (blocking/unblocking) commands every 15 minutes to EWHs, HPs, and EVs to flatten the total demand curve of the TS. The optimization is a Mixed Integer Quadratic Programming (MIQP) problem coded in Python and solved by Gurobi [10].

This controller uses a 24-hour rolling horizon (K =96 time steps of 15 minutes each) to compute the switching commands ($u_{c,t}^{\text{EWH}}$, $u_{c,t}^{\text{HP}}$, $u_{c,t}^{\text{EV}}$) sent to the flexible loads of each customer c for $0 \leq t \leq K-1$, see Fig. 15. The DLC inputs are the estimation of the inflexible load, the prediction of the ambient

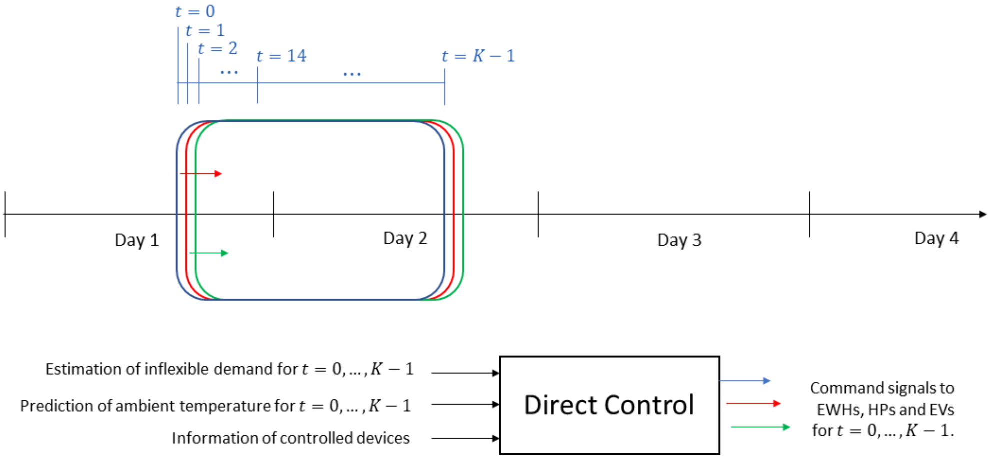


Figure 15: Rolling horizon for DLC with inputs and outputs.

temperature, and the information of the controlled devices, for example, the nominal powers ($P^{\text{EWH}}_{c,\text{nom}}$, $P^{\text{HP}}_{c,\text{nom}}$, $P^{\text{EV}}_{c,\text{nom}}$), the switching commands in the previous 24 hours, the maximum number of blocking intervals in any 24 hours ($K^{\text{block,24h}}_{c,\text{EWH}}$ and $K^{\text{block,24h}}_{c,\text{HP}}$), the minimum ($K^{\text{min,block}}_{c,\text{EWH}}$ and $K^{\text{min,block}}_{c,\text{HP}}$) and maximum ($K^{\text{block,instance}}_{c,\text{EWH}}$ and $K^{\text{block,instance}}_{c,\text{HP}}$) consecutive blocking intervals, and the minimum consecutive unblocking intervals ($K^{\text{min,unblock}}_{c,\text{EWH}}$ and $K^{\text{min,unblock}}_{c,\text{HP}}$) for all EWHs and HPs. For each EV, the DLC receives information of the current SoC and the desired SoC$^{\text{goal}}_{c,\text{EV}}$ at the departure time step t_{goal}, the charger's power $P^{\text{EV}}_{c,\text{nom}}$, the battery capacity $E^{\text{max}}_{c,\text{EV}}$, the maximum OFF-to-ON switches allowed in any 24-hours $N^{\text{max,24h}}_{c,\text{EV}}$, and the OFF-to-ON switching events in the last 24 hours.

The objective of the DLC is to flatten the total 24-hour demand curve by managing the times when the available flexible loads are allowed to operate. For this, we penalize the deviations from a reference value P^{ref} of the total demand P^{tot} at any time t of the 24-hour horizon. For EWHs and HPs, the optimization ensures that the maximum number of blocking intervals in any 24-hour window, and the maximum number of consecutive blocking intervals are not exceeded. In addition, the optimization guarantees the minimum duration of the blocking and unblocking instances for these devices. As for the EVs, the optimization guarantees the EVs reach a minimum SoC value in $K^{\text{min}}_{c,\text{EV}}$ time steps. In addition, it ensures the desired SoC are reached at the departure time. Finally, the optimization does not allow more than $N^{\text{max,24h}}_{c,\text{EV}}$ OFF-to-ON switchings for any 24-hour window.

We tested the DLC performance in a simulation environment. In this test, we control the EWHs and HPs of 32 Single Family Homes (SFHs). In addition, there are four EVs with battery capacities that range from 60 to 80 kWh. The rated powers of the EWHs range from 2 to 8 kW. Similarly, the rated powers of the HPs range from 2.5 to 7 kW, and the charging power for the EVs is 6 or 8 kW. However, the HP demand is not fixed at the nominal value, it changes with the ambient temperature.

For illustration purposes, the parameters used for the flexibility constraints of all EWHs are $K^{\text{block,24h}}_{c,\text{EWH}} = 72$, $K^{\text{block,instance}}_{c,\text{EWH}} = 64$, $K^{\text{min,block}}_{c,\text{EWH}} = 30$, and $K^{\text{min,unblock}}_{c,\text{EWH}} = 8$. For all the HPs we used $K^{\text{block,24h}}_{c,\text{HP}} = 16$, $K^{\text{block,instance}}_{c,\text{HP}} = 8$, $K^{\text{min,block}}_{c,\text{HP}} = 4$, and $K^{\text{min,unblock}}_{c,\text{HP}} = 8$. Finally, $N^{\text{max,24h}}_{c,\text{EV}} = 3$ for EVs. Note that the EWHs are more flexible than the HPs. This simulation assumes that none of the controlled devices were blocked previously, i.e., $u^{\text{EWH}}_{c,t} = u^{\text{HP}}_{c,t} =, u^{\text{EV}}_{c,t} = 1$ for $t < 0$.

The controller reads the predicted inflexible demand P^{inf} and optimally accommodates the flexible load P^{flx} by computing the optimal switching commands for the EWHs, HPs and EVs. Figure 16 presents the DLC results for the simulated test case. There are 7,296 decision variables and 23,623 constraints. The

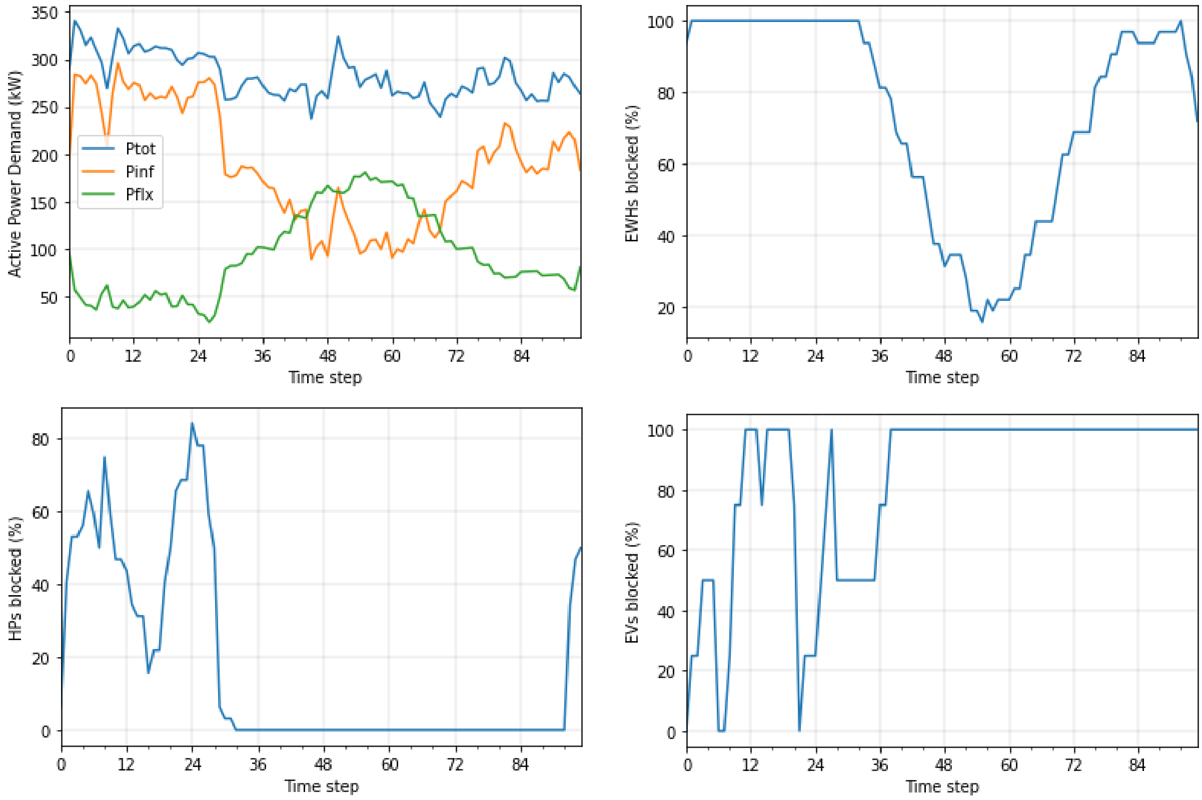


Figure 16: Direct control of flexible loads from 32 SFHs.

solver took five minutes to find a solution with an MIP gap of 0.45%.

In this scenario, the P^{inf} is high at the beginning of the horizon. Therefore, the DLC initially blocks the EWHs and some of the HPs. However, since the HPs are less flexible, they cannot remain blocked for long periods. When P^{inf} reduces at $t = 28$, the EWHs are progressively unblocked before P^{inf} increases again. At the end of the horizon, most of the EWHs and some HPs are blocked again.

The EV chargers are intermittently blocked at the beginning of the control horizon, but they are all allowed to charge for $t > 36$. The resulting total demand, i.e., $P^{\text{tot}} = P^{\text{inf}} + P^{\text{flx}}$, is almost flat with the available controlled devices and their flexibility constraints.

3.3.5 Local verification module

All switching commands for EWHs and HPs are locally verified and corrected before they are passed to the LCD, such that communication issues or invalid actions by the RL agent do not lead to a violation of the flexibility constraints. At every time step, the verification module checks if the 24-hour switching command schedule which is to be saved in the LCD (i) satisfies the flexibility constraints with respect to the previously applied blocking actions and (ii) satisfies the flexibility constraints if it is played in a loop. The first requirement ensures that the system meets the flexibility constraints during normal operation, while the second requirement ensures that the system meets the constraints if communication to the LCD fails for a longer period and the schedule is repeated.

3.4 WP 4: Hardware and infrastructure

3.4.1 WP 4.2: Peer-to-Peer platform

The OrtsNetz Platform is the main channel to communicate with participants in the pilot project. Its central functions are the following:

1. Providing functionalities for the Peer-to-Peer (P2P) trading of certificates of origin
2. Displaying individual and aggregate energy information
3. Displaying electricity cost information
4. Displaying tariff information
5. Computing costs according to the pilot tariffs
6. Providing an interface for customers to enter their preferences regarding load control
7. Providing notification functions
8. Providing an interface for ETH Zurich to access pseudonymized data

Functionalities 1, 2 and 7 were made available during the first year of this project. Functionality 4 is now available such that the customers can see their tariffs. The customers can see the current and historic energy and grid prices depending on their corresponding tariff. For the customers getting a dynamic tariff, the grid tariff price is updated every 15 minutes. The prices are sent from the LCMA running in the cloud (Microsoft Azure) to the P2P platform.

The remaining functionalities 3, 5, 6 and 8 are on hold, since the partner VGT was not able to implement these functionalities before October 2023. In parallel, EKZ is looking for a solution.

3.4.2 WP 4.3: Transformer station active components

In the three TSs, at which the LCSAs are installed, G3-PLC gateway gateways have been installed. These gateways communicate with the LCSAs in the TS via PLC. Furthermore, the gateways are connected to EKZ internal network. The prices and switching tables are sent to the LCSA devices through the gateways. The LCSAs can also be monitored via the gateways. Furthermore, the gateways read consumption data from the smart meters and send these to the Head End System (HES). This data can then be accessed by the LCMA. The gateways are connected to a router that is connected to the EKZ internal fiber network. Currently, only a mobile connection is used, since the fibers are not completely installed in the area.

3.4.3 WP 4.4: Control devices

The LCDs are the devices that receive the switching tables from the LCSAs and then switch the EWHs and the HPs. The LCDs are provided by Swistec. The LCSA devices are developed in collaboration with Neuron. Neuron provided the basis for communication via PLC and an environment where the agents' codes can run. ETH Zurich provided the software of the agents and the verification module. The latter verifies each switching command that is applied on the LCD. This ensures that the EWHs and HPs are operated sufficiently long per day. Furthermore, it prevents the HPs from too many switching operations which could result in equipment damage. In addition to the to the load control, the LCSA also reads the electricity consumption from the customer's smart meter via an MBUS connection. This data is currently not used by the agent. EKZ provided the software infrastructure that handles the data management, the connection to the LCD, and the agents' operation. The setup has been extensively tested on a test setup, see Fig. 18. Currently, 53 LCSAs are installed while there is a potential left for 11 devices where the customers have not responded so far to mail, e-mail, or phone contact.

For controlling the EVs, the consortium decided not to control the vehicles via the charging stations. Instead, the EVs will now be controlled via the internet through an API to the manufacturer. This allows us to see the current SoC of the EVs and as well more convenient monitoring and control via the internet.

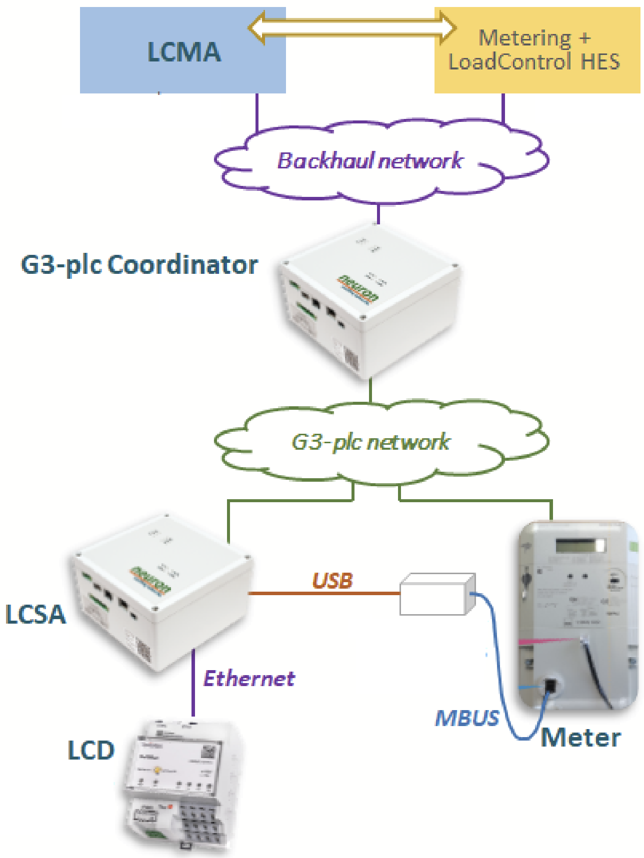


Figure 17: Overview of the system in OrtsNetz. The G3-plc coordinator is the gateway installed in the trafostations. This device connects the G3-plc network with the internet and finally with the cloud, where the LCMA is running and setting prices and switching commands.

3.4.4 WP 4.5: Community electricity storage

The community electricity storage will be installed by the end of November. Long delivery times in the battery storage market lead to a delivery time of over 6 months. The community electricity storage has just been delivered at the end of October. The electricity storage model to be installed is a pixii PowerShaper 2. The battery has a capacity of 48 kW h with a power of 50 kW.

3.4.5 WP 4.6: Algorithms in the field

The cloud infrastructure has been set up to control and monitor the EVs. Furthermore, the infrastructure for the price setting agent, the DLC optimization problem and the ToU algorithm have been set up. Currently, the price setting agent and the ToU algorithm are already sending prices and switching tables to the LCSAs. The DLC optimization problem is already formulated, but running it in the cloud is still resulting in some technical challenges.

On the LCSAs, the algorithms have been extensively tested on a test setup at EKZ. The devices are now deployed with the first software version to the customers. The software includes a trained model for each combination of EWH size and HP. During the project, the agents can be retrained offline and updated via remote connection.

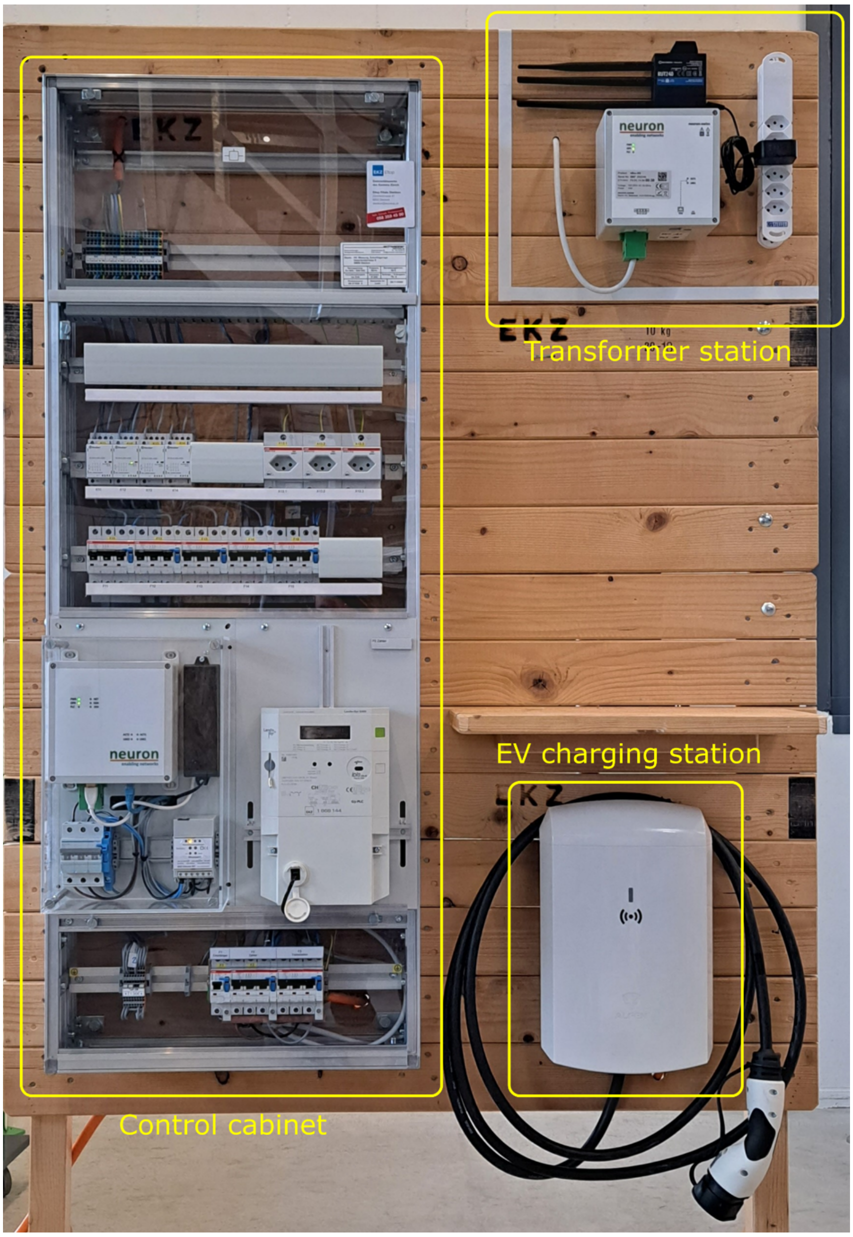


Figure 18: Test setup at EKZ. The EV charging station is not controlled via the LCSA. In the control cabinet, the LCSA is on the lower left side and the smart meter on the lower right side.

4 Evaluation of the results to date

OrtsNetz made significant progress in its second year of the project. Over 600 people in the municipality of Winkel are participating in the project. We have almost reached 100 customers where we control an electrical load by one of the control schemes with 53 LCSAs already installed and 37 customers with EVs. We expect to install a few more LCSAs in the following weeks.

In the last year, the experiment phase of the project has been prepared. WP1 finalized and implemented the study design and tariff schemes that had been developed. In WP2&3, the algorithms for the different control schemes have been developed and are mostly in a first stage to be tested in the field. They will be updated during the project. To date, the performance tests for all algorithms have been made in simulation environments only. Nevertheless, real-time grid tariffs and switching commands are being sent to and used by control devices at customers. In WP4, the control devices have been developed and installed. The hardware infrastructure is ready to apply the different control and tariff schemes. Finally, the software infrastructure is slightly delayed such that not all control schemes are running in the field.

Overall, the project is on track and we have not found issues that could compromise the completion of the project objectives. Still, we faced some challenges that were not contemplated at the beginning of the project: In WP2&3, the RL agent at the household level required several training strategies to obtain a good performance. Moreover, the first disaggregation methodology of flexible and inflexible load was based on power measurements at the TS level. However, the first results were not satisfactory. Therefore, we opted for using smart meter measurements to disaggregate the loads at the household level. As for the DLC, the proposed MIQP formulation could not be solved fast enough with open-source solvers, and we decided to acquire a 14-month license from Gurobi. This commercial solver provided satisfactory results in just a few minutes. The full functionality of all the algorithms will be tested when the software infrastructure is ready. Currently, we are verifying that all device data needed by each algorithm are readily available and correct. In WP4, on the P2P platform, the interface for customer preferences for load control is not ready, since the platform partner did not deliver the EV control functionalities. Thus, we need to build an in-house solution on short notice. Currently, we are setting up this part of the platform and are confident to have it ready by the end of the year. On the hardware side, some additional LCSAs need to be installed. Since the infrastructure is already in place, the challenge is to reach the customers who have not responded so far. On the software and cloud architecture side, the price setting agent and the ToU scheme are already running in the field, while the DLC needs more efforts to be finalized. In summary, WP4 has a delay for the final state of the hardware and infrastructure, but we are confident that the overall project objectives are not hindered.

The consortium is confident that the missing parts will be made available before the end of the year. The project partners are happy about the close collaboration and attitude to solve problems. The work package leaders are in constant communication about ongoing work. All parties of the consortium are looking forward to the next steps of the project and the result of the experiment phase.

5 Next steps

The following tasks are in focus for the next and final project year:

- Within WP1 we look forward to analyzing the first results of the project:
  - Evaluate the impact of dynamical prices on participant behavior.
  - Derive general recommendations with regard to EV smart charging, Demand Side Management, and grid pricing.
  - Investigate the impact of a local community storage battery on TS load peaks.
- Regarding the control algorithms, i.e., WPs 2 and 3, the next steps are:

    - Continuing the development of the RL agent on the DSO level.
    - Improving the adaptability of the RL agent on the household level (Customer agent EWH/HP). Specifically, we will reinvestigate whether the actual smart meter measurements can be leveraged to improve the performance further and make the agent applicable to households with PV generation.
    - Investigating the functioning of the algorithms in the field and identifying opportunities for improvement.
    - Defining performance indices to compare the different control schemes.
    - Gathering data from the pilot project to draw conclusions and recommendations based on the performance of each controller.
- In WP4, the next steps are:
    - Finalizing and maintaining the cloud infrastructure for load control of the HPs and EWHs as well as controlling the EVs.
    - Finalizing the P2P platform with the function that customers can set the EV charging parameters as well as billing of the customers.
    - Installing and operating the community electricity storage.

6 National and international cooperation

Besides the collaboration between the project partners at ETH Zurich and EKZ, there is an active exchange with the chair of Information Systems and Energy Efficient Systems at the University of Bamberg, which is led by Prof. Thorsten Staake. Furthermore, EKZ collaborates with Virtual Global Trading (OrtsNetz platform), Aveniq (IT), Swistec (LCD), Netinium (HES), Neuron (LCSA), Enode (EV connection), HSLU (data analysis) and ewz (HES).

7 Communication

The following list presents the events and articles since the publishing of the last interim report:

- Aufsichtskommission über die wirtschaftlichen Unternehmen (AWU), Visitation EKZ and OrtsNetz, 16. November 2022
- ZHAW Lecture, Lecture on "Intelligente Mess- und Steuersysteme", 20. April 2023
- Zukunft des ZEVs, Presentation on OrtsNetz, course on ZEV, GBS St. Gallen, 9. May 2023
- Verein Zürich Erneuerbar, Presentation on Ortsnetz, 12. May 2023
- EKZ Betriebsleitertagung, Presentation on Ortsnetz, all utility companies connected to the EKZ grid are invited, 12. May 2023
- GLP Thalwil, Presentation on Ortsnetz, 16. May 2023
- EKZ information event, Winkel, September 11th, 2023
- Zukunft des ZEVs, Presentation on OrtsNetz, course on ZEV, Primeo Energie Kosmos (Basel), 7. November 2023
- Newspaper article, Zürcher Unterländer, September 20th, 2023, "Winkel testet das Stromnetzder Zukunft und spart Geld dabei"
- Multiple Newspaper articles and information, Winkel "dorfziitig", Articles in October 2022, November 2022, January 2023, April 2023, May 2023, July 2023, August 2023, September 2023

8 Publications

The following list presents the publications that resulted from OrtsNetz to date:

- T. Brudermueller and M. Kreft, “Smart meter data analytics: Practical use-cases and best practices of machine learning applications for energy data in the residential sector,” in *ICLR 2023 Workshop on Tackling Climate Change with Machine Learning*, 2023
- K. Kaiser, M. Kreft, E. Stai, M. González Vayá, T. Staake, and G. Hug, “Reducing power peaks in low-voltage grids via dynamic tariffs and automatic load control,” in *27th International Conference on Electricity Distribution (CIRED 2023)*, (Rome, Italy), June 2023
- E. Stai, K. Kaiser, J. Stoffel, M. González Vayá, and G. Hug, “Automatic load management in active distribution grids using reinforcement learning,” in *IEEE PES ISGT Europe 2023*, (Grenoble, France), October 2023

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