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ReSIM Case Studies

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Nomenclature

CAPEX	Capital Expenditure
DER	Distributed Energy Resources
DHN	District Heating Network
DSO	Distribution System Operator
EGID	Eidgenössische Gebäude ID (federal building ID)
EV	Electric Vehicles
HP	Heat Pump
LV	Low Voltage
MV	Medium Voltage
NE7	Network Layer 7
OPEX	Operational Expenditure
PTES	Pit Thermal Energy Storage
PV	Photovoltaic
TES	Thermal Energy Storage

1 Description of the Case Studies

This report contains three different case studies that were all performed using the ReSIM simulation platform [1] where different models, data and algorithms developed by various members of the PATHFNDNR consortium were combined and simulated in a sector coupled way. All case studies focus on the same setting of Losone, a municipality in the Swiss canton of Ticino with roughly 6000 inhabitants, while each case emulates the behaviour of future local energy systems and evaluates the benefits and potential drawbacks of different solutions relying on local flexibility and sector coupling. All three case studies use the same synthetic electricity grid model by Oneto et al. [2] which connects base electricity demand estimates by HSLU [3, 4] and PV potential time series based on Walch et al. [5] and the building and heat pump model by Meister et al. [6, 7] as the core of the scenario. Electric vehicle (EV) mobility patterns are based on Parajeles et al. [8]. All distributed energy resources (DER) are given with a resolution at EGID level and are mapped to the closest low voltage node (network level 7) of the synthetic distribution grid using Voronoi regions. They are modified and complemented by additional models and control algorithms as described below:

1.1 Case Study 1: Flexibility Provision from Residential Heating

In the first case study, the focus lies on flexibility provision from the residential heating sector which is modelled by Meister et al. [6] and consists of building thermal models estimating the heat demand based on building characteristics (size, age, insulation) and weather conditions such as ambient temperature and solar irradiation. Each building is heated by a heat pump coupled with an auxiliary electric heater for peak demand and a hot water tank typical for residential applications. Domestic hot water demand is not considered. In this case study it is assumed that the appropriate communication and control framework is in place making it possible to remotely override the heating system operation for all buildings or a selected subset of the building stock, based either on geographic location (i.e. EGID) or the thermal inertia of the building. There are three options to override the heating operation:

1. Switching the heat pump off for a predefined time interval, the space heating can be (partially) supplied by the thermal energy storage (TES) depending on its state of charge in the meantime.
2. Switching the space heating off for a predefined time interval, the building will not be heated during this time, but the heat pump can still charge the TES.
3. Changing the temperature setpoint for the building internal temperature by plus or minus 1°C for a predefined time interval to momentarily increase or decrease the electricity demand for heating.

In Case Study 1, these intervention methods are tested on four days with different combinations of high or low net electricity demand, PV and heat demand. The resulting impact on the building internal temperature, heat demand and grid congestion (maximum line and transformer loading) are then analysed and compared to the base case without intervention into the heating system operation.

1.2 Case Study 2: Flexibility Provision from Optimized Electric Vehicle-Charging

In Case Study 2, EVs are now assumed to be flexible, with flexibility provision being motivated by means of dynamic (i.e. time-varying) retail tariffs. EV charging is optimized by using the algorithm developed by the Urban Energy Systems Group at Empa [9] as a part of the PATHFNDNR project. The same EV penetration and mobility patterns [8] from Case Study 1 are assumed as a basis for the optimization. In

Case Study 2 the building residential heating models are adapted to react to changes in electricity prices by increasing or decreasing the temperature setpoint by one degree. To this end, a high-level control algorithm is introduced for the residential heating systems that identifies, the timesteps with the most extreme tariffs (below the 20th percentile or above the 80th percentile respectively) using a moving window of one week and initiates the appropriate changes to the temperature setpoint.

Three dynamic retail tariffs were used during Case Study 2, as shown in Figure 1 **Error! Reference source not found.** Vario is a real tariff example taken from Groupe E [10]. Vario 2 and Vario 3 are variations of Vario created during the case study to influence the EV charging patterns.

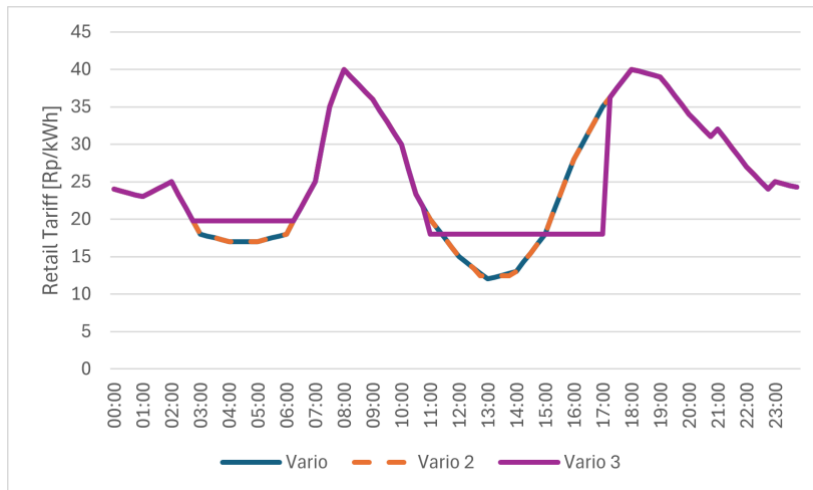


Figure 1: Comparison of the three dynamic retail tariffs that have been used in Case Study 2. Vario is a real dynamic tariff example taken from Groupe E [10]. Vario 2 and Vario 3 are variations of Vario created during the case study to influence the EV charging patterns.

1.3 Case Study 3: Value of Centralized Thermal Storage in District Heating

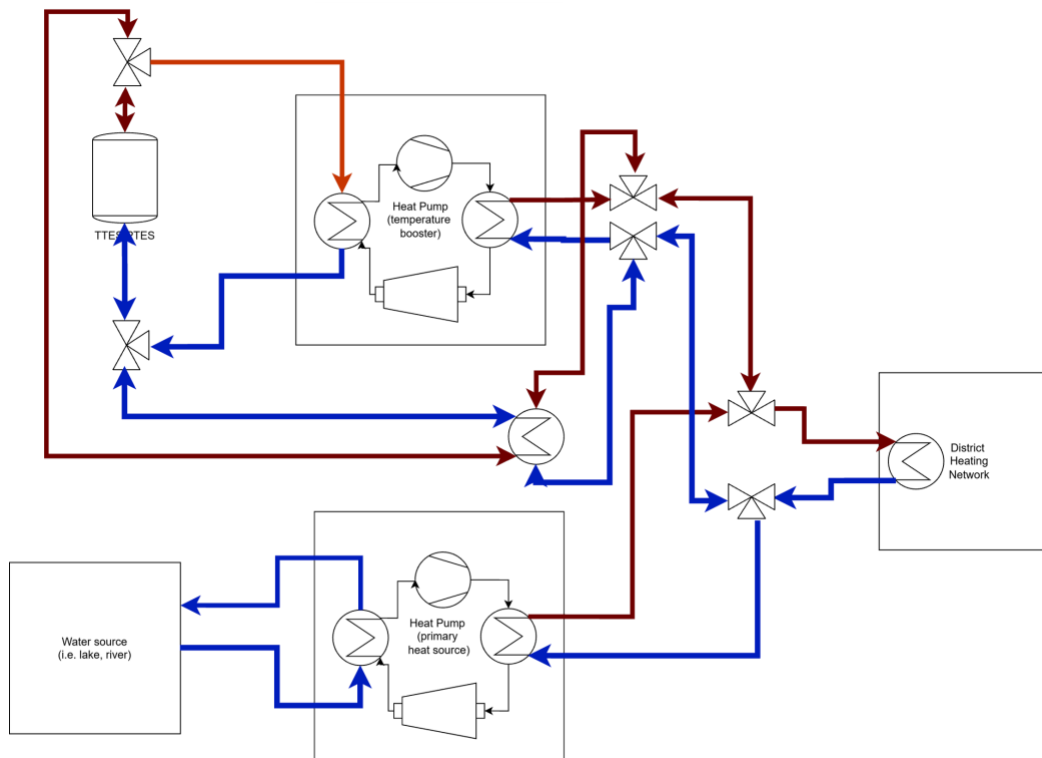


Figure 2: Diagram of central heat supply for DHN. The main source of heat is the primary heat pump. It is supplemented by the addition of the stratified pit thermal energy storage (PTES) which uses an additional, smaller HP as a temperature booster.

Case Study 3 focuses on sector coupling between a centralized district heating system and the electricity distribution system. Therefore, contrary to case studies 1 and 2, where it was assumed that buildings were heated by means of local heat pumps, in Case Study 3, it is assumed that residential heating is provided by a district heating network (DHN), served by an industrial scale centralised heat pump (HP) and stratified pit thermal energy storage (PTES). The detailed diagram of the central heat supply system can be seen in Figure 2. The PTES subsystem also includes an auxiliary HP which is used as a temperature booster to ensure the heat supplied from the PTES always complies with the temperature requirements for the DHN irrespective of its state of charge.

PTES Parameter	Value	Unit
Insulation thickness	0.3	m
Wall thickness	0.4	m
Transmittance U (all sides)	0.098	W/m ² K
α-Value (all sides)	8.1	W/m ² K
Max. temperature	95	°C

Table 1: Parameters of the stratified PTES model (valid for all tested sizes).

For the PTES, two models were used: A simplified single-temperature TES model developed by the ETH Forschungsstelle Energienetze (FEN) and a more sophisticated stratified TES model derived from PATHFNDP WP3 which was developed by the Competence Centre Thermal Energy Storage (CCTES) at HSLU (see Section 2.2 for more details). The simplified model considers a uniform storage temperature and an overall heat transfer coefficient and is used to explore a high number of simulations for different district heating configurations and control algorithms at increased computational efficiency. For selected configurations, the stratified PTES model is implemented to validate the results and provide a more detailed analysis of the TES behaviour. The stratified PTES model was set up with ten stratification layers for all investigated size variations. The bottom and all sides are assumed to be in contact with the earth at a constant temperature of 11°C and the top is assumed to be exposed to the ambient conditions. The pit is assumed to be shaped like a cube. Table 1 provides the PTES model parameters which are constant for all size variations.

The DHN is taken from PATHFNDP deliverable D2.3.2a and was developed in a green field approach using the GridPlan tool developed by FEN in the SWEET SURE project [11]. Heat demand data calculated using the building models from HSLU are used to dimension the DHN (see Figure 3 for reference) with a yearly total heat demand of 28.9 GWh and a maximum simultaneous (peak) demand of 14.74 MW.

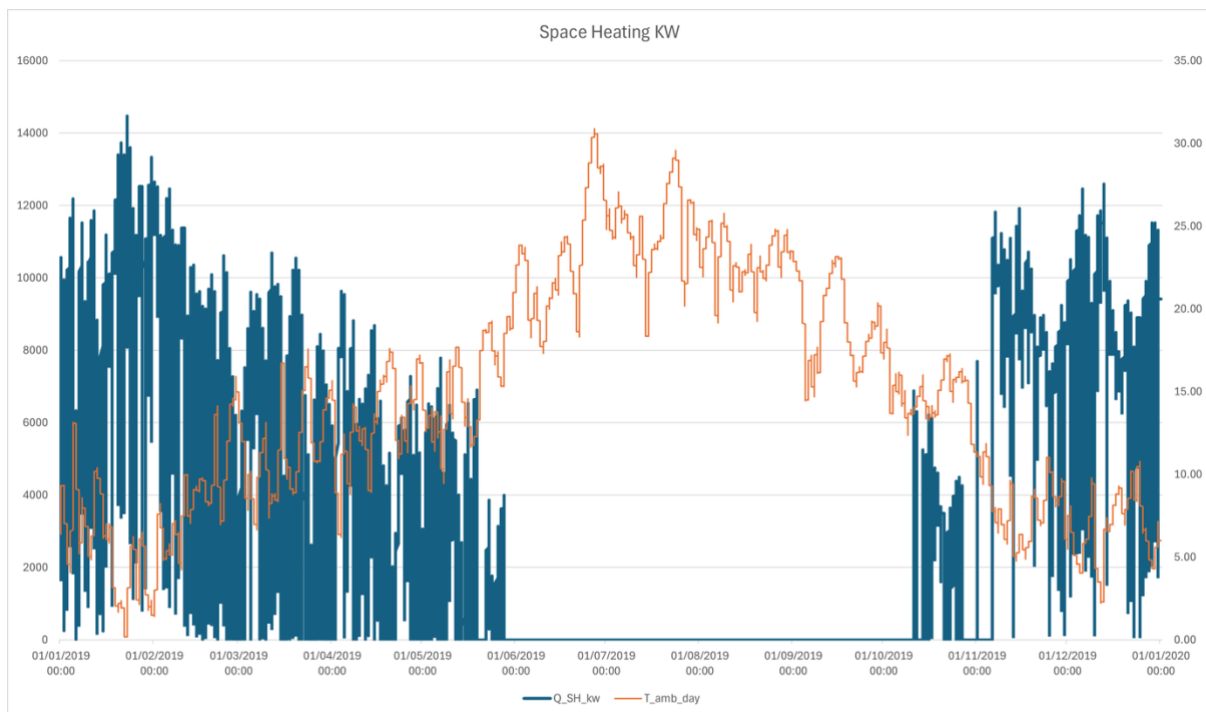


Figure 3: Space heating demand [kW] aggregated for all residential buildings in Losone (left y-axis) and ambient temperature in °C for Losone (right y-axis).

For Case Study 3, five different configurations with different HP and TES sizes have been compared to a reference case without any thermal storage. In the reference case, the HP is sized to meet the total heat demand during the worst hour of the year, with a safety margin of 3.6%. For the remaining configurations, the HP was scaled down in steps, and the TES volume was designed such that it would hold sufficient heat to buffer the heat demand during times when this smaller HP was not able to meet the demand directly. The resulting TES volume was then slightly increased to also be able to fill in the gaps when the heat demand is lower than the minimum output power of the HP. The maximum charging/discharging power of the TES was sized to fill the gap between the HP output power and the maximum heat demand. An auxiliary HP, matching the output power of the TES, was also added to ensure the heat from the TES can always be lifted to the nominal operating temperature of the DHN, which was chosen to be 85°C to match the existing (much smaller) DHN currently operated in Losone [12].

Figure 4, defines the two tariff schemes used to calculate the DH system costs for all configurations investigated in Case Study 3. They are both based on the Vario tariff shown in Figure 1, which is repeated 365 times for the yearly time series and shifted up or down to achieve a seasonal variation between the summer and winter half-year. The main difference between the tariff schemes is the difference between winter and summer prices, which is 30% and 54% respectively.

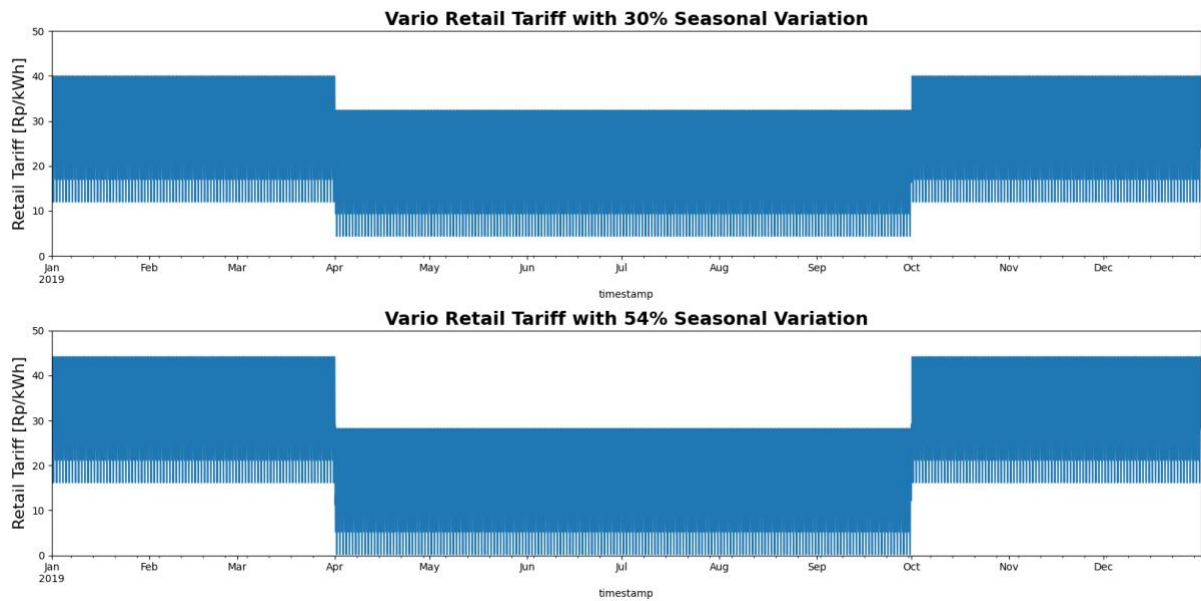


Figure 4: Yearly retail tariffs, based on a single-day example from the Groupe E Vario tariff (Figure 1), with differences in seasonal tariff variability used to calculate the annualized costs for the DH configurations used in Case Study 3. The tariff in the first subplot has 30% reduced prices in the summer half year compared to winter, for the tariff in the second subplot the difference is 54% while the yearly average is the same for both tariff schemes.

2 Utilized methodologies / data / models developed / collected as part of PATHFNDR and the associated deliverable

The following tools, models and datasets were used during the three case studies:

2.1 Utilized Tools

All three case studies were conducted using the ReSIM (ReMaP Simulation Framework) tool which was developed at ETH by Forschungsstelle Energienetze (FEN) during the ReMaP project [1]

2.2 Utilized Models

The tool was populated with the following models from PATHFNDR partners to build a sector coupled model of Losone:

- A synthetic distribution grid of Losone with both medium and low voltage network layers, taken from Alfredo Oneto et al. [2] (RRE at ETH)
- The district heating network designed for the PATHFNDR deliverable D2.3.3a by Alexander Fuchs and Andrea Bellè at FEN
- Building models and heat pump simulation developed by Curtis Meister, Sarah Schneeberger, Andreas Jokiel and Philipp Schütz at CCTES (HSLU) [6, 7]
- EV fleet charging optimization model, by Federica Bellizio, Yi Gao and Philipp Heer at UESL (Empa) [9]
- Stratified thermal storage model developed by Edward Lucas, Malin Siegwart and Andreas Jokiel at CCTES (HSLU) for PATHFNDR WP3

2.3 Utilized Datasets

- PV potential time series from an EPFL study by Alina Walch et al. [5] processed for PATHFNDR by Barton Chen at UESL (Empa)
- Base electricity demand estimates provided by Sarah Schneeberger and calculated according to Meyer et al. [3] (not published yet) based on load profiles from University of Basel [4]
- EV mobility behavior data modeled by Maria Parajeles et al. [8] (PSL at ETH) and partially processed for PATHFNDR by Barton Chen at UESL (Empa)

3 Assumptions

3.1 Case Study 1

In Case Study 1, the following assumptions were made:

- The residential hot water tanks are modelled with a uniform temperature.
- Auxiliary heat is provided by an electric heater whenever the heat demand exceeds the capacity of the HP.
- A 100% HP penetration in residential buildings throughout Losone is assumed.

3.2 Case Study 2

For Case Study 2, the following restrictions were introduced to the EV optimization algorithm:

- Only unidirectional charging is allowed; there is no discharging to the electricity grid.
- No market mechanism for flexibility bids is modelled, and the optimization is simplified to only be tariff-based.
- All trips are rounded to the nearest quarter hour so that there is no movement within a single time step.

3.3 Case Study 3

The following assumptions were made for the modelling of the DHN and the calculation of the operating and investment costs:

- Assuming a regression curve for PTES investment costs from Lüchinger et. al [13] and a US dollar to Euro exchange rate of 0.87 \$/EUR
- For annualized investment costs we assume a lifetime of 20 years and an interest rate of 5%.
- The DHN is assumed to operate at a nominal temperature of 85 °C, which is the case for the current, much smaller, DHN in Losone [12] this also allows the DHN to function without decentralized HPs to reach the required supply temperature.
- A transport model is used to calculate the (energy) flows through the DHN, no hydraulics or pumps are modelled. The heat losses in the DHN are assumed to be 10% of the total heat demand.
- The TES is assumed to be able to switch between charging and discharging within one single timestep (15 minutes).

4 Illustrative Results

4.1 Case Study 1

The following days have been identified as being of particular interest based on the demand and generation timeseries (PV, EV, conventional electricity demand, HP load) and selected as examples in this analysis:

1. Day with the highest heat pump peak load: Wednesday, 23.01.2019
2. Day with the highest residual peak load: Saturday, 05.01.2019
3. Day with the highest PV production peak: Thursday, 23.05.2019
4. Day with the highest simultaneous heat pump load and PV production: Thursday, 04.04.2019

In the interest of brevity, the observations will primarily be illustrated through the results of the first scenario (high HP load). For greater detail regarding the underlying building and HP flexibility models, one may refer to previous outputs from HSLU [7, 6]. The added value of this case study is in the sector coupled view of HP flexibility by also including the electricity grid as well as other distributed resources (EV, PV) in the analysis. Figure 5 **Error! Reference source not found.** shows the results for the base case of the high HP scenario. Aggregated on municipality level, the total demand (conventional electricity demand, EV and HP) peaks at 18:00 at 8.8 MW. At that time, the maximum line loading reaches about 80% and the maximum transformer loading reaches just over 100%. On this winter day, the maximum PV injection of 5 MW is lower than the demand peak and does not cause any grid issues. To relieve pressure on the grid, it would thus be helpful to reduce the electric load from the heat pumps around 18:00.

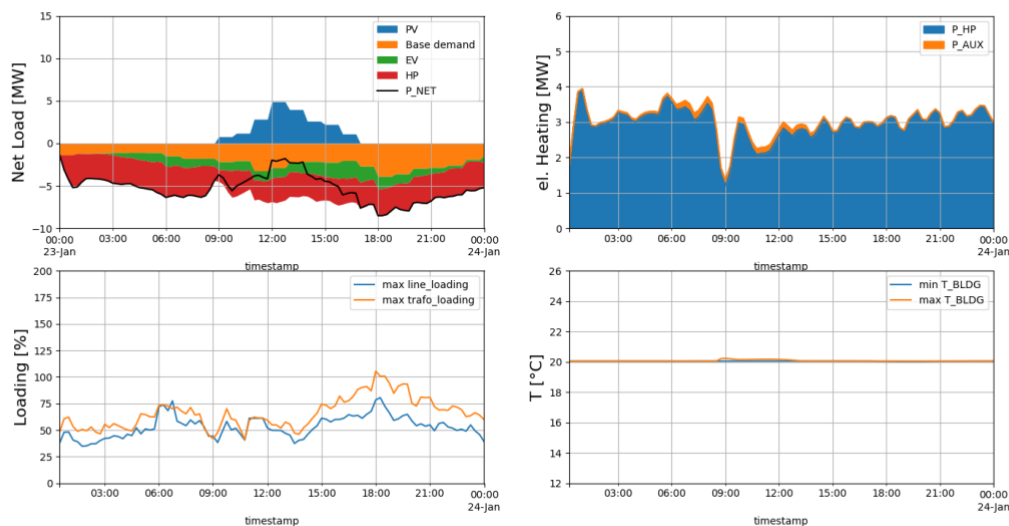


Figure 5: Simulation results for the high HP load scenario, base case without flexibility. Top left: aggregated loads and production with residual PV in black. Bottom left: maximum line (blue) and transformer (orange) loading for every timestep. Top right: aggregated HP and auxiliary heater electricity demand. Bottom right: minimum (blue) and maximum (orange) building temperature for every timestep.

Figure 6, shows the impact of switching all residential heating systems off between 17:45 and 20:45 to address the grid congestion. The plot in the bottom right of the figure shows how the building temperatures are affected by this measure: while the most well insulated buildings only lose fractions of a degree in internal building temperature, in the case of poorly insulated (old) buildings, temperatures drop by a full 6°C. This would have a drastic impact on comfort levels. The heating system electricity demand, shown in the top right subfigure, illustrates the effectiveness of the measure to reduce the grid load; the load from HPs falls to zero during this time slot. However, one can observe that after the intervention, the HP electricity demand rises sharply and exceeds the previous level by 67%. The bottom left plot shows the impact on the grid loading. It is noteworthy that while the measure is successful in bringing the maximum loadings below 100%, the rebound peak loads the grid close to the limit again. This type of intervention has a synchronizing effect on the decentralized HPs since they all receive the off-signal and, crucially, the end of the off-signal at the same time. After the intervention, especially one as long as the one tested in this example, buildings tend to have a temperature deficit compared to their setpoint and will all start to heat at the same time. This type of intervention should thus be limited to shorter periods of time or to buildings with high thermal mass and low heat transfer coefficients.

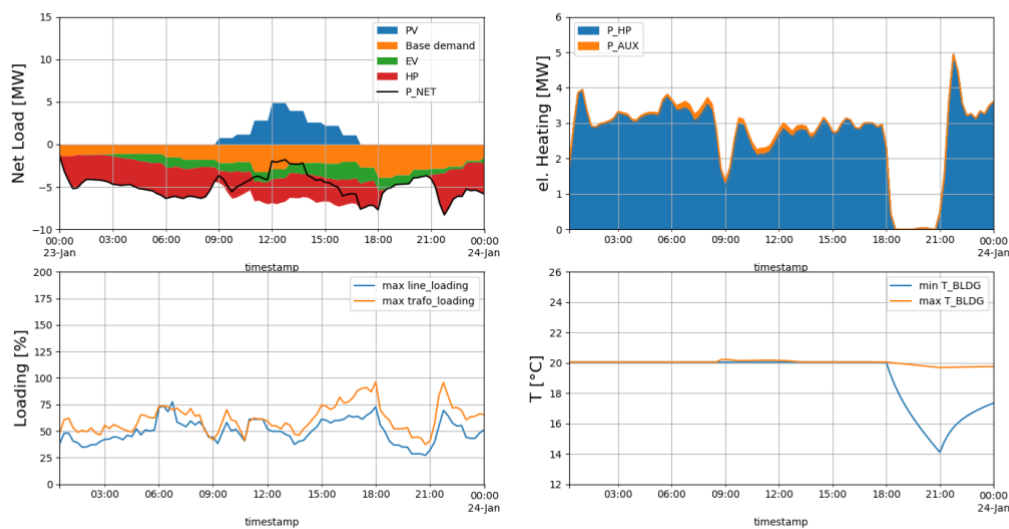


Figure 6: Simulation results for high HP scenario, with space heating switched off between 17:45 and 20:45. Top left: aggregated loads and production with residual PV in black. Bottom left: maximum line (blue) and transformer (orange) loading for every timestep. Top right: aggregated HP and auxiliary heater electricity demand. Bottom right: minimum (blue) and maximum (orange) building temperature for every timestep.

To avoid such a synchronization effect, the setpoint change flexibility option¹ can be used instead. Figure 7 shows the system response to a setpoint change (from 20°C to 19°C from 17:45 until 20:45). There are two major differences between this option and the others described in the previous section: first, the decentralized heating systems do not hand over control completely and second, they still follow a temperature setpoint, albeit a lower one. This means that there is a limit to the change of building internal temperature that is clearly defined, guaranteed² and independent of the duration of the intervention. Once the intervention starts, the heating systems switch off and let the building temperature drop to the new setpoint, at which point the HP operation resumes. Since the time to reach the new setpoint depends on the thermal inertia of the individual buildings, the resumption of HP operation is naturally spread out by the variation in building parameters of the building stock. While this reduces the effectiveness of the intervention as time goes on, it still offers immediate relief and drastically reduces

¹ Changing the temperature setpoint for the building internal temperature by plus or minus 1°C for a predefined time interval to momentarily increase or decrease the electricity demand for heating (as described in 1.1).

² Given that the heating system is dimensioned correctly.

the rebound peak (around 33% instead of 67% increase compared to before the intervention), as can be observed in the figure.

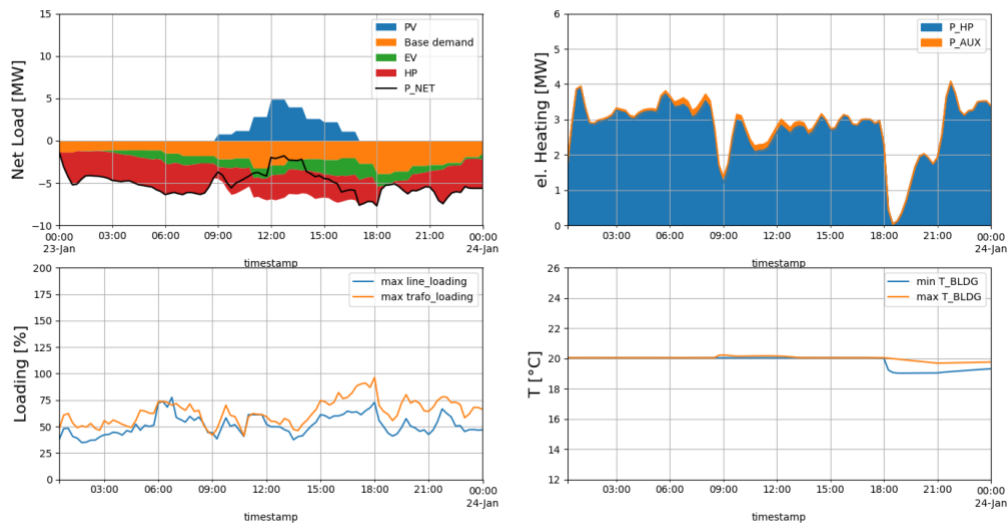


Figure 7: Simulation results for high HP scenario, setpoint reduction by 1°C from 17:45 to 20:45. Top left: aggregated loads and production with residual PV in black. Bottom left: maximum line (blue) and transformer (orange) loading for every timestep. Top right: aggregated HP and auxiliary heater electricity demand. Bottom right: minimum (blue) and maximum (orange) building temperature for every timestep.

4.2 Case Study 2

Figure 8 depicts the grid state of a week in April which we use as base case of the EV flexibility case study. (See Table 2 for an overview of the cases investigated in Case Study 2.) In this base case, none of the EV charging is flexible and the PV injection has been limited to 70% of the theoretical maximum potential, while there is no control of the HPs other than their constant temperature setpoint. During daytime, the figure shows that the PV injection causes a large production surplus in the distribution grid that causes the transformer and line loadings to increase sharply and exceed the 100% loading threshold for some of the transformers (note that the studied system consists of several LV networks connected to the MV, hence there are many MV/LV transformers in the case study). Evening demand peaks (combining conventional demand, HPs and EV charging) also reach around 5 MW. In our example, this demand peak does not result in a transformer overloading because the demand is distributed throughout the grid resulting in a more uniform transformer loading (compared to the loading induced by the PV, which are more concentrated in some of the considered LV networks). As can be seen from the bottom graph in Figure 8 **Error! Reference source not found.**, the voltage magnitude stays within the industry standard range of 0.9-1.1 per unit as per EN 50160 norm. Therefore, the main issue in this case is an overloading issue of the transformers caused by excess PV.

Name	Base Case	Case 1	Case 1b	Case 1c	Case 2
Share of flexible EV-charging	0%	100%	100%	100%	30%
Tariff	-	Vario	Vario 2	Vario 3	Vario 3

Table 2: Overview of cases in Case Study 2

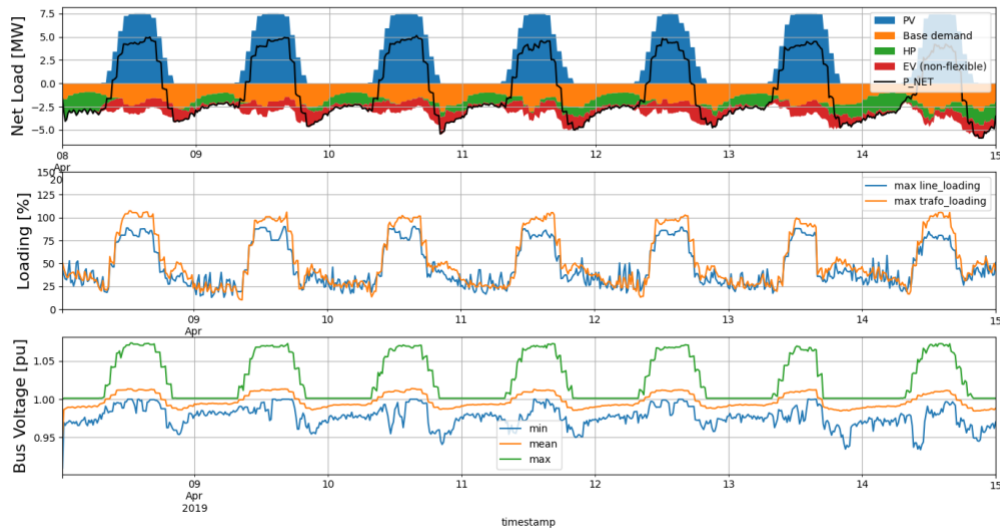


Figure 8: Base case for the analysis of EV charging flexibility. The figure shows the distributed energy resources aggregated at municipality level for a week in April in the top graph with the black line representing the net PV production after all loads are subtracted. The middle graph depicts maximum line loading (blue) and transformer loading (orange) for every time step of the same period. It is important to note that it is not one singular element that is loaded the most for all time steps but rather different elements depending on the time step and the state of the grid. The third graph shows the mean bus voltage in orange while the blue and green lines depict the minimum and maximum voltages within which all buses are situated for any given time step.

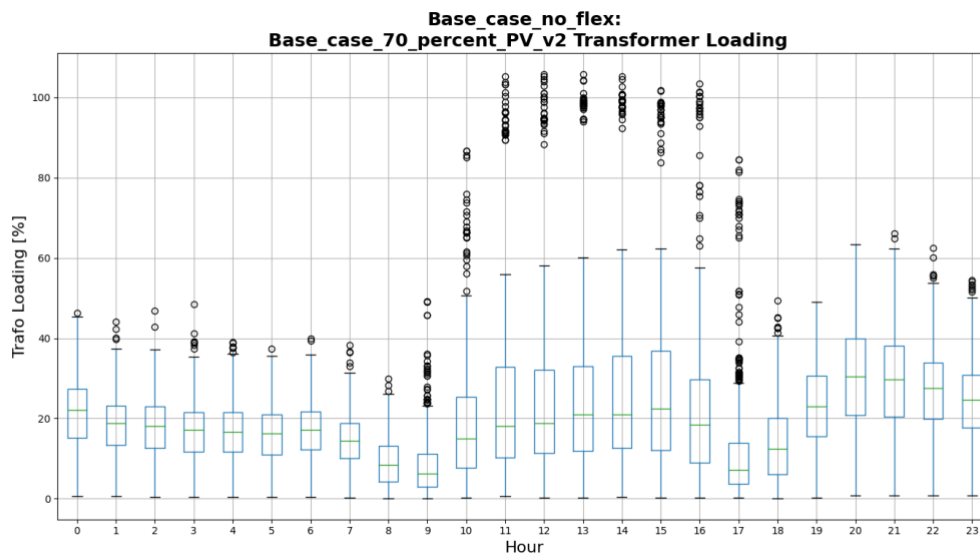


Figure 9: Transformer loading distribution for the base case. Data from all NE6 transformers is collected for the full week and grouped by time of day.

If the EV charging is optimised based on the Vario retail tariff (see Figure 1) the optimizer pushes as much of the charging as possible into the small period with the lowest electricity price at around 1 PM. The resulting electricity demand peak is even larger in magnitude than the peak PV injection, which previously caused the main bottleneck in the distribution grid and we try to cancel out by means of EV-charging shifting. Thus, an adjusted version of the Vario tariff, here referred to as Vario 2, has been created where the period of low retail tariff around noon is prolonged and flattened out so that there is

no single minimum. Vario 2 thus offers five consecutive time steps with the lowest retail tariff instead of the singular time step in the Vario tariff, resulting in a slightly more spread-out EV charging peak which is enough for the power flow solver to run reliably. As can be seen in Figure 10, the resulting EV charging demand is still too concentrated to effectively absorb the PV surplus during the day and therefore does not alleviate the transformer loading issue. On the weekend, the EV schedules are flexible enough that the resulting demand peak leads to even larger congestion and voltage problems than the PV had caused originally in the base case, with the voltage for some buses dropping below 0.7 per unit (see Figure 11).

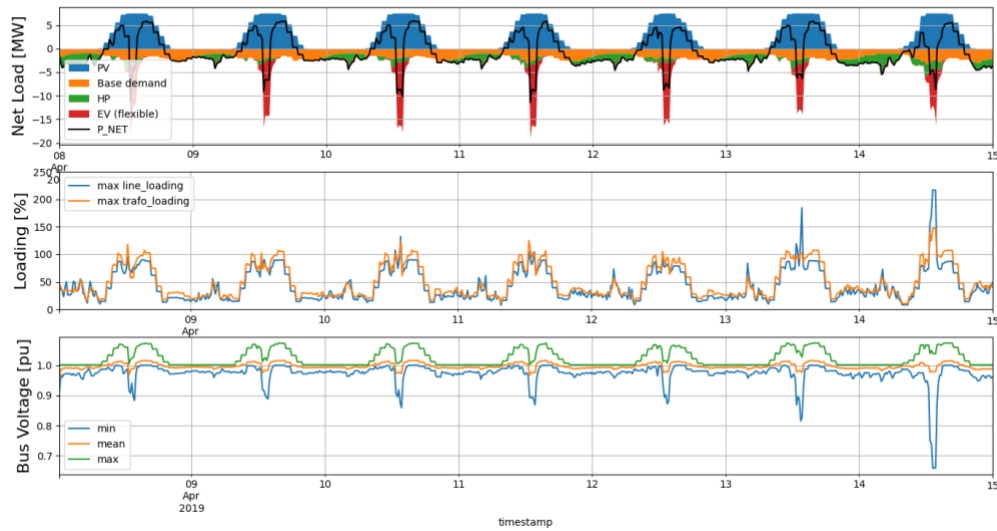


Figure 10: Grid state for 100% flexible EVs with optimized charging based on the Vario 2 tariff.

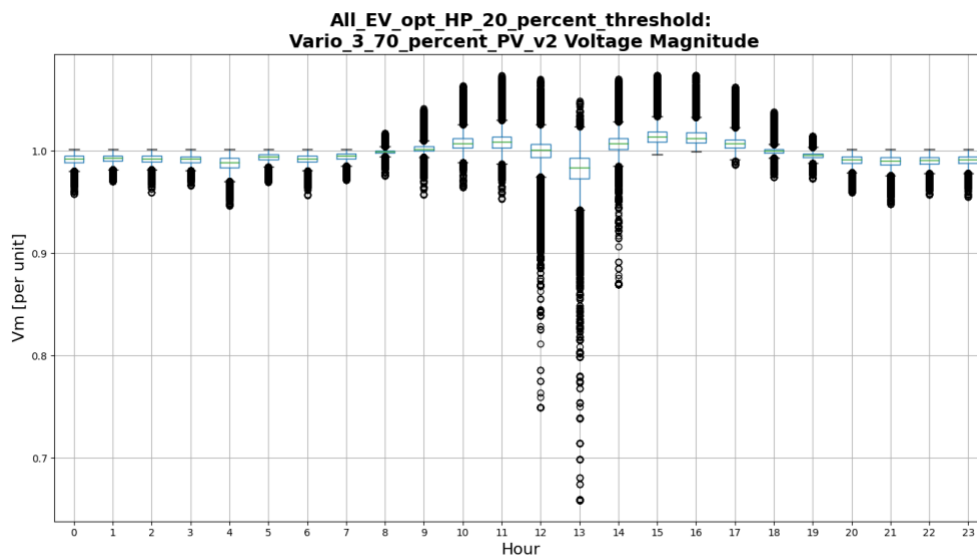


Figure 11: Bus voltage magnitude distribution for a 100% flexible EV fleet reacting to the Vario 2 tariff (in per unit). Data from all NE5 and NE7 buses is collected for the full week and grouped by time of day.

A further increase in the length of the low tariff period, now lasting from 11 AM to 5 PM, in the Vario 3 tariff variation (see Figure 1) helps to spread out the EV load enough that the grid state improves for most days, as can be seen in Figure 12. On Sunday, however, the cars that arrive at the charging station shortly before the tariff increases again for the evening still cause a large spike in the demand as the

optimiser tries to make the most of what remains from the low electricity price period. The consequence is both overloading of lines and transformers as well as undervoltage problems. A glance at the transformer loading distribution in Figure 13 shows that the overloading is a very localized problem, only affecting one transformer.

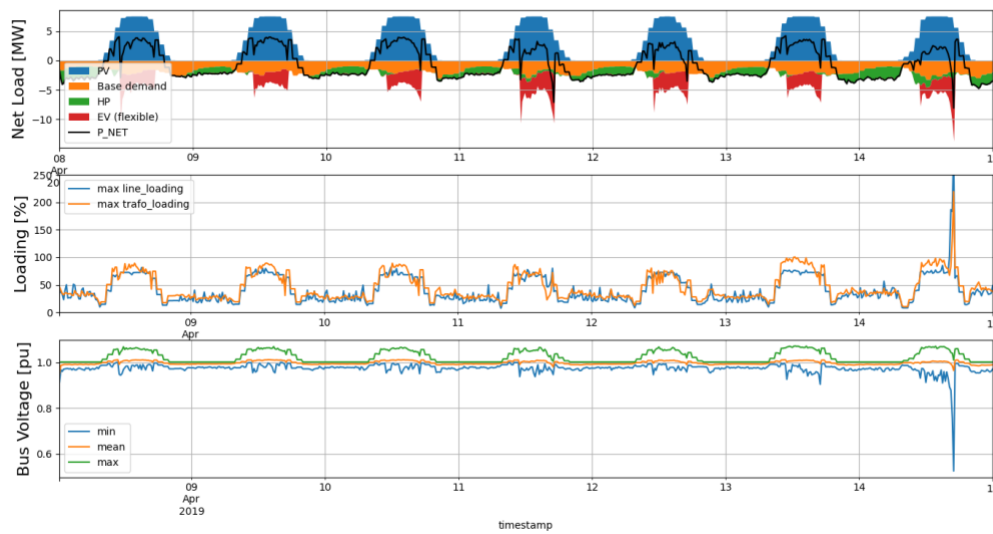


Figure 12: Grid state for 100% flexible EVs with optimized charging based on the Vario 3 tariff.

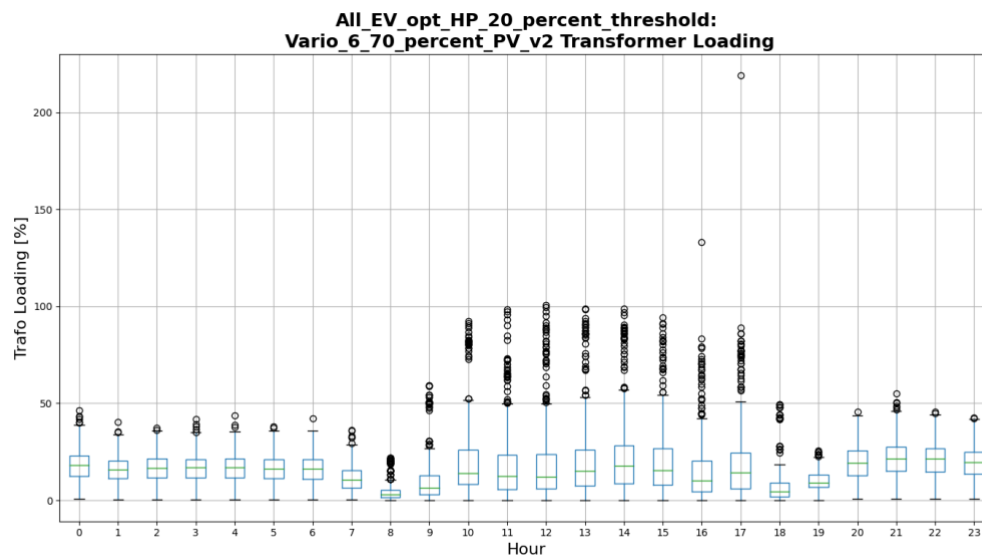


Figure 13: Transformer loading distribution for a 100% flexible EV fleet reacting to the Vario 3 tariff. Data from all NE6 transformers is collected for the full week and grouped by time of day.

Figure 14 and Figure 15 further illustrate the mismatch of the spatial distribution between PV generation and EV demand by mapping the grid state at 12 PM (Figure 14) during an instant where the grid loading is still PV-dominated and at 5 PM (Figure 15) when the EV charging demand has taken over. It is interesting to note that the overvoltages and undervoltages appear at different grid nodes. This means that there is some limit to the extent to which the PV generation and EV demand can balance each other across the distribution grid. It shows that apart from scheduling restrictions and energy requirements based on the EV's movements, the network topology of the distribution grid can also be a limiting factor

to the effectiveness of the EV flexibility measures. It is thus not just necessary to manage the net load aggregated across the entire distribution grid but at a higher spatial resolution: If the net load can be managed within a single feeder instead, this is probably more valuable for effective congestion management.



Figure 14: Graphic representation of the distribution grid state with color gradients for bus voltages and line loading showing the result of a 100% flexible EV fleet reacting to the Vario 6 tariff at 12 PM

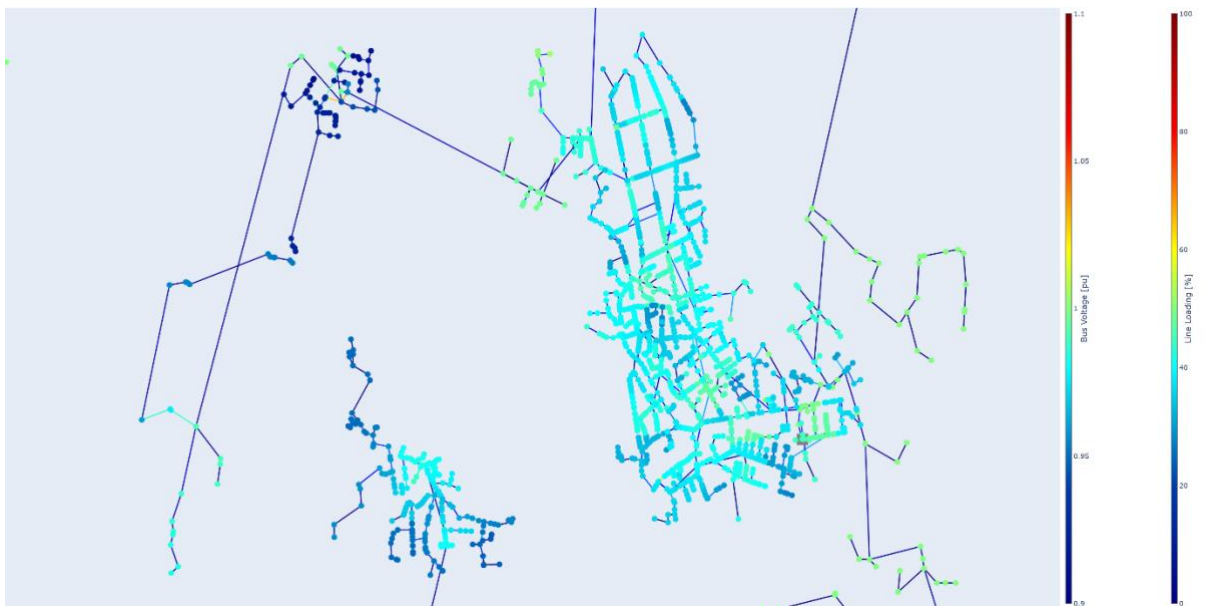


Figure 15: Graphic representation of the distribution grid state with color gradients for bus voltages and line loading showing the result of a 100% flexible EV fleet reacting to the Vario 6 tariff at 5 PM.

In an additional scenario, the share of EVs that are assumed to flexibly adjust their charging schedule based on the dynamic tariff are reduced to 30% of the fleet, to help manage the rebound effect caused by the tariff-based optimization. Figure 16 illustrates the resulting grid state of this scenario. Note that the EV demand is now split into non-flexible (red) and flexible (purple) in the top graph of the figure. While the optimizer still creates demand spikes towards the end of the low tariff period, the resulting impact on the grid is now smaller due to the smaller number of flexible EVs. The bus voltages thus stay within the $\pm 10\%$ per unit range required by regulation, as illustrated by the bottom graph of the figure.

In addition, while there are still some transformers that get slightly overloaded, it happens less often and at fewer transformers compared to the base case. This can be observed by closely comparing the transformer loading distribution for the partially flexible EV fleet in Figure 17 to the same graph for the base case given in Figure 9. The bottom graph of Figure 16 **Error! Reference source not found.** shows that the overvoltage problem has been eliminated for the working days.

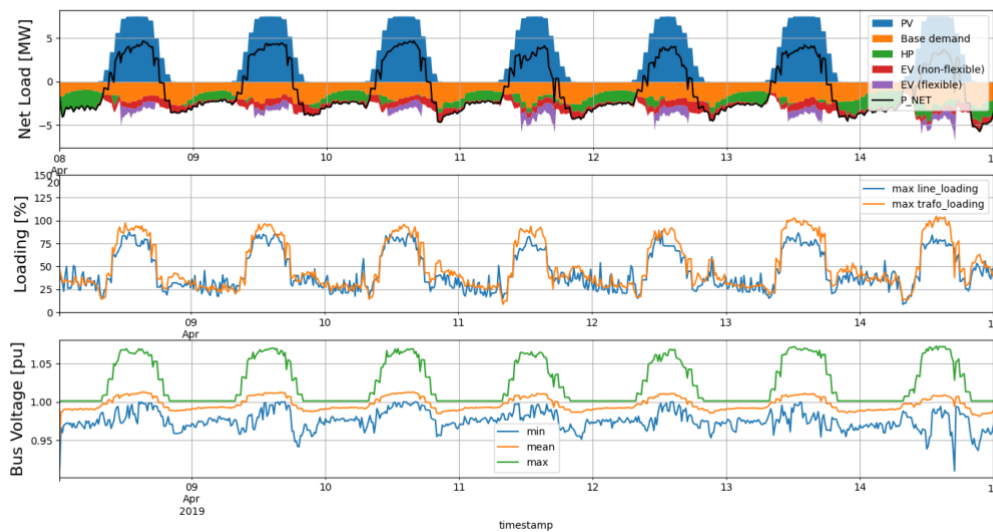


Figure 16: Grid state for 30% flexible EVs with optimized charging based on the Vario 3 tariff.

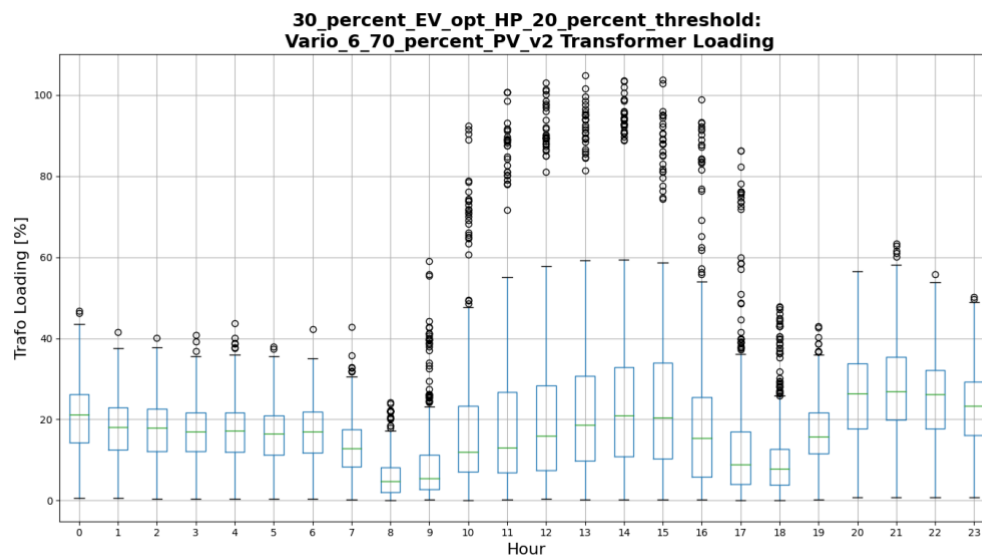


Figure 17: Transformer loading distribution for a 30% flexible EV fleet reacting to the Vario 3 tariff. Data from all NE6 transformers is collected for the full week and grouped by time of day.

4.3 Case Study 3

For Case Study 3, one year simulations have been performed at 15 minute resolution to capture both the seasonal performance of the TES and the intraday behaviour. According to the criteria described in Section 1.3, six configurations with different primary HP and TES sizes have been simulated to examine

their heating behaviour throughout the year and estimate the resulting annualized costs to quantify the value of the flexibility they can provide.

Configuration Name	Primary HP Size [MW]	Auxiliary HP Size [MW]	TES storage capacity [GWh]	TES charge/discharge power [MW]
Reference Case	15	0	0	0
12 MW HP	12	2.5	0.03	2.5
10 MW HP	10	4.5	0.17	4.5
7.5 MW HP	7.5	7.5	1.86	7.5
5 MW HP	5	10	6.5	10
3.5 MW HP	3.5	11.5	10.5	11.5

Table 3: Overview of district heating system heat provision configurations tested in Case Study 3. Let us recall from Section 1.3 that the peak heat demand is 14.47 MW and the yearly heat demand is 28.9 GWh.

Figure 18 shows the temperature evolution of each layer in the stratified TES during a full year. The depicted TES is modeled with 10 discrete vertical stratification layers of equal height and corresponds to the 5 MW HP configuration from Table 3 and with a storage size of 6.5 GWh, representing 22.5 % of the yearly heat demand. The same data is also reflected in the state of charge depicted in Figure 19 (orange line), where it is compared to a simulation with the same conditions but using a simplified single-temperature TES model for increased computational efficiency (blue line). As can be seen from the graphs, at this size the TES is primarily used for seasonal heat storage, going through a single charge/discharge cycle during the year overlayed with smaller short term variations in the state of charge. The state of charge for the stratified TES model in Figure 19 is calculated based on the medium

temperature across all layers. As can be seen, it shows good agreement with the simplified TES model for this storage size and operating mode.

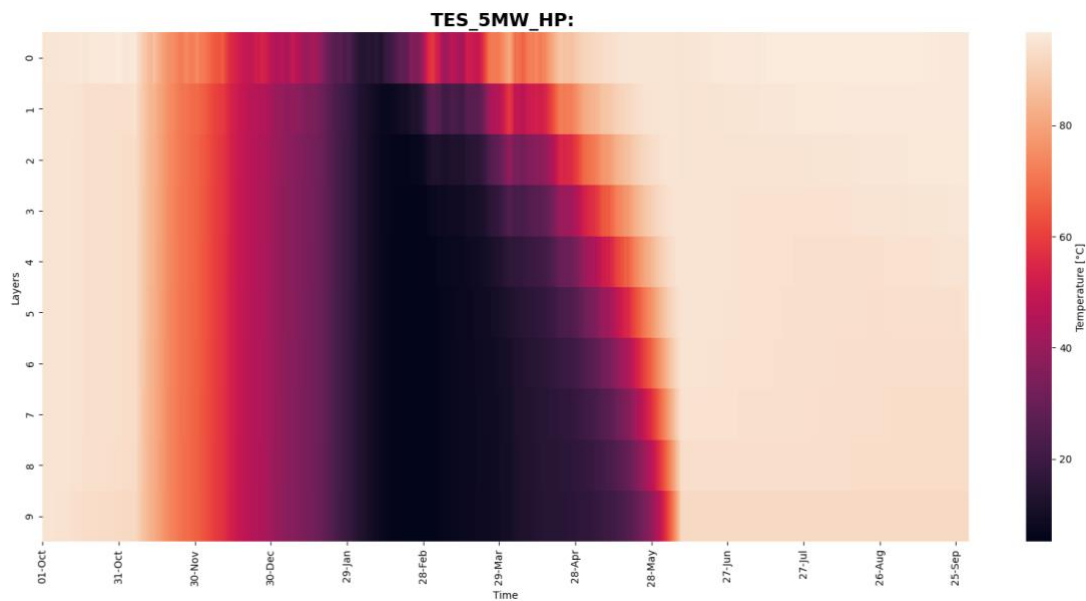


Figure 18: Heat map of the stratified TES layer temperatures across the year for a 5 GWh TES size. Y-axis represents the layers from bottom (Layer 9) to top (Layer 0) and the x-axis time. The temperature scale is in degrees centigrade.

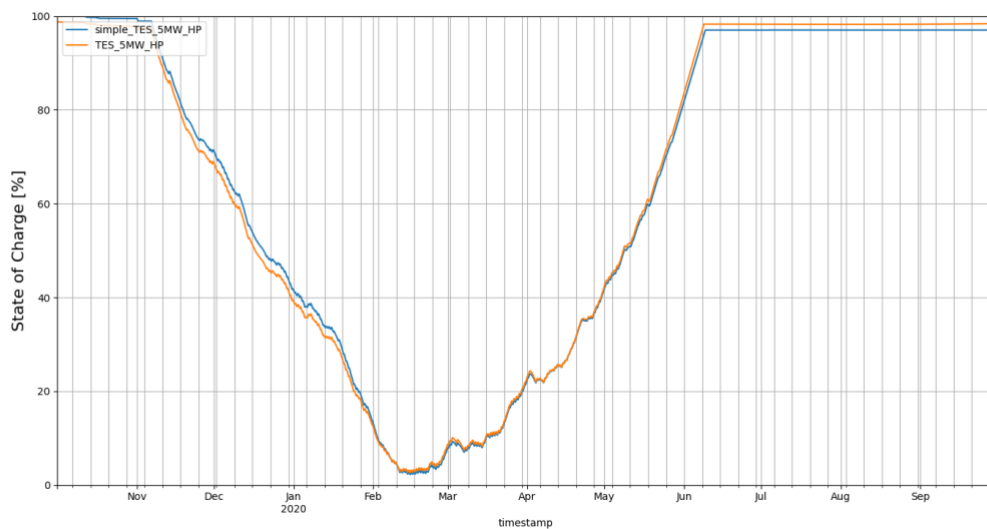


Figure 19: TES state of charge (in percent) comparison of the HSLU's TES model and a simplified uniform temperature TES model. For the stratified TES, the SoC is calculated using the average temperature across all layers. Both TES models have a storage capacity of 6.5 GWh.

Figure 20 and Figure 21 show comparisons of the annualized costs (combining both OPEX and annualized CAPEX costs) for two different tariff schemes, one per figure. Both tariff schemes are based on the Vario tariff defined in Figure 1 and are illustrated for the full year in Figure 4. For Figure 20, the summer tariff is 30% lower than the winter tariff and for Figure 21 the seasonal difference is 54%. The values in both figures are based on simulations with the simplified TES model.

Heating System Control Algorithm

Basic heating system dispatch algorithm:

- If the heat demand exceeds the primary HP's output power, the TES is used to provide peak power.
- If the heat demand is lower than the primary HP's minimum output power and the TES is sufficiently charged, the TES can be used to cover the heat demand on its own.
- Otherwise, the primary HP can either do direct load following or provide some extra heat to recharge the TES, if necessary.

Tariff-based control

The tariff-based control algorithm works mostly according to the same scheme and physical limitations as the basic control algorithm described above. Whenever there is any freedom on how to dispatch the TES and primary HP, however, the tariff-based control algorithm will take the current retail tariff into account: If the current tariff is within the highest 30% for the week, it will try to avoid using the primary HP and drawing electricity from the grid as much as possible by using the TES instead. On the other hand, if the tariff is within the lowest 30% for the week, the algorithm prioritizes using the primary HP and charging the TES as much as possible to take advantage of the low energy cost.

The reference case, without TES, leads to an annualized cost of 3.83 million Euros for the 30% seasonal difference tariff scheme depicted in Figure 20. The two smallest TES sizes manage to reduce the annual costs slightly even when using a purely power- and TES state of charge-based control algorithm, described in Textbox at the top of the page. The smallest TES size achieves the largest cost reduction at 4.8% while the 167 MWh TES leads to 1.2% in cost savings. If the tariff-based control algorithm, described in the text box on the right, is used, a cost reduction can be achieved for all TES sizes compared to the case without tariff-based control. For the smallest TES, the cost savings increase to 6.6% compared to the reference case and for the largest TES (10.5 GWh) a cost reduction of 0.5% can be achieved using tariff-based control. Interestingly, the medium TES size (6.5 GWh) does not reduce costs compared to the reference case regardless of control algorithm.

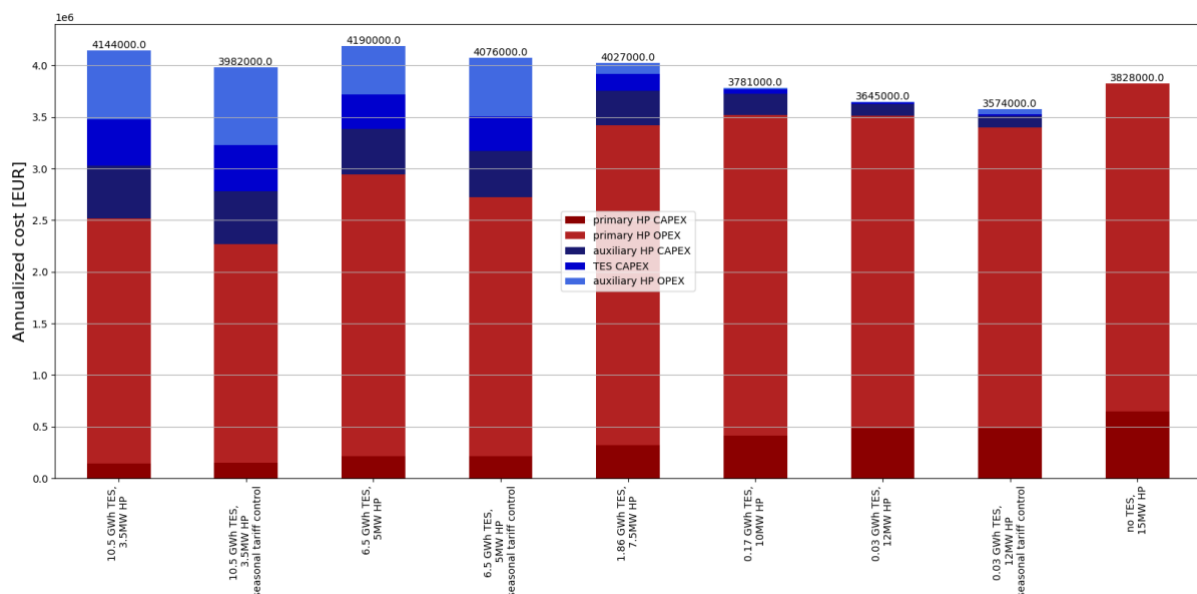


Figure 20: Cost comparison for different DH centralized heat production configurations (TES sizes from 0 to 10.5 GWh), where the retail electricity tariff was 30% lower during the summer months. Primary HP related costs are depicted in red and TES + auxiliary HP costs in blue. Darker shades represent annualized CAPEX and lighter shade OPEX costs. All costs are calculated based on the same tariff, columns with "seasonal tariff control" in the label come from scenarios that used a control algorithm reacting to changes in the tariff.

For an increased seasonal spread in electricity prices, as seen in Figure 21, the annualized costs go up overall because the prices in winter, when the majority of the heating demand occurs, are slightly higher. The configurations with the two smallest TES sizes still manage to reduce the annualized costs by 1.1% for the second smallest and 4.6% for the smallest size respectively. Using tariff-based control (see text box on previous page for definition), the largest and smallest TES configurations manage to reduce the costs by 3.1% and 6.2% compared to the reference case. The medium TES sizes (6.5 GWh and 1.86 GWh) lead to increased costs compared to the reference case (5.3% and 5.1% respectively, without tariff-based control and 2.4% with tariff-based control).

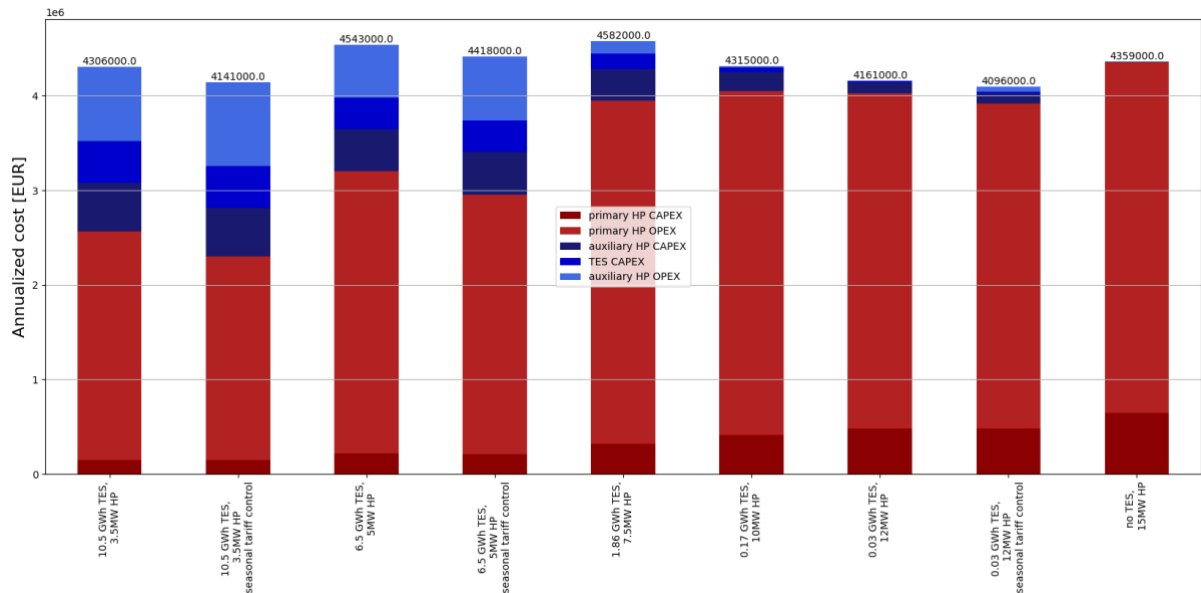


Figure 21: Cost comparison for different DH centralized heat production configurations (TES sizes from 0 to 10.5 GWh), where the retail electricity tariff was 54% lower during the summer months. Primary HP related costs are depicted in red and TES + auxiliary HP costs in blue. Darker shades represent annualized CAPEX and lighter shade OPEX costs. All costs are calculated based on the same tariff, columns with "seasonal tariff control" in the label come from scenarios that used a control algorithm reacting to changes in the tariff.

5 Key findings and take-away messages for the stakeholder

The case studies performed using the ReSIM environment support and validate several of the findings resulting from other pieces of work performed in PATHFNDR. Below, we summarize findings illustrated by the specific case studies described in this working document. Let us note that these findings are in agreement with the overall PATHFNDR findings, but they make up only a small portion of them. For more extensive discussion of PATHFNDR findings, the reader is referred to the corresponding synthesis report [14].

The findings below are relevant to the following stakeholders: electricity distribution system operators (DSOs), energy departments of municipalities, electricity and heat provision utilities, heating system suppliers and EV charging suppliers.

5.1 Flexibility Provision from Residential Heating Systems

Questions relevant to PATHFNDR:

1. Can the heating of buildings provide flexibility to the DSO without compromising the comfort of the tenants?
2. Are there any practical considerations in implementation?

In short: Yes, the buildings can offer flexibility, but its provision shall be coordinated to avoid rebound effects. The flexibility can be achieved by temporarily modifying the temperature setpoint of the building heating system.

Changing the temperature setpoint of the residential heating systems by plus or minus one degree, depending on flexibility needs, strikes the best balance between fast response (i.e. reduction of the demand), guaranteed thermal comfort and small rebound effect. The latter is due to differences in the thermal mass and heat transfer coefficients of individual buildings that naturally spread the timing when the changed setpoint is reached and the HP must be switched on again. From a grid perspective, this option therefore allows effective response to congestion issues while avoiding the creation of new congestion issues at the end of the intervention period. This is especially true when reducing the setpoint to temporarily reduce the grid load. Scheduled increases in temperature setpoint tend to have a less significant impact.

The mechanism proposed based on this case study therefore is that the DSO can remotely reduce the temperature setpoint of heat pumps, but local control remains with the local heating system, i.e. the DSO does not directly control (e.g., switch off) heat pumps. Each building is left free to ramp the heating up again when it drops below the new (lower) setpoint.

Having the DSO directly controlling (e.g., switching off) the buildings' heat pumps overriding the local control (as already in place by some DSOs today) can, in principle achieve a similarly acceptable result, but it requires a more complex rule from the DSO (e.g., based on knowledge of buildings' thermal properties such as the building's thermal mass and insulation level) if the comfort level is to be

guaranteed. This type of intervention should be limited to shorter intervention periods and targeted at buildings with high thermal mass and low heat transfer coefficients.

If exposed to dynamic tariffs, it could also make sense for homeowners to implement changing temperature setpoints on their own to avoid operating their HP during traditional demand peaks (especially in the evening) or potentially preheat their homes during the day utilizing PV power.

5.2 Flexibility Provision from Optimized EV-Charging

Questions relevant to PATHFNDNR:

1. Can dynamic tariffs motivate a shift of EV charging such that it provides flexibility to the DSO?
2. Are there any practical considerations in implementation?

In short: Yes, EV charging can offer significant flexibility, but having it coordinated via tariffs might be challenging, as, in the presence of appropriate automation and intelligence, it can result in an excessive synchronization of EV charging and hence shifting the problem to other time instances.

While EVs can theoretically offer a lot of flexibility, even without bidirectional charging, the potential for large rebound effects or overcompensation is significant, especially if all the EVs follow the same optimization strategies and receive the same dynamic tariffs. Dynamic tariffs with one singular timestep with the lowest price are to be especially avoided. If possible, exposing parts of the EV fleet to statistically equal tariffs (daily average, minimum, maximum, etc.) with slightly different timing or introducing a peak power component to the tariff could help avoid concentrating EV demand on narrow time periods.

As has been shown by the results in Section 4.2, the challenge is not just to match the power injection and withdrawal throughout the day but also across the distribution grid, as there may be bottlenecks in shifting energy across the grid. If the net load can be managed within a single feeder this would be more valuable for the congestion management of the distribution grid.

Tariffs to motivate EV charging flexibility shall be selective (in terms of participating EVs and in terms of the location) and be penalizing peak charging (i.e., having a power component, as opposed to only a time-dependent energy component).

5.3 Value of Centralized Thermal Storage in District Heating Systems

Questions relevant to PATHFNDNR:

1. Do the benefits from the additional available flexibility justify the cost of adding thermal energy storage (TES) to a HP-based district heating network?
2. What storage size seem to make sense under which conditions?

In short: Adding TES to a HP-based district heating system is a choice that can be justified by the electricity price economics, but it is not needed from the electricity distribution grid perspective.

Due to its central location and large HP size, flexibility provided by the district heating system is not suitable for alleviating distribution grid congestions (as opposed to flexibility received by decentralized small-scale heat pumps), but on the other hand having a district heating network (instead of local heat pumps) reduces the loading across the grid, hence also reducing the need for flexibility. Flexibility

offered by means of a TES can be of value in the presence of time-varying electricity prices, as a means to lower the overall power purchase (and hence heat provision) cost.

The addition of a utility-scale TES to the district heating system offers added flexibility to the operator to decouple the heat demand from electricity prices. An investment in TES is financially viable if there is sufficient variation in the electricity tariffs, depending on the size and operating mode of the storage, either on a daily or a seasonal time scale. The financial viability varies by TES size:

- Small TES (less than 1% of the yearly heat demand) are able to take advantage of the daily variation in electricity prices to reduce operating costs while keeping the additional investment cost low.
- Medium sized TES (6%-22.5% of yearly heat demand): Under the conditions tested here, medium sized TES do not seem to profit enough from seasonal price differences to recuperate the additional investment cost through energy cost savings
- Large scale TES (up to 30% of the yearly heat demand), provide seasonal flexibility allowing the operator to profit from seasonal price differences and convert cheap summer electricity into valuable winter heat in addition to the day-to-day flexibility taking advantage of short-term electricity price fluctuations.

Let us also note that, even though not explicitly illustrated in the case study, a peak power component in the electricity tariff could additionally motivate the installation of a TES.

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