Demonstration Site Requirements

Deliverable 9.2

SUMMARY

This document develops a detailed description of the demonstration sites in the GENTE pilot projects and presents their respective scenarios, solutions, and evaluations.

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Impressum

Internal Reference

Deliverable No.	D 9.2 (2024)
Deliverable Name	Summary of demo-case requirements, scenarios, solutions and evaluation for each site
Lead Participant	HSLU
Work Package No.	WP9 - Demonstration, coordination and evaluation
Task No. & Name	T 9.3 Demonstration, monitoring and evaluation in Switzerland
Document (File)	GENTE-D9.2-SummaryDemoCaseRequirementsScenariosSolutionsEvaluation-PU-P_R0
Issue (Save) Date	2025-04-16

Document status

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Abstract

The ERA-Net GENTE project aims to develop a distributed governance toolkit for local energy communities (LECs). This toolkit includes advanced digital technologies such as the internet of things (IoT), distributed ledger technology (DLT), edge processing and artificial intelligence (AI) for autonomous energy resource management within and across LECs and for flexibility provision to energy networks.

The solutions developed within GENTE for the governance of LECs will be validated first at the lab levels, and then in real full-scale environments in order to increase the technology readiness level (TRL) levels of solutions. For that, GENTE project elements will be tested in pilots with diverse characteristics.

The foundational structure, test cases, and methods for calculating key performance indicators (KPIs) were outlined in Deliverable 9.1, titled “GENTE Test Cases, Assessment Framework, and KPIs.” This document defines the objectives for each pilot site and establishes a systematic framework for KPI evaluation to measure the success of the project’s solutions.

Building on this, Deliverable 9.2, “Summary of Demo-Case Requirements, Scenarios, Solutions, and Evaluation for Each Site,” presents detailed results from each demonstration site. It includes an in-depth analysis of site-specific requirements, implemented scenarios, applied solutions, and the corresponding evaluations, providing a comprehensive overview of the project's progress and outcomes.

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List of Abbreviations

AA	Am Aawasser, Switzerland
AI	Artificial Intelligence
API	Application Programming Interface
BEMS	Building energy management system
CELL	Collaborative Energy Living Lab
CO_2	Carbon dioxide
COP	Coefficient of Performance
DER	Distributed energy resources
DLT	Distributed ledger technology
DSO	Distribution System Operator
EC	Energy community
EEM	Energy efficiency measure
ER	Exploitable results
EV	Electric vehicle
GRU	Gated recurrent unit
HSBLL	HSB Living Lab, Sweden
ICT	Information and communications technology
IoT	Internet of Things
IPMVP	International Performance Measurement and Verification Protocol
KPI	Key Performance Indicators
LEC	Local energy community
LL	Living Lab
LSTM	Long short-term memory
MWh	Megawatt-hour
NTO	Non-technical objective
PV	Photovoltaic
RES	Renewable energy sources
RSME	Root mean square error
SCADA	Supervisory control and data acquisition
SOC	State of Charge

t/MWh	tonnes per Megawatt-hour
TCP/IP	Transmission Control Protocol/Internet Protocol
TO	Technical objective
TRL	Technology Readiness Level
UC	Use case

1. Introduction

The ERA-Net GENTE project aims to develop a distributed governance toolkit for local energy communities (LECs). This toolkit includes advanced digital technologies such as the internet of things (IoT), distributed ledger technology (DLT), edge processing and artificial intelligence (AI) for autonomous energy resource management within and across LECs and for flexibility provisions to energy networks.

The solutions developed within GENTE will be tested in two demonstrators at different scales in Switzerland – Am Aawasser – and Sweden – HSB Living Lab. Originally a third demonstrator in Türkiye was included, but unfortunately they had to leave the project prematurely.

Within Work Package 9 (WP9), the report for Deliverable 9.1 presents the validation methodology in the form of a test case assessment framework and Key Performance Indicators (KPIs). This report for Deliverable 9.2 presents each demo site's respective test case scenarios, requirements, evaluation criteria, and results. The report for Deliverable 9.3 will present the assessment of each test case against the KPIs and identify best practices to aid replication.

2. Demonstration Sites

In this section the different demonstration sites are discussed. Each site describes their respective test scenarios, requirements, and evaluation criteria.

2.1. Am Aawasser - Switzerland (HSLU)

2.1.1. Overview

The Am Aawasser community has 23 apartments and a commercial space of 600 m^2 (Figure 1). The community is able to achieve a high level of autarky: there is local electricity production onsite (run-of-river hydro, rooftop PV) and controllable energy resources (heat pump, local energy storage, controllable building services and comfort settings). The hydro energy source has 85 kWp and produces around 120-300 MWh/a with a potential for 380 MWh/a. The PV has 124 kWp and produces around 80-110 MWh/a. The total battery storage capacity is 260 kWh, and the total thermal storage capacity is 10.5 m^3. The electric usage for the community as a whole is around 200 MWh/a.

The Am Awasser community has an existing optimization platform provided by third party company Eco Coach[1]. The platform provides near real time sensor measurements of the testing site and is connected to the EcoCoach cloud based on MS Azure. The EcoCoach Cloud uses an API for accessing the data generated by various sensors located onsite.

Figure 1 - Am Aawasser, Switzerland

[1] "ecoCoach." Accessed: Jan. 14, 2025. [Online]. Available: https://ecocoach.com/

Implementations

Due to the departure of Reengen, the originally planned IoT platform could not be used to interface with the hardware at the Am Aawasser testing site. As a result, a new approach was adopted, where all energy optimizations were conducted within a simulation environment. Despite this shift to a simulated approach, it was still possible to obtain real data readings from the testing site to ensure accurate input for the simulations. However, the ability to close the control loop by sending control commands to energy units, such as the heat pump or thermal storage unit, was not possible due to the absence of the necessary hardware.

The simulation approach integrated the following elements:

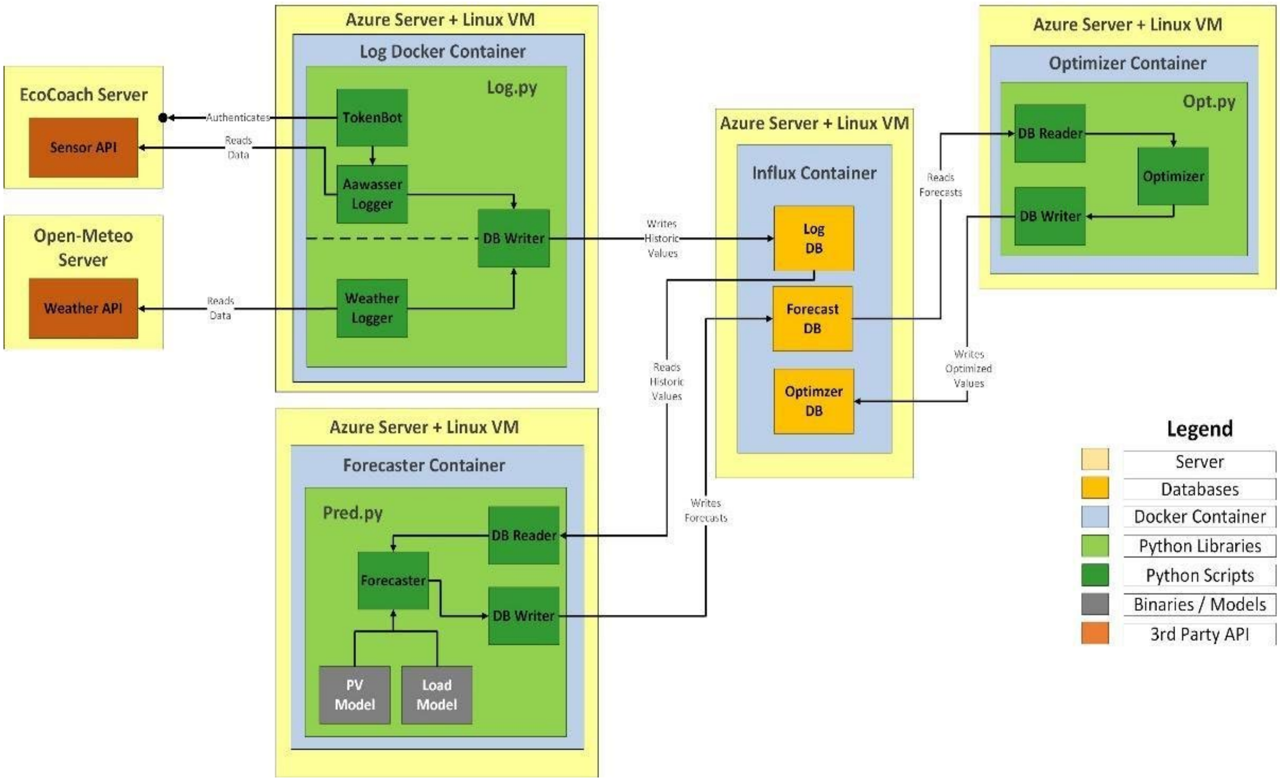

Figure 2 - System architecture for Logger, Forecaster and Optimizer

1. Logger

The Logger communicates with both the testing site API and a weather API. It processes the acquired data and writes it to our central database. The Logger is built using several custom-developed Python libraries, which provide all the necessary functionalities to retrieve data from the APIs, post-process the information, and store it in the central database.

2. Forecaster

The Forecaster uses the up-to-date data stored in the central database to predict both power consumption and production at the testing site for the next 24 hours. This tool is also built using several custom-developed Python libraries. The primary library within this system is capable of creating, training, and executing various forecasting models, including state-of-the-art neural networks, to generate accurate day-ahead predictions for both energy consumption and production.

3. Optimizer

The Optimizer utilizes the forecasts to solve an optimization problem aimed at the optimal utilization of all energy flexibilities within the testing site. Specifically, it calculates how the energy storage units should be charged or discharged to optimize a specific cost function. This cost function defines the target of the optimization and can be tailored to different objectives: CO_2 reduction (test case 1), self-consumption optimization (test case 2), or load peak reduction (test case 3).

Toolkit Addition from the Am Aawasser Site

All self-developed python libraries are set up as their own private PiPy package to serve as a blueprint for any further energy community projects. The packaging makes installation and reuse easy. Furthermore, all developed scripts can be run within their own Docker container on almost any Linux system. Any energy community specific parameters can be adjusted in separate configuration files. As such both the libraries and the scripts are part of the toolkit offered by the GENTE project to support the creation of smarter local energy communities.

2.1.2. Functional Performance Tests

Before running any of the test scenarios, it is essential to evaluate the functional performance to ensure that the system operates correctly. Note that the functional performance test involving the IoT Gateway has not been conducted due to the departure of Reengen.

2.1.2.1. Data Collection

The objective of this test is to demonstrate that all required data— including meteorological, load, and generation data—can be successfully aggregated and stored in the centralized database (InfluxDB).

The functional test was conducted by running the logging script over a prolonged period of 30 days and reviewing the collected data. An example for PV yield and electricity demand is shown in Figure 3. The blue lines show the total power from PV installation while the purple line represents the power demand for House 1. During this timeframe, both continuous and periodic data entries were successfully recorded in the database. This confirms that the data acquisition system is functioning as intended.

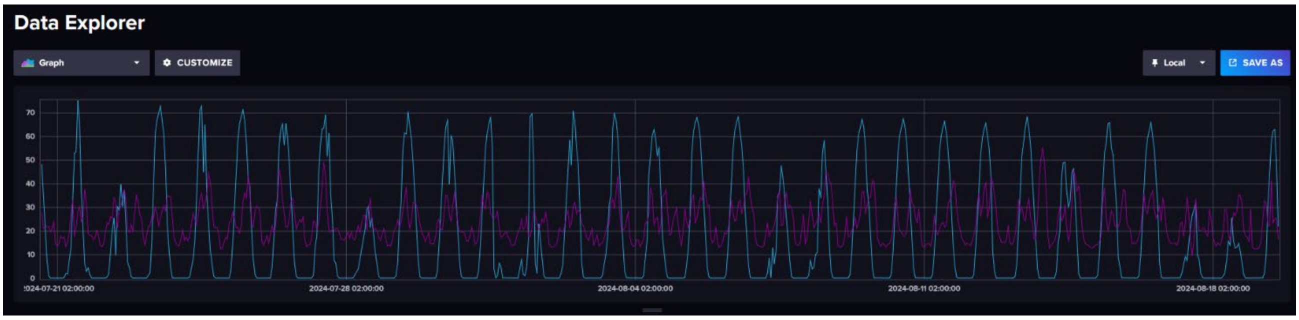

Figure 3 - Time series data from InfluxDB

2.1.2.2. Forecasting Evaluation

Another aspect of functional performance testing involves evaluating both the production and consumption forecasts. The benchmark for this evaluation is a straightforward "last-day-equivalent" algorithm, which assumes that the production and load for the upcoming day will be identical to those from the previous day. This test was conducted by running the developed forecasting algorithm on the test set and comparing its results with those of the benchmark algorithm.

Benchmark Comparison

Load Model

The load model's performance was evaluated by comparing its mean absolute loss to that of the benchmark. The developed model achieved a Mean Absolute Model Loss of 5.201 kW, significantly outperforming the benchmark, which had a Mean Absolute Loss of 9.39 kW (Table 1). This demonstrates the superior accuracy of the load model in forecasting compared to the simple "last-day-equivalent" approach.

Table 1 - Load model performance

Model	Absolute Loss	Relative Loss
Load Model	5.201 kW	22.74 %
Load Benchmark	9.39 kW	36.33 %

Furthermore, when analysing the non-absolute mean error, the relative loss decreases to 1.352%. Since the optimization algorithm focuses on balancing energy within the system, this non-absolute error is more aligned with the actual metric we aim to pursue. As this loss compares the integrated error with the total integrated power, we will refer to it as the **relative energy loss**, given that energy is the integration of power.

A random sample prediction of the Load Model (orange) is compared to the target values (blue) and the day-before benchmark (green) in Figure 4 and Figure 5 during two different time periods. These figures illustrate the model's accuracy in forecasting load, highlighting its improvement over the benchmark approach.

PV Model

The PV model was assessed by measuring its absolute and relative losses compared to the benchmark. The model achieved an Absolute Loss of 3.562 kW and a Relative Loss of 18.57%, significantly better than the benchmark, which had an Absolute Loss of 8.193 kW and a Relative Loss of 42.71%. (Table 2) This indicates that the PV model is considerably more accurate in forecasting than the benchmark.

Furthermore, the PV model's relative energy loss is even lower, with a value of only **0.435%**.

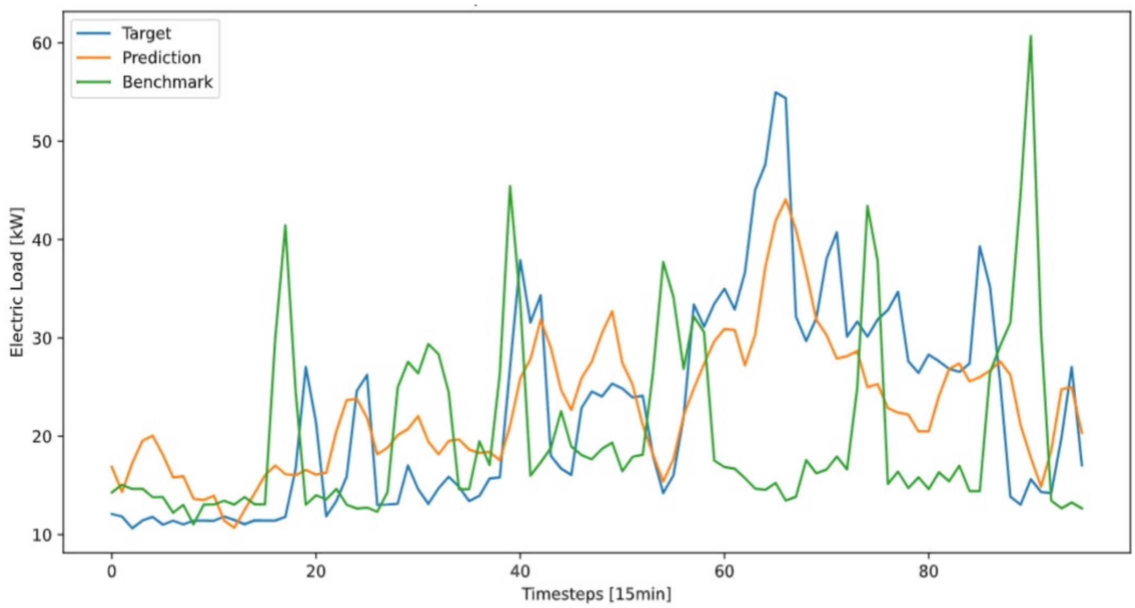

Figure 4 – Comparison between load model and benchmark

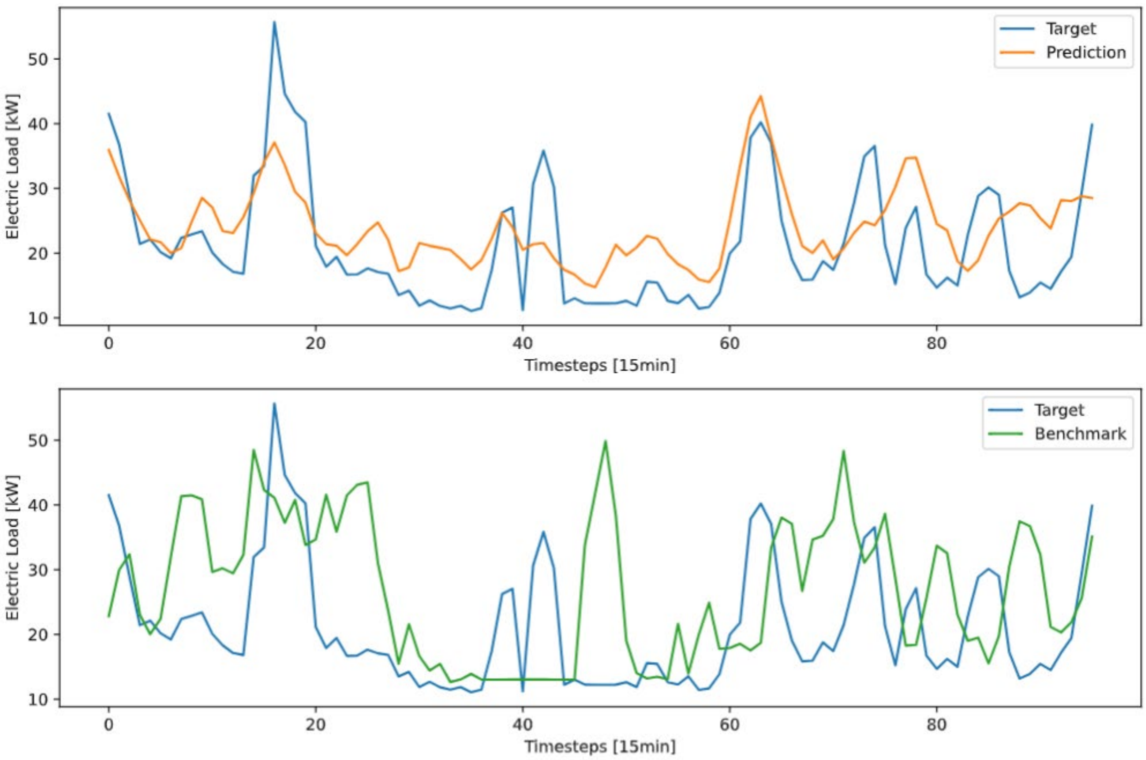

Figure 5 - Comparison between load model and benchmark, example 2

Table 2 - PV model performance

Model	Absolute Loss	Relative Loss
PV Model	3.562 kW	18.57 %
PV Benchmark	8.193 kW	42.71 %

A random sample prediction of the PV Model (orange) is compared to the target values (blue) and the day-before benchmark (green) in Figure 6. This comparison visually demonstrates the model's accuracy and its improvement over the benchmark approach.

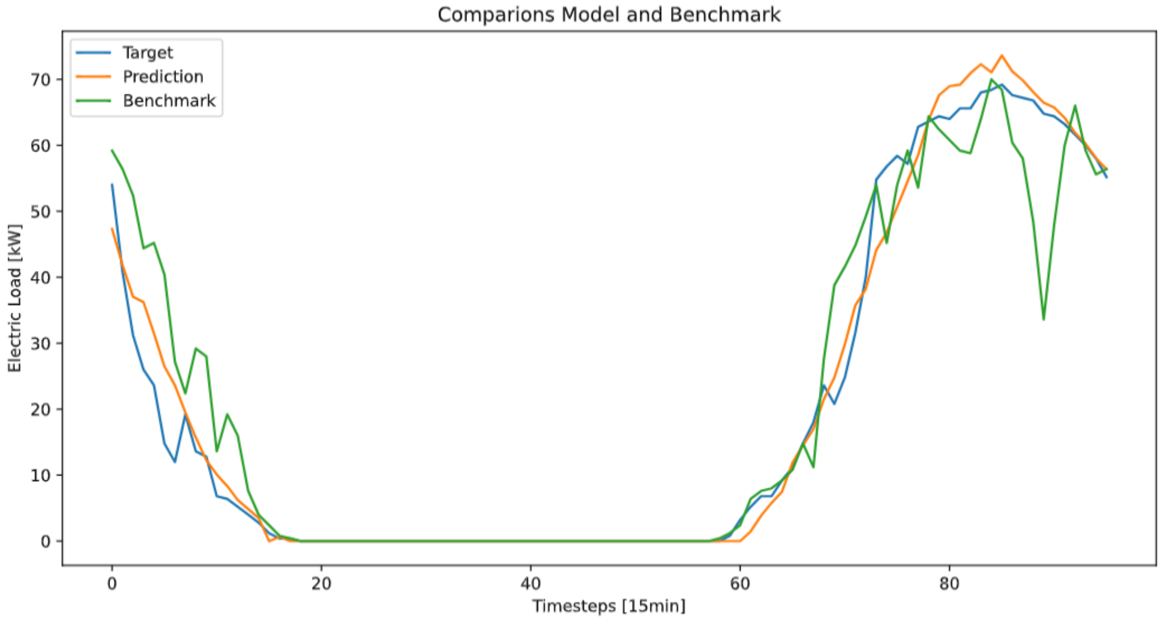

Figure 6 – Comparison between PV model and benchmark

2.1.3. Test Scenarios

2.1.3.1. Test Case 1 - CO_2 emissions reduction

In this test case, the loss function of the Optimizer is adjusted to minimize CO_2 emissions. To achieve this, each energy source is assigned a CO_2 equivalence, enabling the system to factor in carbon emissions during the optimization process. Once these adjustments are made, the entire optimization system can run as usual, generating future target levels for all energy flexibilities within the system.

2.1.3.2. Test Case 2 - Increase in community autarky

Similar to Test Case 1, Test Case 2 also requires an adjustment to the Optimizer's loss function. In this scenario, the focus is on reducing energy imports, which in turn maximizes self-consumption and increases the autarky of the testing site.

2.1.3.3. Test Case 3 - Peak load management

For Test Case 3, the Optimizer's loss function is adjusted to focus on managing peak load. The objective is to minimize the maximum load on the grid by using all available energy flexibilities. This adjustment helps distribute the load more evenly throughout the day, reducing peak demand and improving grid stability.

2.1.4. Requirements

In Deliverable 9.1, the prerequisites for the different test cases were outlined. However, due to the departure of Reengen, we had to adapt the field trials to simulation trials, which also led to changes in the requirements. For the simulation tests to function correctly, the following requirements must be met:

- Connection Establishment:
    - Between Scripts and Database (InfluxDB)
    - Between Scripts and Am Aawasser site
    - Between Scripts and open-meteo.com which is a provider of weather data used by the prediction algorithm.

- Script Executability:
    - All developed code must run within the Docker environment.
    - All code is provided on GitLab. The links are provided in the toolkit (D1.3).

- Library Availability:
    - Private PyPi libraries must be installable and accessible within the Docker environment.

2.1.5. Evaluation

This section details the methods used to evaluate the test scenarios, including the calculations and results. The evaluation begins with an assessment of CO_2 reduction, followed by an analysis of increased community autarky, and concludes with an evaluation of peak load reduction.

2.1.5.1. Test Case 1 - CO_2 reduction

The HSLU Optimizer will demonstrate the ability to reduce the CO_2 emissions of the LEC. This tool, developed by HSLU, makes decisions on flexible assets (flexible loads such as batteries or heat pump) while taking into account data from PV forecast and consumption forecast.

The goal of the Optimizer is to manage and control the energy assets within the LEC by determining optimal setpoints. It will run for a designated period to validate the use case. For this period, CO_2 emissions will be calculated by assessing the consumption of locally generated renewable energy and compare this to a baseline.

It is assumed that electricity generated and consumed locally from renewable sources has a lower carbon footprint compared to electricity imported from the grid. It is expected to show the advantages of low CO2 community generated electricity as an alternative to building new centralized carbon-based power plants. Table 3 provides an overview of CO_2 emissions from electricity generation across various countries. Spain, a consortium member country, was selected as the baseline. Its CO_2 emissions per MWh fall below the average in Europe of 0.294 t/MWh [2], positioning it in the middle range—not among the highest or lowest emissions levels of the countries in Europe.

Table 3 - CO_2 per MWh for Switzerland, Sweden, Germany, Spain, and locally produced

Electricity from	CO_2	Comments
Switzerland	0.044 t / MWh	[2]
Sweden	0.0407 t / MWh	[3]
Germany	0.39 t / MWh	[2]
Spain	0.174 t / MWh	In 2023 [4]
Locally produced electricity e.g. in an LEC	0.023 t / MWh	[5] Renewable Energy

Table 3 highlights that standard electricity in Switzerland has exceptionally low CO_2 emissions. This is largely due to the country's reliance on hydropower, followed by nuclear energy, both of which are

[2] "Nowtricity: CO2 emissions by country." Accessed: Nov. 13, 2024. [Online]. Available: https://www.nowtricity.com/

[3] "Carbon intensity of the power sector in Sweden from 2000 to 2023." Accessed: Nov. 13, 2024. [Online]. Available: https://www.statista.com/statistics/1290491/carbon-intensity-power-sector-sweden/#:~:text=In%202023%2C%20Sweden's%20power%20sector,lowest%20in%20the%20European%20Union.

[4] "Carbon intensity of the power sector in Spain from 2000 to 2023." Accessed: Nov. 13, 2024. [Online]. Available: https://www.statista.com/statistics/1290486/carbon-intensity-power-sector-spain/

[5] "Stiftung myclimate." Accessed: Oct. 23, 2024. [Online]. Available: https://www.myclimate.org/

recognized for their minimal carbon output. As already mentioned, to provide a more representative CO_2 equivalence on a European scale, data from Spain has been used for comparison in this test.

CO_2 reduction can mainly be achieved by using the LEC's own low carbon footprint. Any increase in autarky therefore automatically reduces CO_2 emissions. To calculate the CO_2 reduction potential, autarky data from the next section (1.1.5.2) is used for calculations. The annual electricity usage is about 200 MWh for the Am Aawasser demo site. Before activating the Optimizer, the annual CO_2 emissions are calculated as shown in Table 4.

With the optimization, the LEC's autarky increases from 61.91% to 74.81%. While this slightly raises the CO_2 emissions generated internally by the LEC, it significantly reduces CO_2 emissions from external sources. The optimized calculations are as shown in Table 4.

This results in an overall reduction of 24% in the LEC's CO_2 emissions, totalling 3.9 tons per year. This key performance indicator (KPI) has been met, with a target range of 0–30% [6] in CO_2 emissions reductions.

Table 4 - CO_2 emissions results, with and without optimization

	Without optimization	With optimization
CO_2 emissions externally from electricity supplied by the grid	200 MWh * (100%-61.91%) = 76.18 MWh 76.18 MWh * 0.174 t / MWh = 13.26 t	200 MWh * (100%-74.81%) = 50.38 MWh 50.38 MWh * 0.174 t / MWh = 8.77 t
CO_2 emissions internally from electricity by the LEC	200 MWh * 61.91% = 123.82 MWh 123.82 MWh * 0.023 t / MWh = 2.85 t	200 MWh * 74.81% = 149.62 MWh 149.62 MWh * 0.023 t / MWh = 3.44 t
Total per year	16.1 t	12.2 t
Change		-3.9 tons (24% reduction)

2.1.5.2. Test Case 2 - Autarky increase

To increase the LEC's autarky, the Optimizer's loss function is adjusted to prioritize reducing electricity imports, thereby maximizing self-consumption and enhancing the site's autarky. This improvement is primarily achieved by adjusting the battery state-of-charge setpoint and optimizing heat pump control.

[6] "D9.1-Test Cases Assessment Framework and KPIs." Accessed: Jan. 14, 2025. [Online]. Available: https://genteproject.com/

The following figure (Figure 7) illustrates the LEC's feed-in point power: positive values indicate power drawn from the grid, while negative values represent power fed into the grid.

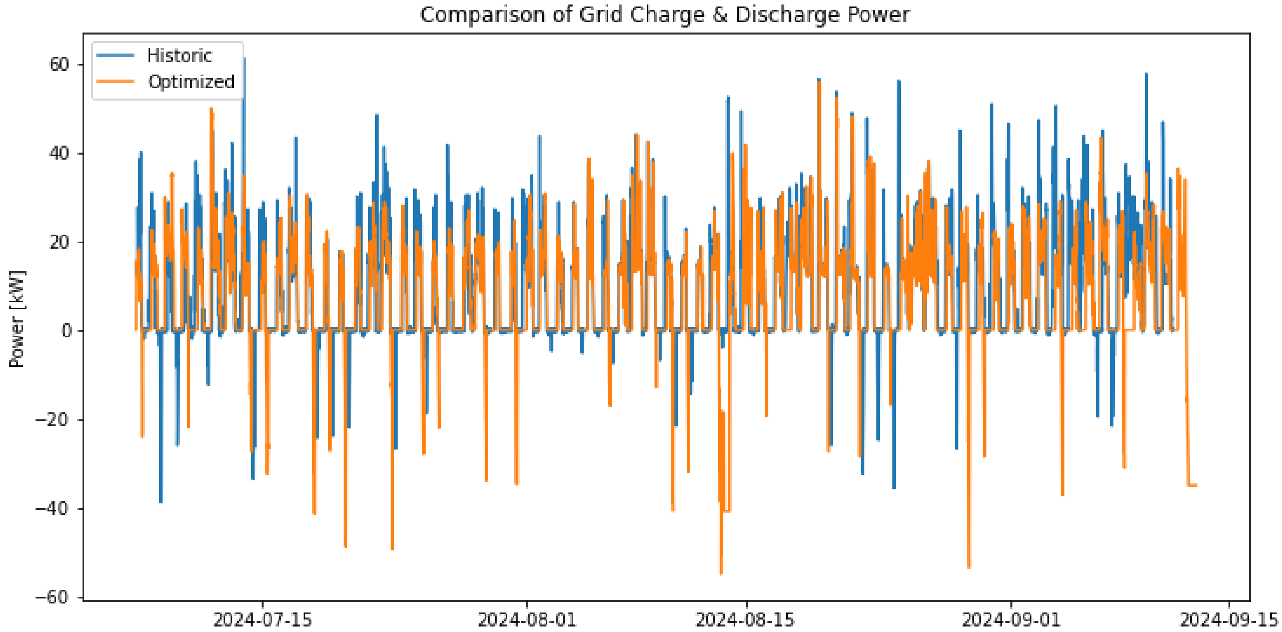

Figure 7 - Power at the feed-in point of the LEC

This optimization results in an increased autarky for the LEC meeting the target range defined in D9.1. Autarky was calculated over the period from July 7, 2024, to September 13, 2024, yielding the results shown in Table 5.

Table 5 - Energy communities autarky, with and without optimization

Autarky without optimization	61.91 %
Autarky with optimization	74.81 %
More directly consumed electricity from LEC with optimization	25.8 MWh per year, equals to 20.84%
Reduced amount of electricity from grid with optimization	25.8 MWh per year, equals to -33.87%

2.1.5.3. Test Case 3 - Peak load reduction

The third test case in Am Aawasser is related to the reduction of peak load from the grid. The graphs below illustrate the grid's charge and discharge power, household power consumption, battery charge and discharge rates, as well as weather-related data such as cloud cover and rainfall. Based on this data, the key calculations have been performed over the period from July 7, 2024, to September 13, 2024, yielding the results shown in Table 6.

Table 6 - Peak load reduction results, with optimization

Reduction in grid power	-1.88 kW
Reduction in grid power relative	-19.78 %
Export reduction	-0.73 kW
Export reduction relative	-131.12 %

Table 6 reveals that the Optimizer is expected to reduce power peaks (grid-supplied power) by approximately 20%. Particularly striking is the 131% reduction in energy exports, largely attributed to significantly improved forecasting for both PV generation and load. This enhanced forecasting enables a better battery charging strategy, with longer charging cycles and delayed full charging. As a result, the Optimizer helps to smooth out the power fed into the grid, especially from the PV installation. The power is illustrated in Figure 8 showing a sample day on 12th to 13th of August 2024, with optimized battery charging for the same time period shown in Figure 9.

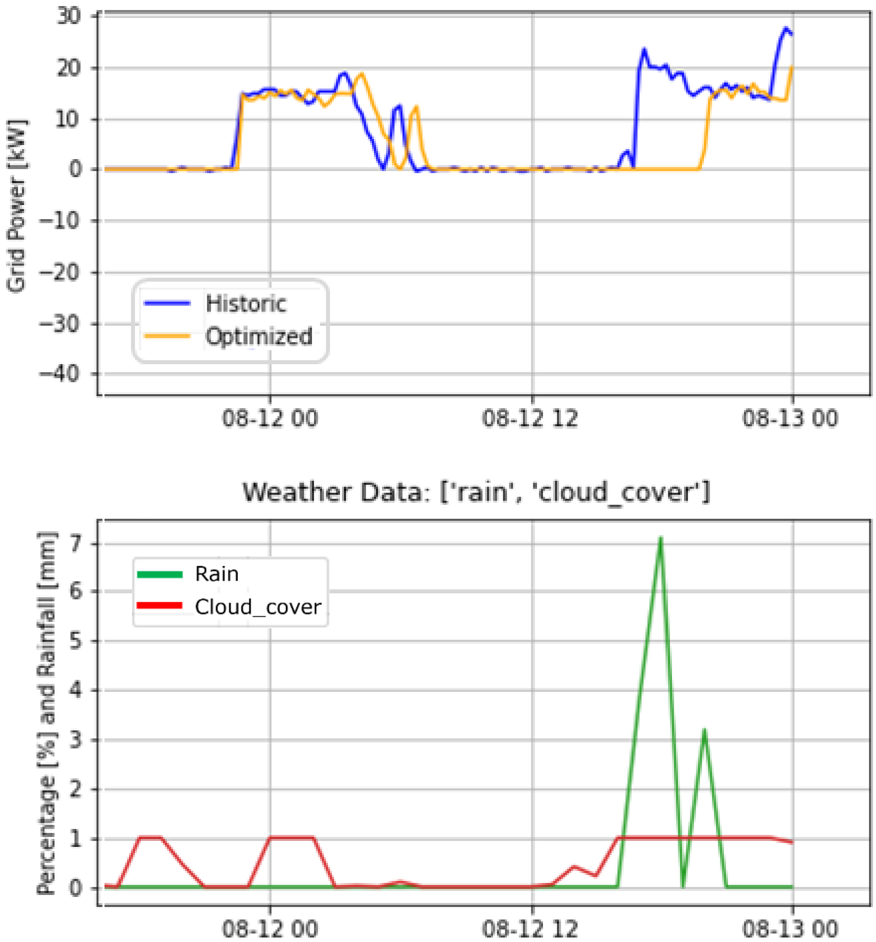

Figure 8 - Grid power cumulated with weather data, 12th to 13th August 2024

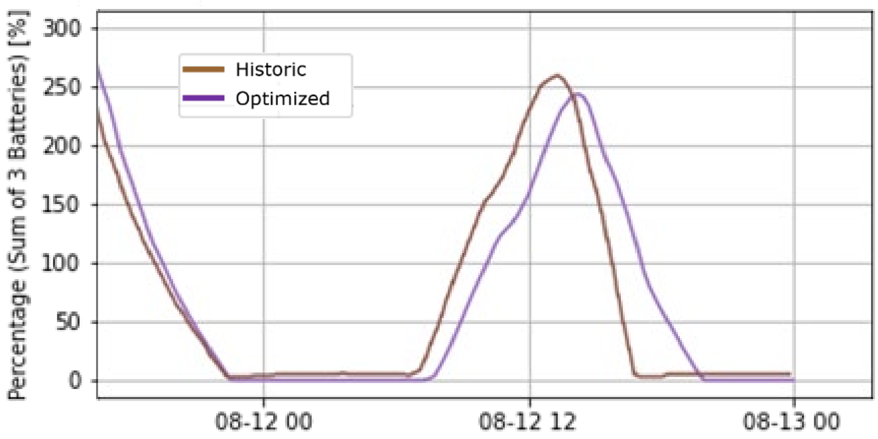

Figure 9 - Battery state of charge (SOC), 12th to 13th August 2024

As shown in Figure 8 and Figure 9, charging is delayed based on the weather forecast, resulting in increased battery capacity available for use in the second half of the day. If data is analysed during longer period, similar results can be derived from graph (see Figure 10 and Figure 11).

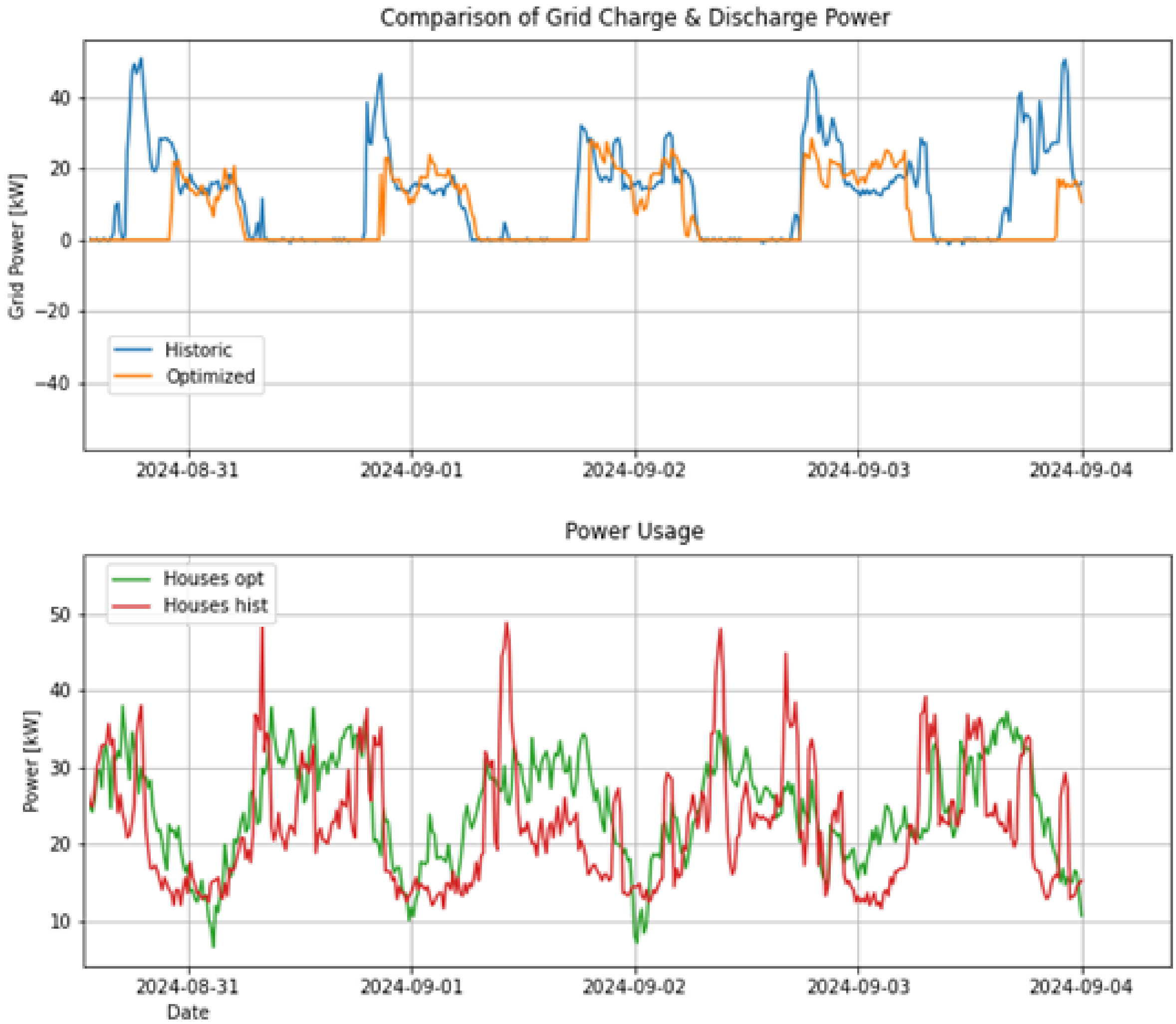

Figure 10 - Grid charge & discharge power and power usage, 31st August to 4th September 2024

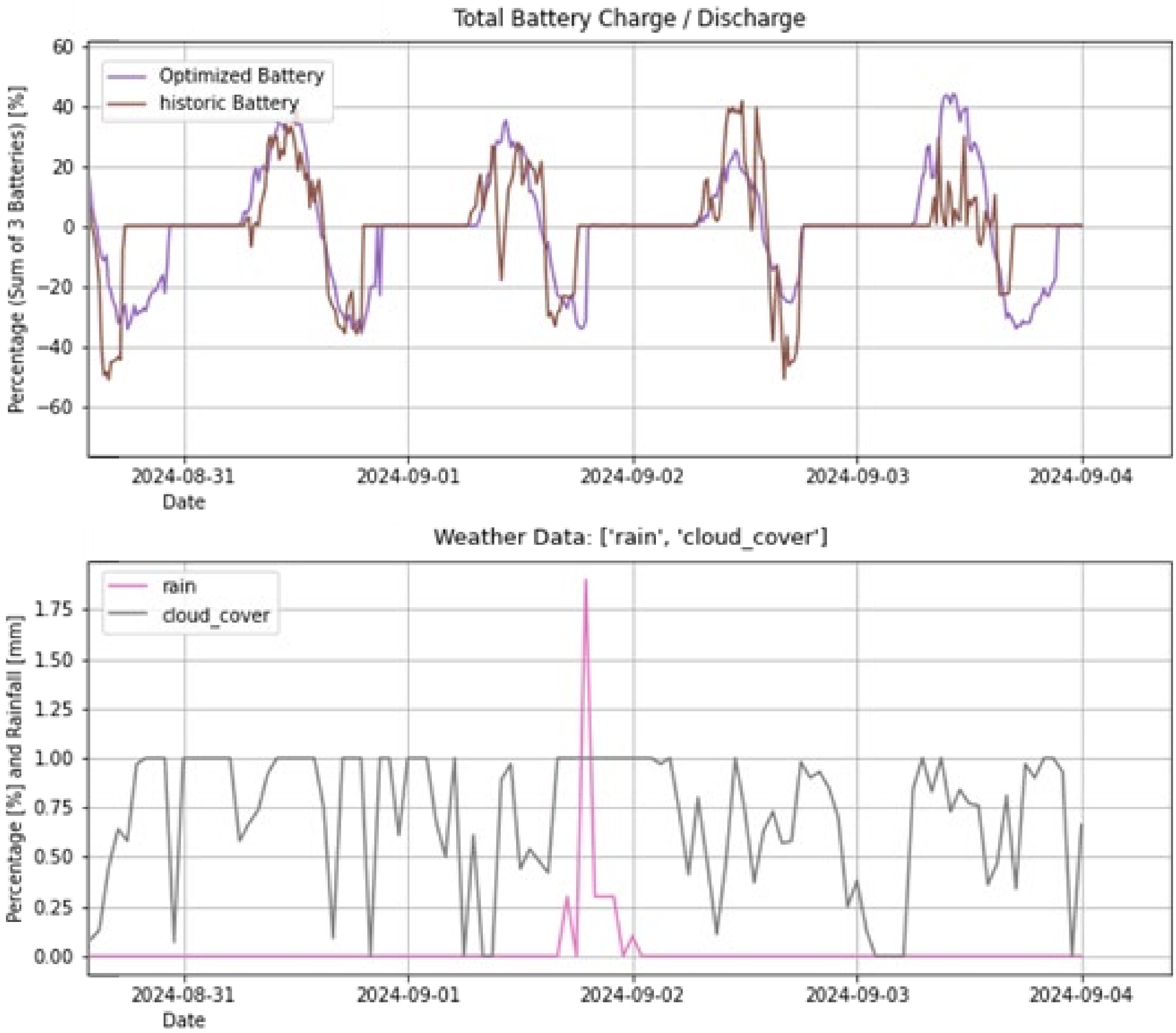

Figure 11 - Battery state of charge (SOC) cumulated with weather data, 31st August to 4th September 2024

2.2. HSB Living Lab – Sweden (Chalmers)

2.2.1. Overview

HSB Living Lab (HSBLL) [7] is a smart residential modular building consisting of 29 apartments for students, HSB members and visiting researchers. The apartment sizes range from 30 – 83 m^2. Several distributed energy resources (DER) and advanced metering and sensor systems (approximately 2000 sensors that collect various building data depicting the resident behaviour's impact on energy consumption) are deployed at the building.

The building contains: Photovoltaic (18kWp), two air-to-water heat pumps (2 x 9kW), three hot water storage multifunctional tanks (3 x 0.5 m^3), two EV charging (2 x 32A with 3-phase outlets), and a district heating network that provides approximately 80% of the total heat load of the building. The electricity consumption of the community is 83.5 MWh on average per year. As of 2023, the community was able to achieve energy autarky of 14.59% (up from 13.25% in 2022).

Currently, the HSBLL community energy optimization is through building energy management system (BEMS) provided by third party company – Jeff Electronics, hosted on a web-based SCADA system called Web Port. The platform provides close-to-real-time sensor measurements and heating systems controls at HSBLL, and the platform is connected to the cloud. Web Port uses an application programming interface (API) and Modbus to connect to other installations to read, write, and retrieve data including historical data generated by various sensors located onsite.

Figure 12 - HSB Living Lab, Chalmers, Sweden

[7] https://www.hsb.se/hsblivinglab/

2.2.2. Implementations

The originally planned IoT platform integration of all demonstration sites could not continue due to the exit of Reengen. However, energy optimizations at HSBLL testing site were conducted near real-time from on-premise system with provision of additional potentiality for cloud computing. The help of API technology made it possible to obtain real data readings from the testing site to ensure accurate input for the optimization algorithm. The control of energy units, such as the heat pump, district heating and thermal storage units, was seamlessly achieved using the setpoint control commands generated from the developed BEMS. The implementation approach integrated the following elements: servers, different python scripts in modules, third party APIs, database, DERs, etc. as shown in Figure 13.

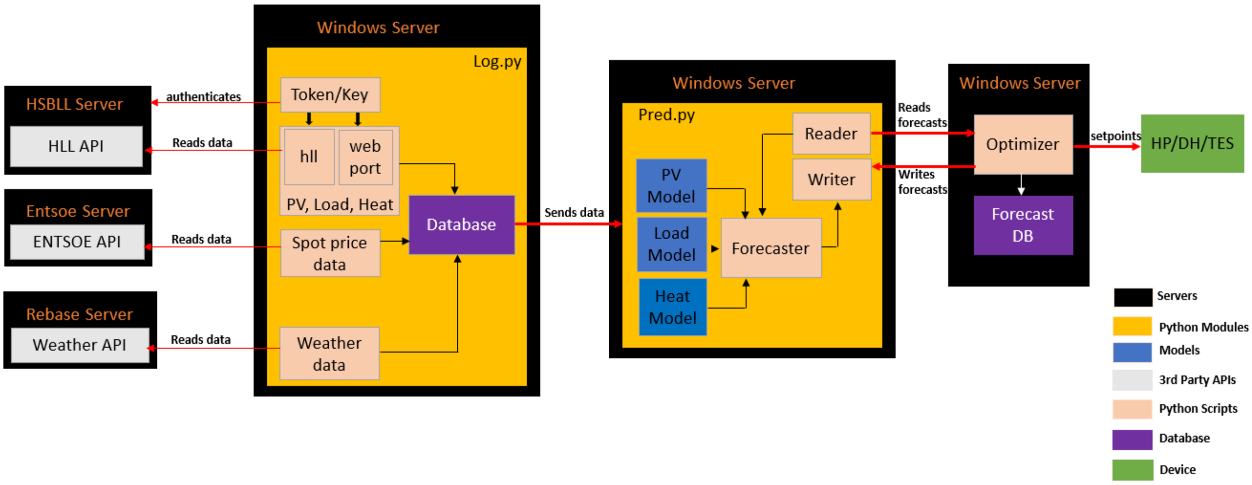

Figure 13 - Implementation of HSBLL energy optimization system

1. Data Log

This data log script that is situated in a Python module fetches all required data such as weather variables, spot price, electricity load, PV generation and heat load, as well as sensor data like *indoor_outlet_water_temp* from heat pumps through a tokenized API. Some of the data is acquired from HSBLL portal while others are from Web Port and stored in our on-premise database. The data log has the capacity to retrieve any size of data from the APIs and store it in the database without delay.

2. Forecaster

The Forecaster situated in the predict module leverages the pre-trained forecast models to predict a day-ahead PV generation output, electricity and heat loads of HSBLL on hourly timestamp. It can also read and write data to the optimizer. The forecaster is built in such a way that its output is an input to the optimizer. The optimized values for variables such as PV output, electricity consumption and heat load are used for the next cycle forecast.

3. Optimizer

The Optimizer solves the predefined optimization problem using some input variables including PV, electricity and heat loads forecasts, as well as a heat pump's coefficient of performance (COP), spot price, temperature, etc. It calculates the appropriate set points that could provide flexibility in the optimal dispatch of heat pumps, district heating system and thermal energy storage in the testing site. The calculated set points are either sent directly using Modbus Communication Protocol to the devices (heat pumps, district heating system) or via Jeff Electronics platform Web Port. The objective function defines the target of the optimization under different test cases including CO_2 reduction (test case 1), energy cost reduction (test case 2), or energy autarky increase (test case 3).

2.2.3. Functional Performance Tests

As mentioned earlier, functional performance was the first test carried out to ensure that all algorithms operate as expected before proceeding with the test scenarios. The test is basically on solutions developed in HSBLL site without considering the IoT Gateway since Reengen is no longer in the project. The test was conducted to check the correctness of the installations and operations of the solution developed to ensure it can be integrated into the GENTE toolkit. The communication and execution of the control commands between BEMS and heating sources like heat pumps and district heating systems as well as data collection from them were tested. Table 7 is the result.

Table 7 - Functional performance test result

Functional performance test:					
Communication response	Requirements	Expectations	Evaluation: KPIs	Measured variables	Results
- Control command execution	Modbus, API token/key, database	Send/recieve control commands	KPI_BEMS_3: Delay/latency in data collection/delivery	Setpoints	<2s
- Data collection/storage		Fetch and store data		Weather/historical	

2.2.3.1. Data Collection

The objective of this test is to demonstrate that all required data — including meteorological, electric and heat load, as well as PV generation data — can be successfully read through the API and be aggregated. The functional test was conducted by running the data log script to collate a 1-year PV, electricity and heat load data as shown in Figure 14, Figure 15, and Figure 16, and subsequently reviewing the collected data. During this timeframe, both continuous and periodic data entries were successfully recorded in the database. This confirms that the data acquisition system is functioning as intended.

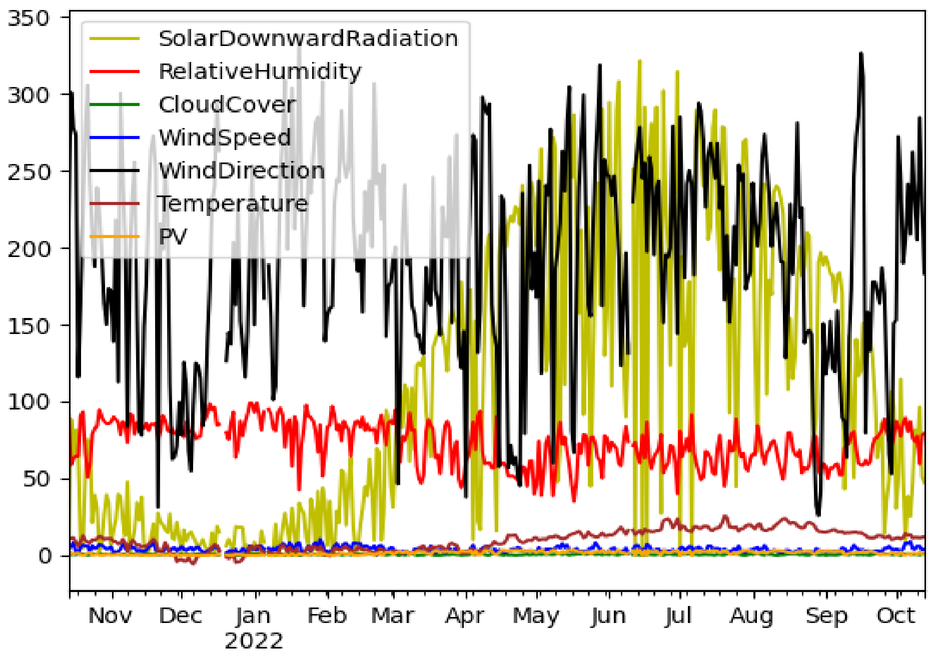

Figure 14 - Distribution of the input variables over a period of 1 year

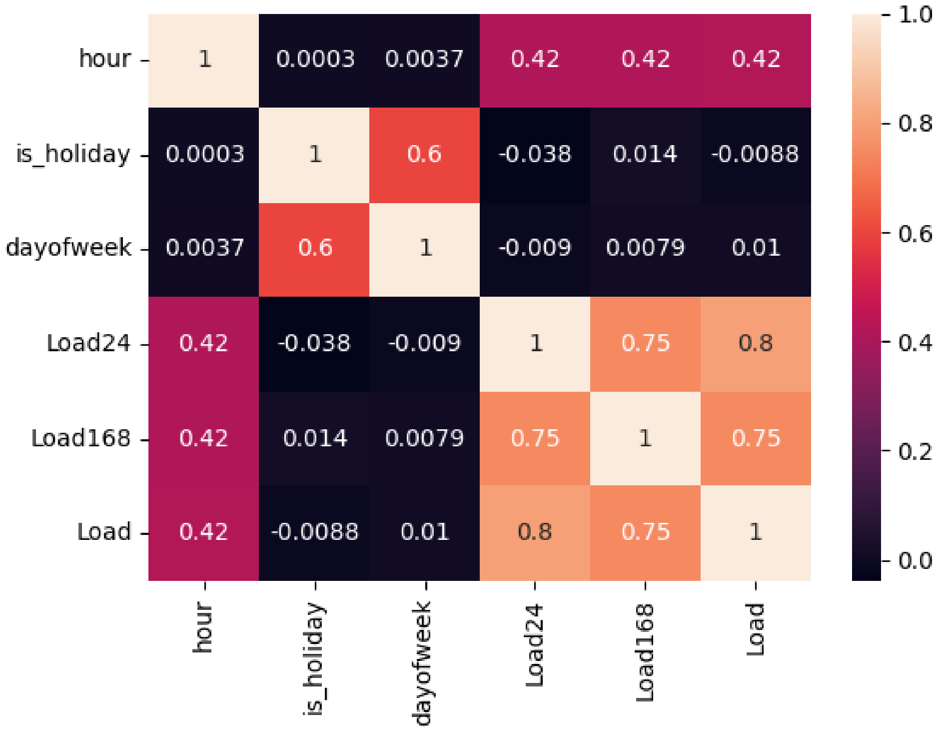

Figure 15 - Heat map of correlation test on load demand

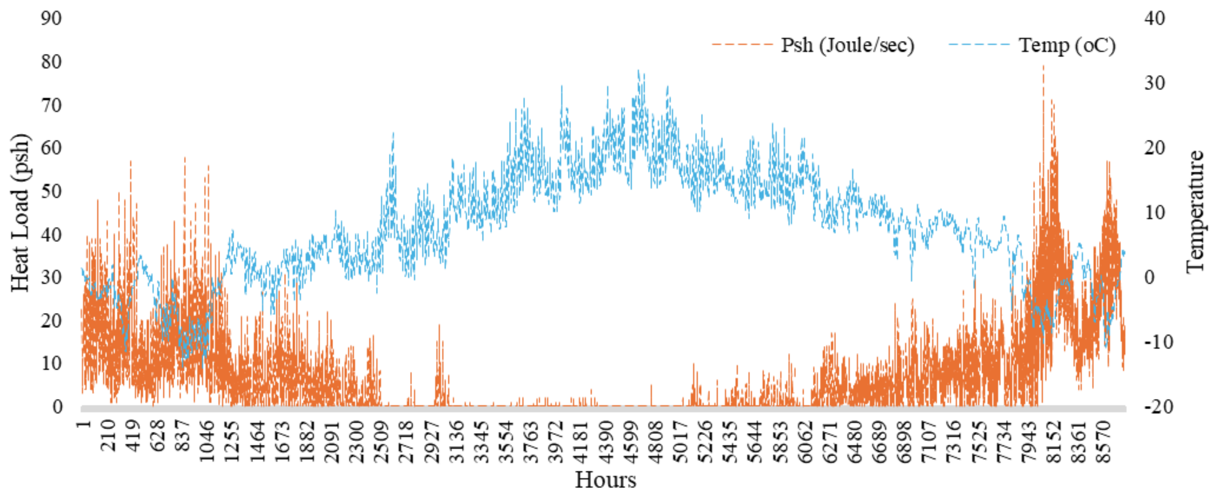

Figure 16 - Heat load and temperature variations in HSBLL over the period of 1 year

2.2.4. Forecast Evaluation

This aspect of validation for the technical developments in GENTE verified the forecasting algorithms developed and tested in the HSB Living Lab. It evaluated and assessed the accuracy and validity of the prediction algorithms for the PV generation, electricity consumption and heat demand forecasts. One-year historical data was used in training forecast algorithms and hourly predictions with 10 minute resolution were tested on the PV generation, building loads and heat demands at HSB Living Lab. The test results were computed by quantitative method and compared between two neural networks algorithms: long short-term memory (LSTM) and gated recurrent unit (GRU).

2.2.4.1. PV Model

A direct approach where PV output power is forecasted directly using historical data and its associated meteorological data was leveraged. The developed model achieved a root mean square error (RSME) of 1.0757 kWh (as shown in Table 8) in a day-ahead forecast in a building with maximum generation of 7.412kWh. The model was validated with a 7 consecutive day, i.e. 168 hours, test dataset. The plots of predicted versus actual distribution are shown in Figure 17.

Table 8 - Result of PV forecast evaluation across different metrics

Models and their performances on PV generation data		
KPI	LSTM	GRU
KPI_FO_1: Forecasting error	1.0757 kWh	1.1560 kWh

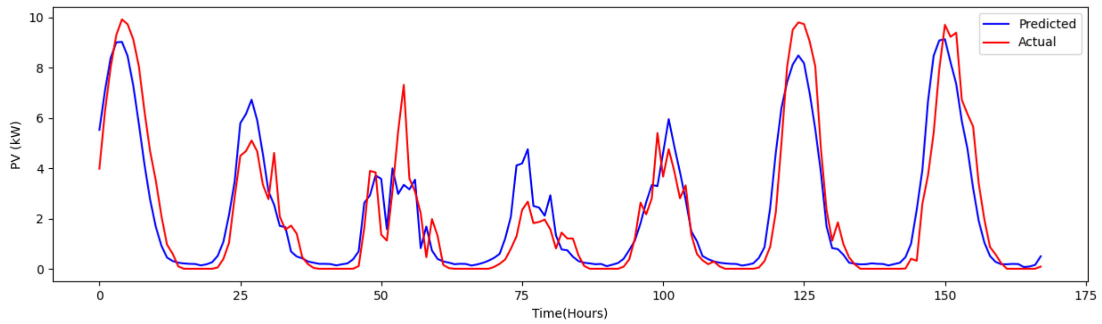

Figure 17 - Model prediction error on PV forecast

2.2.4.2. Electricity Consumption Model

Historical load data was used in modelling the consumption profile of HSBLL. The correlation test carried out helped in determining the most correlated variables between the targeted variable (electricity load) and some variables including calendar and weather variables that influence electricity consumption. As shown in Table 9, RSME of 1.1960 kWh was achieved in an hourly forecast for a 24 hour-ahead period in a building with hourly max consumption of 10.53 kW. The predicted plot versus the actual electric demand is shown in Figure 18.

Table 9 - Result of electricity load forecast evaluation across different metrics

Models and their performances on electricity load data		
KPI	LSTM	GRU
KPI_FO_1: Forecasting error	1.2036 kWh	1.1960 kWh

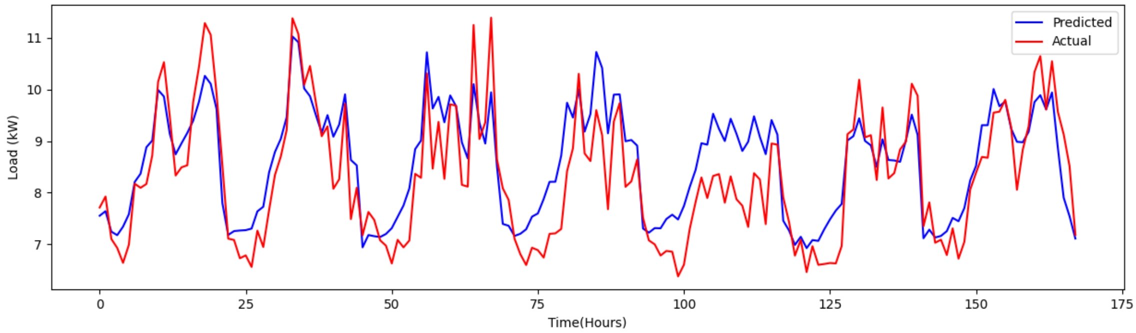

Figure 18 - Model prediction error on electricity load

2.2.4.3. Heat Demand Model

Historical heat data emanating from hot water, floor, and space heating provided by both district heating system and heat pumps was used in training the thermal demand forecast model. External and internal factors affecting the heat consumption of the buildings were also considered. From the heat transfer analysis carried out, it was discovered that factors such as mass of the building, its specific heat capacity considering the heating systems, and variation in temperature are very influential factors. The best model (as seen in Table 10) achieved RSME of 1.5468 kWh in a day-ahead forecast in a building with max daily heat load of 12.184 kWh. The predicted plot versus the actual heat load is shown in Figure 19.

Table 10 - Result of heat load forecast evaluation across different metrics

Models and their performances on heat load data		
KPI	LSTM	GRU
KPI_FO_1: Forecasting error	1.9734 kWh	1.5468 kWh

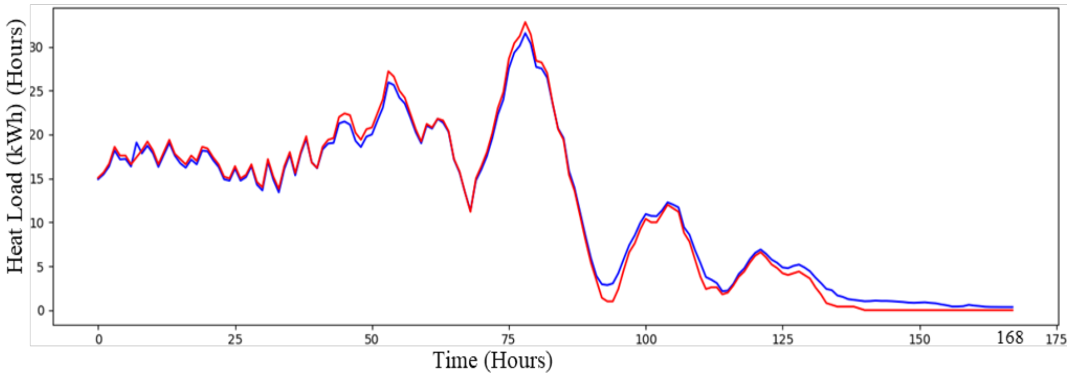

Figure 19 - Model prediction error on heat load

2.2.5. Test Scenarios

Three test cases such as energy cost reduction, CO_2 minimization, and autarky increase have been defined. The test cases are performed with different levels of complexity ranging from optimization between district heating and heat pump operation, to utilization of thermal energy and battery storage for increased flexibility.

2.2.5.1. Test Case 1 - CO_2 emissions reduction

This test is performed with an objective function defined to utilize the optimal dispatch between the heat pump and the district heating in minimizing the CO_2 emissions. Though the average CO_2 emission factor for electricity consumption from the grid and district heating in Sweden is low, the developed optimization algorithms further reduced it. The building energy optimization for CO_2 reduction was run for a period of 7 days (168 hours). A baseline scenario was generated by operating just the heat pump and the district heating without optimization.

2.2.5.2. Test Case 2 - Reduction in energy cost

This test case validates the reduction of energy cost through building optimization and more efficient operation of the heat pump. The optimization algorithm was run during the winter when heating and electricity consumption is highest.

2.2.5.3. Test Case 3 - Autarky increase

This test with an objective function defined to maximize the utilization of power from PV generation to cover electrical demand and reduce import from the grid. The optimization algorithm developed was run across different seasons of the year to ascertain the extent of self-consumption achievable at HSBLL, and how effective autarky increase could be in grid flexibility provisioning in the building.

2.2.6. Requirements

There are several requirements to run the different scenarios demonstrated at HSBLL. Data, communication platform, and other resources including DERs are key requirements.

2.2.6.1. Data

The data utilized includes spot market price at 5 minute resolution; network tariffs including fixed costs (e.g. connection fees and tax) and variable costs (e.g. charges per kWh consumed) that apply during different periods (e.g, peak versus. off-peak hours); heat demand and electricity demand historical profiles at 5 minute resolution; heat pump COP; carbon intensity data; and the cost per unit of carbon emissions in Sweden.

2.2.6.2. Communication platform

API and Modbus Transmission Control Protocol/Internet Protocol (TCP/IP) were utilized to read and write real-time data, including optimization-generated setpoints, to over 2,000 sensors at the testing site via a web portal. In Modbus TCP/IP, messages are transmitted with a TCP/IP wrapper and sent over a network. Access to external APIs is secured using authentication mechanisms such as tokens or keys.

2.2.6.3. Other resources including DERs

To perform these tests, the following energy assets were required:

- Heat pump
- Heat storage
- Connection to the district heating
- Battery storage
- EV station
- PV system
- Smart meters

2.2.7. Evaluation

Here the test cases defined in D9.1 for HSBLL are validated using the designated KPIs.

2.2.7.1. Test Case 1 - CO_2 emissions reduction

According to reports from the Swedish Energy Agency and Göteborg Energi, the average CO_2 emission factor for grid electricity consumption in Sweden is approximately 0.013 kg CO_2/kWh, while the emission factor for district heating ranges from 0.05 to 0.10 kg CO_2/kWh. This is among the lowest in Europe. As a result, the CO_2 penalty or cost - representing the social cost of carbon (i.e. the cost of damages per ton of CO_2 emissions) - is calculated and used as a benchmark for CO_2 emissions reduction assessment.

The CO_2 cost of electricity and district heating under the energy optimization solution developed in GENTE was compared to the baseline scenario, and the percentage reduction was recorded. Additionally, the reduction in final energy consumption at the building was analyzed against the baseline. Demonstrations conducted over a 168-hour period confirmed CO_2 reductions, with comparative results presented in Table 11.

Table 11 - Result of CO_2 reduction test case

KPI	Name	Baseline scenario	Optimized scenario
KPI_ENV_1	CO_2 emissions during operation	409.36 kg CO_2/kWh	383.46 kg CO_2/kWh
KPI_ENV_2	Reduction of CO_2 emissions	-	25.90 kg CO_2

The LEC optimization tool developed in GENTE for the HSBLL site can achieve a 6.3% reduction in CO_2 emissions compared to a baseline controller. The impact of CO_2 reduction using this tool would be even more significant in countries like Poland, where the emission factor for grid electricity is 0.7 kg CO_2/kWh, and for heating, it ranges between 0.1 - 0.25 kg CO_2 per kWh.

2.2.7.2. Test Case 2 - Reduction in energy cost

Tests were conducted over a 168-hour period (1 week) to assess the reduction in energy costs and the efficiency of heat pump operation using the developed building optimization algorithm, considering spot market prices and network tariffs for both electricity and the district heating system. Results are presented in Table 12.

Table 12 - Result of energy cost reduction test case

KPI	Name	Baseline scenario	Optimized scenario
KPI_EC_1	Energy cost savings	€134.78 / week	€112.22 / week
	Reduction of energy costs	-	€22.56 / week @ SEK_to_EUR = 0.092

The LEC optimization tool developed in GENTE for HSBLL site can reduce energy cost by 16.7% compared to a baseline controller. It was also observed that the optimization tool clearly flattens the electric load, reducing peaks and dips. This means that the problem of peak demand can be addressed using the flexibility provided by both heating sources, thermal and battery storage.

2.2.7.3. Test Case 3 - Autarky increase

For the actual demonstration at HSBLL, increasing autarky is not feasible because the total PV installation (and consequently its production) will always be lower than the building's electricity demand during PV generation periods. As a result, all locally produced PV energy will be fully self-consumed, achieving 100% autarky, which cannot be further improved.

However, to illustrate the role of the BEMS in enhancing autarky, we will instead present results from simulation studies. These simulations were conducted using the same objective function defined for Test Case 3 while utilizing historical load demand data with scaled-up PV production. Specifically, PV production was increased by 6 kWh during periods of PV generation based on one day of historical data for four different seasons of the year. Simulations were run over a 168-hour (one week) period. The results are presented in Table 13.

Table 13 - Result of autarky simulation

KPI	Name	Baseline scenario	Optimized scenario
KPI_EN_2	Final energy consumption in the LEC	2793.65 kWh / week	2325.71 kWh / week
KPI_EN_4	On-site renewable energy consumption in the LEC		
	Summer	66.88 kWh / week	174.09 kWh / week
	Winter	2.12 kWh / week	44.26 kWh / week
	Spring	75.26 kWh / week	146.3 kWh / week
	Fall	8.61 kWh / week	80.57 kWh / week
KPI_EN_5	LEC self-consumption quota	100 %	100 %
	Autarky	5.47 %	19.14 %

These results show that using the LEC optimization tool developed in GENTE autarky can be increased significantly in the HSBLL across different seasons, especially during winter, if PV production is improved. Autarky increased from 5.47% with the baseline controller to 19.14% after optimization based on the simulated result. The simulations showed a change in load profile when PV production exceeded demand, with surplus energy utilized for charging EVs, batteries, and thermal storage tanks instead of being exported to the grid.

3. Conclusion

Sites in both Switzerland and Sweden were able to demonstrate improvement in their assigned test cases.

At Am Aawasser in Switzerland, CO_2 emission reduction of 24% was shown to be achievable with the developed Optimizer, alongside an autarky increase of 12.9%. The relative reduction in grid power was shown to be 19.78%.

For HSBLL in Sweden, CO_2 emission reduction of 6.3% was achieved by the optimization tool compared to the baseline controller. The optimization tool reduced energy costs for the LEC by 16.7%. An increase in autarky of 13.67% was shown to be possible in simulations with an increased PV capacity.

Deliverable 9.3 will assess the test case results against the defined KPIs from Deliverable 9.1 and identify best practices to aid in replicability.

FUNDING

This project has received funding in the framework of the joint programming initiative ERA-Net Smart Energy Systems' focus initiative Digital Transformation for the Energy Transition, with support from the European Union's Horizon 2020 research and innovation programme under grant agreement No 883973.