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SolHOOD

Solar energy neighborhoods – Optimal design and operation of heat, cold and electricity supply on the neighbourhood scale

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Abstract

In this project, planning methods and control strategies for solar energy neighborhoods are being developed. The aim is to make optimal use of solar energy, storage technologies as well as thermal and electrical connection of buildings. One focus is on the heat supply in the winter and in this context on alternatives to conventional air-to-water and ground source heat pump systems. The consistent use of synergies and sector coupling at the neighborhood level will allow to reduce the CO_2-intensive winter electricity consumption and provide a high degree of flexibility for interaction with the electricity grid.
The technical approach consists of the development and application of a simulation and system optimization framework, with which a) the optimal system variants with respect to different target functions (costs, emissions) can be determined in the planning phase and b) efficient model-predictive control strategies can be identified for the neighborhood level.

Contents

List of Acronyms

AEM Advanced Energy Management

ASHP Air-Source Heat Pump

CF Carbon Footprint

CHP Combined Heat and Power

DHW Domestic Hot Water

GHG Greenhouse Gas

GSHP Ground-Source Heat Pump

HP Heat Pump

KPI Key Performance Indicator

MILP Mixed-Integer Linear Programming

MPC Model Predictive Control

oemof Open Energy Modelling Framework

PVT PhotoVoltaic-Thermal Solar Collector

RC Resistance - Capacitance

RPC Remote Procedure Call

SH Space Heating

1 Introduction

1.1 Current situation and motivation of the project

About 100 TWh, and thus 45 % of Switzerland's final energy consumption, are attributable to the building stock. Around 75 % of this energy serves heating purposes. From this, three quarters are currently provided by fossil fuels. With the goal of decarbonization, the Swiss Energy Strategy envisages a strong electrification of the heating sector. Together with the likewise planned electrification of mobility, this will greatly increase the electricity demand, especially in winter, when the CO_2 emissions of the grid electricity are particularly high. It is therefore essential to limit the increase of winter electricity and energy demand of the building sector to a minimum. Besides other measures, this requires the implementation of maximally efficient heat supply systems.

Newly installed heating systems mostly rely on heat pumps using either ambient air or ground as a renewable heat source. Both of these variants have their drawbacks. Air source heat pumps have low efficiencies in winter due to the low ambient temperatures. Further, they can cause noise disturbances. Geothermal heat pumps have good efficiencies also in winter, but they have higher costs, and the installation of ground sources is often restricted by water protection laws and can be difficult to fit into densely built-up areas. This calls for improvements and alternatives to these systems.

Compared to the case of isolated individual buildings, the search for alternative solutions is more challenging for densely built-up neighborhoods, e.g. due to small available areas for solar installations. On the other hand, the neighborhood scale offers opportunities to use synergies, e.g. via shared energy transformation and storage units.

1.2 Purpose of the project

Solar energy technologies (thermal, photovoltaic, and PVT) are expected to play an important role in the context of efficient heat supply solutions at the neighborhood scale. Solar heat can provide directly usable heat or be the source for a heat pump, e.g. in combination with low-temperature (ice) storage units. Due to its ability to provide both heating and electricity, PVT has potential synergies with sustainable combined heat and power systems (with renewable fuels) that allow for substituting grid electricity by own-produced low-carbon electricity in winter. Based on such synergies in connection with centralized or distributed storage systems, high-performance solar neighborhoods can be designed. An important prerequisite for this is the availability of suitable modeling and planning tools.

A review on system modeling tools showed a lack of usable tools for the neighborhood scale. Those that exist are difficult to use and further develop, because they are either developed within companies and hence disconnected from the open source community, or based on commercial software. However, some interesting collaborative platforms for the development of multi-energy systems exist, such as the Python-based "oemof". SPF and IGT are already working on the development of an energy system optimization framework on the basis of "oemof" within the project OptimEase, where the goal is to optimize the energy supply of building clusters connected electrically. The approach of SolHOOD is to continue this development and to expand the framework with additional features and tools necessary for answering the specific questions related to high solar fraction neighborhoods including thermal and electrical networks.

The consideration of energy systems on a neighborhood scale also presents opportunities as regards their operation strategies. With the help of smart control strategies, neighborhoods can reach a high flexibility to react to price and carbon footprint (CF) fluctuations. Model predictive control (MPC) algorithms are a promising method, which will be applied and further developed in the SolHOOD project. The tools for implementing such advanced energy management (AEM) strategies will be closely related to the tools developed for the system design optimization.

1.3 Objectives

The overarching goals of the SolHOOD project are to develop:

Goal 1 Smart planning methods to achieve high-performance energy supply systems (heat and electricity) for neighborhoods, making optimal use of solar energy resources and using sector coupling synergies.

Goal 2 Alternatives to standard air and ground source heat pump systems, with low grid electricity demand in winter at the neighborhood scale.

Goal 3 Innovative advanced energy management (AEM) system based on model predictive control (MPC) to optimize the operation of complex energy systems in neighborhoods, using forecasts of the electrical and thermal demands, weather data, dynamic electricity tariffs and environmental impacts of grid electricity.

The project is structured into the following five work packages with related objectives:

WP 1: Boundary conditions and KPIs

- Identification and definition of neighborhood typologies representative for the Swiss market
- Identification of relevant boundary conditions that favor the use of solar technologies
- Definition of KPIs for the evaluation of system designs and operation strategies

WP 2: Development of modeling and optimization environment

- Development of new component models for use in optimization routine
- Parametrization of the thermal characteristics of buildings
- Integration of tools for the efficient calculation of the solar resource
- Setup of multi-objective optimization routine

WP 3: System design and optimization

- Application of the multi-objective optimization framework to identify promising technology combinations
- In depth-analysis of found optimal technology combinations and comparison to reference cases based on KPIs
- Asses the robustness of the method by a global sensitivity analysis on relevant parameters

WP 4: Advanced energy management strategies (AEM)

- Development and evaluation of model predictive control strategies for key technology combinations identified in WP 3
- Evaluation of the potential of MPC at the neighborhood level

WP 5: Case studies

- Test and verify developed methods and tools on real case studies
- Identify optimization potentials for the present and future implementations

2 Procedures and methodology

2.1 Boundary conditions and evaluation methods (WP1)

2.1.1 Typical hourly profiles of carbon footprint of the grid electricity mix

The Swiss electricity mix for at hourly time step is generated with the electricity system modeling tool EcoDynElec[1] that was built in the EcoDynBat project. It is based on ENTSO-E data for modeling the exchanges and productions on the European grid at the hourly and sub-hourly timescale. Swiss consumption mix modeling is refined with additional data from Swissgrid (imports and exports) and from the Swiss Federal Office of Energy (losses, correction to missing productions in ENTSO-E data). The GHG emission profile of the low voltage electricity Swiss consumption mix is shown for 2020 and 2021 in Figure 1. This output is used to assess the GHG emissions of building electricity consumption.

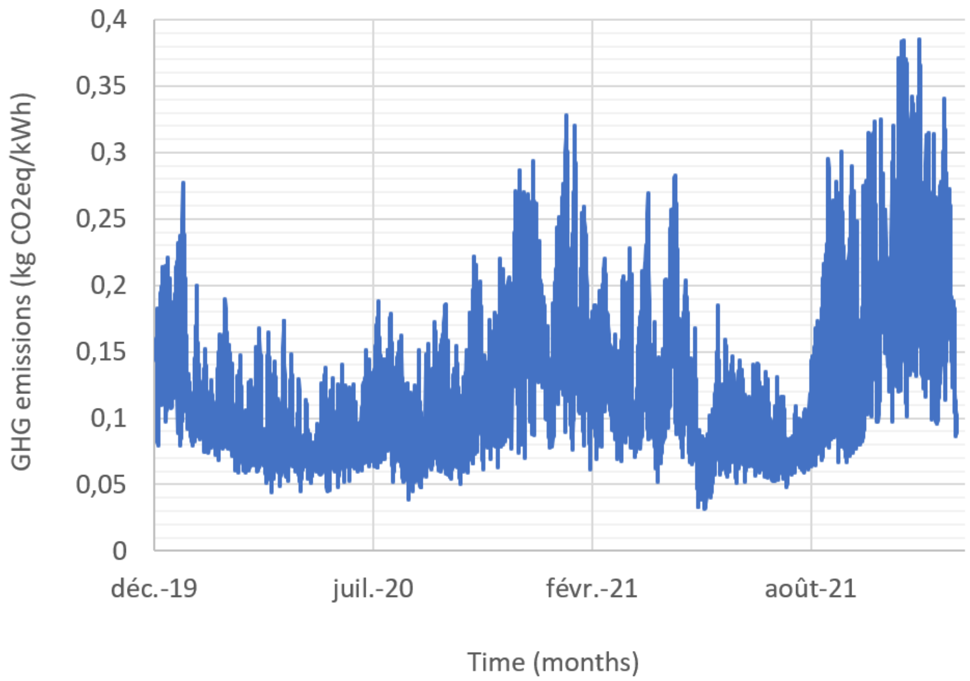

Figure 1: Hourly step GHG emissions of the Swiss electricity consumption throughout 2020 and 2021.

2.2 Development of modeling and optimization environment (WP2)

2.2.1 Modelling and optimization framework

For energy system modeling and optimization, we have developed the optihood framework, which is based on the open-source python package oemof (**o**pen **e**nergy **mo**delling **f**ramework) presented by Hilpert et al. (2018). In oemof, one can define energy systems as combinations of linear component models (sources, transformers, sinks, and buses) as well as define optimization target functions. Oemof then makes use of pyomo, an open-source modeling language for optimization problems, in order to formulate a MILP (mixed-linear integer programming) solution. This optimization problem, in turn, can be solved with different solvers.

[1] `https://github.com/LESBAT-HEIG-VD/EcoDynElec`

Currently, we use the commercial solver gurobi, which offers a free academic license. Other solvers like cbc, glpk, etc. which can be used together with pyomo, may be used. In an optimization problem, one is interested in finding a solution within a defined region of the parameter space (defined by a set of constraints) that minimizes or maximizes a target function, e.g. costs, environmental impact or energetic efficiency. The optihood framework extends oemof by defining energy systems for groups of buildings, where each building can then have a set of components. Therefore, the basic construct of oemof is modified in a sense that the components (sources, transformers, buses and sinks) are grouped by buildings and the results (time series of energy production/consumption, costs, emissions, etc.) can be obtained per building. Moreover, optihood allows a simplified definition of the optimization scenario/problem using either a configuration (or config) file or an Excel file. The optihood framework is an open source software published in GitHub[2] and its development has been shared between this project and the SFOE-sponsored project OptimEase (SI/502189-01).

2.2.2 Formulation of an optimization problem

The first step when modelings an energy system is to define the scenario (available components, inputs, parameters, etc.) for the optimization problem. This can be done using either a configuration (or config) file or an Excel file. All components that the optimizer shall consider, as well as parameter values for their efficiencies, connections between the components and the building to which they belong, have to be defined in the config/Excel file. Further, the input config/Excel file is also used to define basic constraints e.g. the minimum and the maximum allowed capacities of a heat pump (HP). An example of the input Excel file for a configuration with four buildings and with allowed components CHP (combined heat and power), HP and gas boiler, is shown in Figure 2. For each component, a number of properties is defined, such as its connections to buses, efficiencies, capacity range (if the capacity is an optimization variable), cost, etc. Energy transformers, buses, and storages are defined in a similar manner on the other Excel sheets. The config file was introduced to make the scenario definition more intuitive and less prone to errors. The config file, therefore, can be used as an alternative way of formulating an optimization problem and will be described further in Section 3.2.5.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	label	building	active	from	to	efficiency	capacity_DHW	capacity_SH	capacity_el	capacity_min	lifetime	maintenance	installation	planification	invest_base	invest_cap	heat_in
2	CHP	1	1	naturalGasBus	electricityProdBus,shSourceBus,dhwStorageBus	0.25,0.6,0.6	100	100	65	5	20	0.05	0.15	0.05	20505	834.58	0.107
3	HP	1	1	electricityInBus	shSourceBus,dhwStorageBus	3.5	150	150		5	20	0.05	0.15	0.05	10786	869.85	0
4	GasBoiler	1	1	naturalGasBus	shSourceBus	0.9		100		5	40	0	0.15	0.05	4288.4	75.98	0
5	CHP	2	1	naturalGasBus	electricityProdBus,shSourceBus,dhwStorageBus	0.25,0.6,0.6	100	100	65	5	20	0.05	0.15	0.05	20505	834.58	0.107
6	HP	2	1	electricityInBus	shSourceBus,dhwStorageBus	3.5	150	150		5	20	0.05	0.15	0.05	10786	869.85	0
7	GasBoiler	2	1	naturalGasBus	shSourceBus	0.9		100		5	40	0	0.15	0.05	4288.4	75.98	0
8	CHP	3	1	naturalGasBus	electricityProdBus,shSourceBus,dhwStorageBus	0.25,0.6,0.6	100	100	65	5	20	0.05	0.15	0.05	20505	834.58	0.107
9	HP	3	1	electricityInBus	shSourceBus,dhwStorageBus	3.5	150	150		5	20	0.05	0.15	0.05	10786	869.85	0
10	GasBoiler	3	1	naturalGasBus	shSourceBus	0.9		100		5	40	0	0.15	0.05	4288.4	75.98	0
11	CHP	4	1	naturalGasBus	electricityProdBus,shSourceBus,dhwStorageBus	0.25,0.6,0.6	100	100	65	5	20	0.05	0.15	0.05	20505	834.58	0.107
12	HP	4	1	electricityInBus	shSourceBus,dhwStorageBus	3.5	150	150		5	20	0.05	0.15	0.05	10786	869.85	0
13	GasBoiler	4	1	naturalGasBus	shSourceBus	0.9		100		5	40	0	0.15	0.05	4288.4	75.98	0
14																	

Figure 2: Example of an Input table for transformers of the type HP, CHP and gas boiler for the case of an energy system for four buildings.

2.2.3 Solar radiation processing

Task 2.3 on radiation processing was almost completed in 2022 with the "weather class" able to compute radiation on tilted surfaces and take into account a horizon mask. In 2023, a new tool was created to help compute how many solar panels can fit on a rectangular roof, depending on its dimensions and orientation. This tool, implemented in a Python class called "calepinage," lets you input details about the roof and the reference solar panel to find out the maximum number that can be installed, whether facing south or parallel to the arbitrarily oriented building's main axis. The "calepinage" class allows considering different aspects like the location, the size of the roof and its orientation in order to optimize the distance between adjacent collector strings to lower reciprocal shadowing and adjust the collector placement to adapt correctly to the available roof space. By using both the "calepinage" and the "weather" class, one can then calculate how much useful solar energy can be collected by the solar panels in a given localized roof.

[2] https://github.com/SPF-OST/optihood

2.2.4 Optimization

The optimization procedure uses a predefined, not necessarily constant, time resolution, which we chose to be one hour. Input data like the climate as well as the energy demand profiles for domestic hot water, space heating and electricity have to be provided in this time resolution. The demand profiles for space heating could be replaced with a linear RC (Resistance - Capacitance) building model implemented within the framework. The optimization then tries to match the demands in each hour. If it fails to do so, the problem is declared as infeasible and an error message is displayed.

Optihood offers two optimization modes. In the *dispatch mode*, the capacities of the components are fixed, and the optimizer tries to find the optimal scheduling of their operation, which minimizes the target function, e.g. costs. In the *investment mode*, the optimizer, in addition to optimizing operation, finds the capacities of the components that minimize the target function. This mode is suitable for determining the optimal choice between alternative technologies while sizing the selected components.

It is further possible to run a multi-objective optimization, i.e. where one tries to minimize two or more target functions at once, and to find the corresponding Pareto front (see result example in Figure 3), with the help of the epsilon constraint method. If, for instance, the two target functions are costs and CO_2 emissions, the procedure is as follows. First, the optimizer executes separately a cost optimization and a CO_2 emission optimization. These two results provide the end points of the Pareto front, the case with minimum cost and the one with minimum carbon footprint. The resulting domain is then resolved successively by a number of cost optimizations while constraining the CO_2 emissions to different values between the values at the end points.

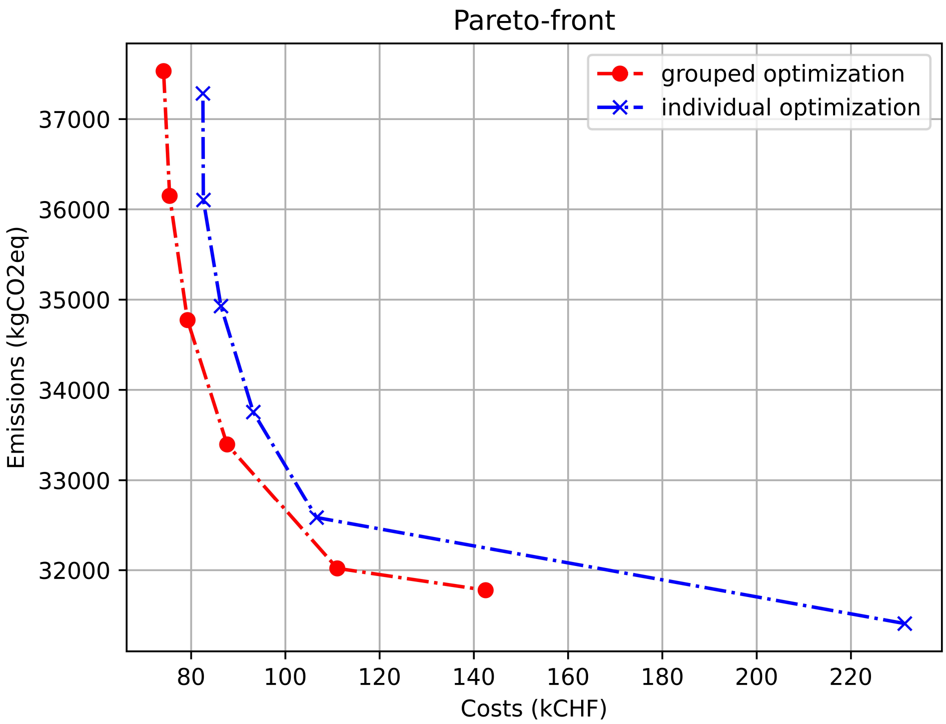

Figure 3: Example of a Pareto front established with multiple optimization runs (points are the results of the runs), during which different value for the emissions were imposed. Each position on the line represents a system configuration that satisfies the same energy demand profile. Points on the Pareto front (Pareto optima) are such that one cannot lower cost without at the same time increasing emissions, or vice versa. The simulated scenario consists of 6 buildings with internal energy links between the buildings. The costs are annual costs, where investment costs are annualized.

2.3 Advanced energy management strategies (WP4)

2.3.1 Framework for model predictive control

Smart operation strategies could help in optimally utilizing the synergies between the buildings in a neighborhood. Such strategies incorporate flexibility by allowing the energy systems to react to the fluctuations in price and carbon emissions. To analyze the potentials of this approach, we use a model predictive control (MPC) combined with a simulation environment used as a digital twin of the energy system with a concept schematically represented in Figure 4. Here, the real system behavior is represented by a detailed simulation environment e.g. TRNSYS (our choice for SolHood) or Polysun. Such an environment would depict the situation in reality with detailed models for energy systems and storage technologies and therefore would work as a digital twin of the analyzed case. The detailed simulation environment would invoke optihood framework every 15 minutes to run an optimization in dispatch mode with a forecast horizon of the next two days. The goal of optimization could be to minimize the operation costs, grid electricity consumption or GHG emissions. At this stage, the simulation environment would need to formulate the optimization problem for optihood, including definition of boundary conditions (cost, impact, weather and energy demand). We consider perfect predictions of the weather, energy demand and grid electricity impacts. This is an idealization and the improvements in KPIs due to MPC will, hence, represent the maximum possible improvement. The sensitivity of MPC to deviations in predictions will, however, be analyzed by varying the gap between the predictions and the actual data. Additionally, the status variables of technologies, e.g. storage temperature, would also need to be maintained between optihood and the simulation environment. Once the optimization is complete, the results from optihood would be used to set the control variables within the simulation environment. The operation in the simulation environment would, therefore, adapt automatically to increased demand or increased solar energy production. For example, a heat pump could operate when PV electricity is available by overcharging thermal storage tanks in order to reduce the energy production cost in the early evenings when people return home.

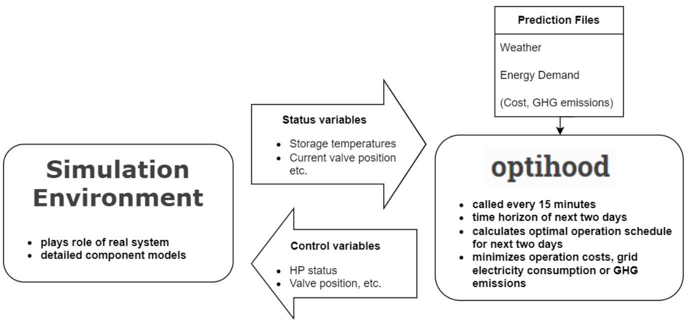

Figure 4: Schematic representation of the MPC framework.

2.3.2 Optimization of control strategies

While optimizing the control strategies, the goal could be either to minimize the operation costs or GHG emissions. The operation costs would arise from the use of primary energy sources for the production of electricity/heat. For example, use of grid electricity would incur higher operation costs in contrast to using PV electricity. In general, the operational costs and emissions are linked to one another. Renewable technologies such as PV and solar thermal benefit from cost-free operation, and likewise produce zero emissions during operation. Whereas, using natural gas or grid electricity adds to the operation cost and also to operational GHG emissions.

The optimizer (optihood) returns the control variables (as shown in Figure 4), based on which the simulation environment decides how the system should be operated in the next time steps until new control decisions are provided, e.g. after 15 min. Some key aspects which could be adapted when optimizing the operation of an energy system in a neighborhood are listed below:

- Heat pump management
  - Operate heat pumps when PV electricity is available or grid electricity is cheaper (or comes with low emissions). Such systems can then also react to variable electricity tariffs (or CO_2 impacts).
  - Operate heat pumps when they are efficient, i.e. when the outdoor/source temperature is higher.
- Thermal energy storage management
  - Avoid charging of storage if the demand prediction doesn't require it and/or if PV or solar thermal energy production is expected soon. This way one can reduce storage energy losses and increase the PV self-consumption.
- Room temperature management
  - If MPC is used also for controlling the indoor room temperature, then the required flow temperature to the heating distribution system can be controlled better, thanks to the anticipation of the heating loads.
  - One can also relax the comfort constraints and allow the room temperature to be in a larger range. This allows the optimizer to optimally shift loads using the building thermal inertia as an extra (and cost free) storage capacity and thereby reduce costs or emissions.
- Battery management
  - Use electricity from the battery when grid electricity is expensive or has high CO_2 load.
  - If the tariff or the CO_2 impact of grid electricity is low, then the MPC can decide to charge the battery with grid electricity (if PV production is not anticipated) and use it later when the tariff is higher.
  - Store PV electricity in battery when the demand is less than the PV production. The optimizer could choose whether to feed in the overproduction from PV or to store it in the battery for later use.

2.4 Case studies (WP5)

2.4.1 Case study 1

The identified case study 1 consists of a small neighborhood of 6 buildings (constructed between 1995-2004) in Zurich with a total energy reference area of 26 728 m^2including a small living space of 193 m^2. The heating demands of these buildings are currently met using fossil based technologies (gas/oil-fired boilers). An overview of the energy reference area and annual energy demands of each building is given in Table 1. The demand profiles were evaluated for each office building (and also for residential space in Building 6) using the demand profile generator of the nPro design tool[3]. This tool provides demand profile generation methods for different types of buildings (residential, office, shops, etc.) based on the energy reference area and the building subcategory. The nPro tool defined several building subcategories relevant for Switzerland (e.g. Minergie building standards). The 'multi family house constructed between 1995-2004' building category was used for the residential space, while for offices the subcategory 'existing' denoting the existing office building stock in Switzerland was considered. The specific annual energy demand assumptions used within this case study from the nPro tool are summarized in Table 2. In order to account for the randomness associated with the use of DHW and electricity, the standard demand profiles from nPro tool were shifted using random time shifts sampled from a Gaussian normal distribution. The weather data of a typical year in Zurich, obtained from MeteoSwiss, was used within the analysis.
Each building was represented by a building model to simulate the annual space heating demand. The thermal comfort temperature range of 22-24°C was assumed during day (and 20-24°C at night). Thermal capacity and window areas (including a factor for shading) were estimated based on the energy reference area, the year of construction, etc. based on the following sources and assumptions:

[3]https://www.npro.energy/

Table 1: Overview of energy reference area and annual energy consumption demands of the case study 1.

Building	Residential space [m^2]	Office space [m^2]	Electricity demand [MWh/y]	DHW demand [MWh/y]	SH demand [MWh/y]
1	0	10080	454	81	1240
2	0	1548	70	12	190
3	0	4834	218	39	595
4	0	3380	152	27	416
5	0	3994	180	32	491
6	193	2892	134	27	397

Table 2: Specific annual energy demands for office and residential spaces assumed within case study 1.

Building usage	Electricity demand $[kWh/m^2y]$	DHW demand $[kWh/m^2y]$	SH demand $[kWh/m^2y]$
Office	45	8	123
Residential	22	21	88

- Total envelope area from eValo and 3D swisstopo.
- Infiltration through the building envelope was estimated with 0.2 W/(m2K).
- Shading factor of 0.2 (reduction of g-value due to active blinds).
- Window g-value and u-value were based on "Merkblatt Fenster – Das Fenster in der Energieberechnung".
- Opaque components u-value was obtained from eValo.
- Thermal mass between 0.1 – 0.15 kWh/(m2K) was assumed based on SIA 380/1:2016.

Internal heat gains within the buildings were calculated based on SIA 2024, by multiplying the specific values with the energy reference area. SIA 2024 provides the standard hourly profiles for heat gains resulting from occupancy and equipment for different types of buildings (including offices and residential spaces). For the mixed-use building (building 6), internal heat gains were calculated separately for the office and residential spaces. The fitting method described later in section 3.2.2 was then used to obtain the effective thermal resistances for each building.
The results of this case study will be documented in the final report.

3 Activities and results of the year 2023

3.1 Boundary conditions and evaluation methods (WP1)

3.1.1 Boundary conditions for the use of solar technologies (Task 1.2)

Boundary conditions on roofs

The increase in solar installations, together with the increasing adoption of roof gardening solutions in new environmentally-friendly districts, has augmented the competition for installation space at the roof level. Roof gardens and solar installations need to be combined on top of the buildings (see Figure 5) as more and more cantonal authorities are imposing them for new buildings (e.g. Neuchatel) or even during renovation (e.g. Bale, Bern, Zurich, Lucerne, St.Gallen, etc.).

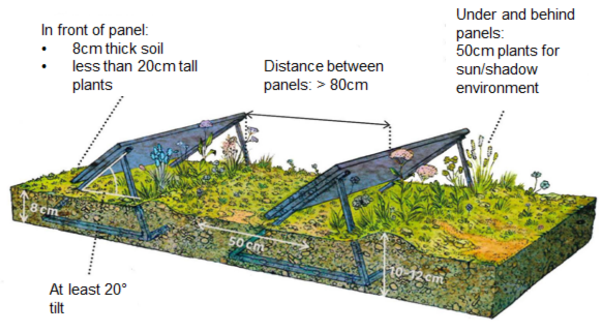

Figure 5: Garden and solar installations can be combined on building roof to satisfy local regulations (SPADOM).

This has to be further combined with the restrictions on the available surfaces imposed by the work-place safety, which requires, e.g., minimum escape distances from roof entrances, minimum passageways for maintenance or surfaces reserved for individual or collective protection (see SUVA (2022b) and SUVA (2022a)).

During 2023, the features and characteristics of flat roofs have been revisited in order to derive a condensed table providing the most important indications relating to the combination of PV panels and garden surfaces on building roof. The resulting features are shown in Figure 6.

	PV on flat roof	**PV integrated on garden roof**
Inter-distance between panel rows	Based on row inter-shadowing at noon on winter solstice.	Based on living space required by garden roof vegetation.
Distance to roof edge	> 60 cm (if pathways) > 25 cm (if no circulation / pathway)	
Panel tilt	Free (at least > 1% to enhance rain cleaning).	> 20° (to leave vital space for plants)
Ballast	Ballast or roof hooks computed accoring to SIA 261.	Roof garden soil (8 cm in front of PV, 10-12 cm on the back, >50 cm in width) – assessment with SIA261 required.
Operating costs	2-6 ctsCHF/kWh$_e$	For garden roofs: add 0.5 ctsCHF/kWh$_e$ [x]
Vegetation heights	n.a.	< 20 cm in front; <50 cm on the back.

[x] «Couts d'exploitation des installations photovoltaïques», Suisse énergie, Article Numéro 805.523.F

Figure 6: Main features to be taken into account in the planning phase of a flat roof solar installation with or without vegetation or gardening.

3.1.2 Typical hourly profiles of carbon footprint of the grid electricity mix (Task 1.3)

The following influential aspects in the temporal determination of GHG emissions of the swiss electricity mix have been identified:

- The national (uncontrollable) production of photovoltaic panels and wind turbines is only determined by local weather variables (radiation, temperature and wind velocity).
- The national hydroelectricity production has a controllable part with lake reservoir plant and uncontrollable part with run-of-river plant. The water stock in reservoir and productivity is subjected to seasonal influences from precipitation and snow melting.
- Pumped storage hydro power plant is controllable and often used during peak demand.
- The national demand of electricity is the aggregated regional demands, respectively highly influenced by their local weather conditions (radiation, temperature and wind velocity).
- The national demand is also influenced by the economic activity of the day. The demand is higher during weekdays than weekend days and holidays.
- Following an offer-demand principle that ensure equilibrium of the grid at the European scale, the controllable production technologies and the exchanges (imports and exports) are activated to meet the residual demand (i.e. the demand minus the uncontrollable production).
- Due to the high amount of exchange between Switzerland and its neighboring countries, the previous aspects in those countries also affect the final consumption mix in Switzerland, especially regarding exchanges with Germany and France.
- All the previous aspects interact and are reflected with the price of electricity in many different ways and temporal horizons (long-term, day-ahead, infra-day).
- The installed production capacities evolve each year due to new and closed production facilities.

EcoDynElec is a tool to generate and analyze the electricity mix profiles of historical year. If those historical profiles are jointly used for building assessment with climate data from other historical year, it induces temporal and physical inconsistencies. Depending on the application of such method, this inconsistency can have more or less importance in the reliability of the results. The optimization of building energy systems consist in controlling the production and storage in response to variability in the demand with the objective to minimize GHG emissions. An inconsistency between the building needs calculation and the impacts of electricity should be avoided as it would affect each time step of the optimization process, thus leading to less reliable CO2-optimal control. Furthermore, in a real time application such as predictive control, it is necessary to jointly predict local climate conditions and the global electricity system in which the building take part. A coupled modeling of the dynamic interactions in the electricity system could be a solution for the price of highly complex efforts in terms of collecting data and building a reliable and robust mathematical model.
A much simpler and straightforward statistical approach is adopted in this work to use correlated climate and electricity mix data in building performance assessment. It is based on the historical data generated with EcoDynElec and the Typical Meteorological Year (TMY) used in building performance simulation. TMY are standardized weather data sets defined for a given location and used in building performance simulation. They contain hourly time-series that are statistically selected among a bank of data from a period of at least 10 years to represent the most frequent climatic condition. The goal and deliverable of this task is to create a similar "Typical Electricity Year" (TEY) that represent hourly GHG emissions profiles that are sufficiently representative and realistic in terms of temporal variability to be reliably used in building performance assessment.
While the end result and the field of application are similar for TMY and TEY, the logic behind TMY design can't be directly translated to electricity mix due to the geographical and temporal interactions occurring in an electricity system between weather, electricity demand and production. Several specificities of the studied systems have to be noted:

- Both the demand and production components of an electricity system are heavily influenced by local weather conditions.
- Geographical scope: while TMY are defined for local conditions based on regional weather observations, the GHG emission of electricity at the grid is considered to be the same at any place in Switzerland[4]. Hence, our TEY is defined at national scale.
- Due to the interactions between the national grid and many local weather conditions across the country, the TEY must be built according to the 24 TMY-related weather stations covering Switzerland. The advantage is that a unique TEY can be used jointly with any of the 24 TMY used in the process.
- Unlike weather data, a 10-years average approach to construct a typical electricity mix is not relevant because older years are obsolete due to the rapid evolution of the installed capacities, especially for the case of photovoltaic in Germany that directly affects the exported electricity mix to Switzerland. (This statement is valid when considering physical average mix, but not necessarily when considering marginal mix. Marginal mix is related to production technologies that are identified by they merit order, the latter does not evolve in the same manner than the national installed capacities.)

The method to produce TEY is described as follow. TEY time-series has been synthesized for a given historical year by associating each meteorological day from a Typical Meteorological Year (TMY) [5] with a corresponding day from the historical year of an electricity mix data. The selection is operated by minimizing the difference in weather and other conditions according to the parameters given below. The TMY and weather data for the chosen historical year is retrieved form Meteonorm. The electricity mix data are retrieve from EcoDynElec for the years 2021 and 2022.
The historical hourly GHG emission profiles according to each selected day are then assembled to form the TEY, an artificial hourly profile, statistically compatible with the 24 swiss TMY and representative of the conditions of the electricity system in a given year. This approach allows us to construct an artificial profile for one year of the hourly GHG emissions of the grid, maximizing their correlation with the weather patterns of the TMY. The principle is illustrated with this example. For a typical 5th January and the weighted weather conditions over Switzerland according to 24 TMY data, the day with the closest historical conditions in 2021 is identified to be the 2nd February. Hence, in the TEY, the hourly GHG emissions of the electricity mix is set to be the historical GHG emission profile of the 2nd February 2021 from EcoDynElec. The methodology is explained in Figure 7:

1. Load historical meteorological for the chosen year and the 24 weather stations according to the SIA 2028.
2. Compute daily averages on the following variables: air temperature, global horizontal solar radiation, wind speed, relative humidity, and water reservoir levels.
3. Load TMY data from the 24 weather stations and compute daily averages of the same weather variables.
4. Matching: this calculation is performed for each weather station. For each day of the TMY, a vector containing the distance values to each day of 2021 is calculated. The distance is defined as the weighted sum of differences between each meteorological variable.
5. Weighting: For each day, the weighted sum of distances over the 24 weather stations is calculated. A distance is weighted by the population of each canton the weather station belong to. If multiple stations are in the same canton they are weighted based on the population of the district where they are located (an administrative division between the municipality and the canton).
6. A typical year based solely on a mixture of days from 2021 is synthesized by selecting the day that has the minimum distance over all the weather stations. The "nearest day of 2021" to the weather and electric system conditions of a day mutual to all 24 weather stations.

[4] according to the physical approach and national security of supply adopted in EcoDynElec modelling
[5] Generated using Meteonorm 8.2 between 2000 and 2020

7. Load hourly GHG emissions of a kWh of electricity from the chosen year (from EcoDynElec).
8. Associate the identified nearest day (bullet point 6) with the corresponding day in the chosen year and its hourly GHG emissions.
9. Finally, a TEY with hourly values of GHG emissions of the swiss electricity mix is generated as a recombination of historical days from the chosen year. The TEY is consistent with weighted average conditions of 24 TMY data over Switzerland and compatible with those TMY data.

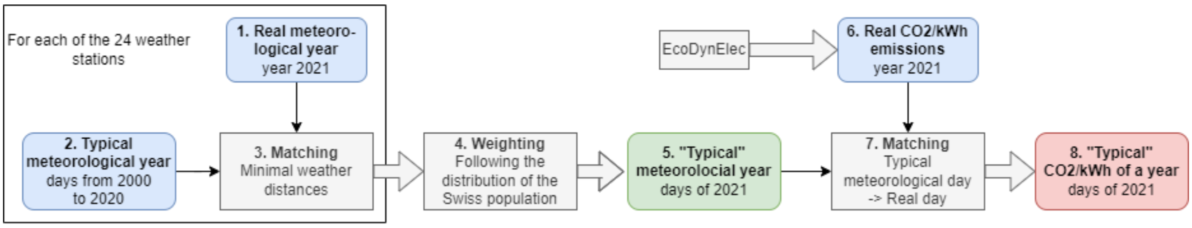

Figure 7: Algorithm established to synthesize 'typical' years of GHG emissions related to electricity consumption in Switzerland.

Figure 8 displays the results obtained as a hourly profile of GHG emissions of the electricity consumed in Switzerland. The red curve represents the synthesized profile, selecting the closest day (in terms of weather conditions) from 2021 for each day of the typical meteorological year. The gray interval corresponds to an uncertainty interval set between the min and max profiles over a given number of closest days-profiles. The number of closest days-profiles that are selected is determined to match the same range of uncertainty observed in the historical years from EcoDynElec. The observed historical variations to the 6-year average of the annual average GHG emissions of the electricity mix between 2016 and 2022 is approximately -20% to +20% .

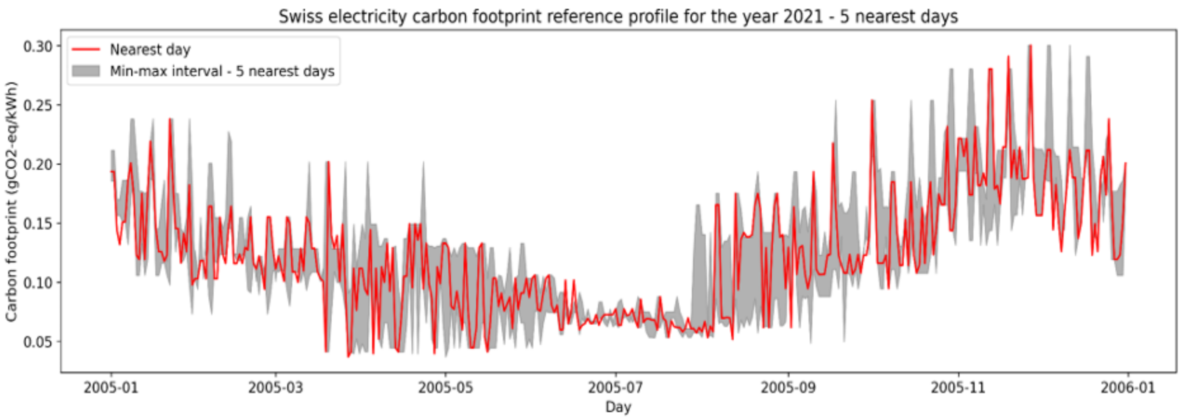

Figure 8: Typical hourly profile synthesized from the typical meteorological year and the days of 2021.

The decision to choose *the* nearest day was made to ensure the preservation of extreme values, which would not have been retained by methods like "averaging the nearest N days". In order to assess the uncertainty of the calculated values, we also consider a range representing the minimum and maximum greenhouse gas emissions, derived from the five closest days of a chosen typical day. This selection allows for an annual average GHG emissions range of -18 % to +25 % around the "nearest days" GHG emissions profile, which is close to the observed historical variations around the 6-year average of annual average GHG emissions of the electricity between 2016 and 2022, as shown on Figure 9.
It is worth noting that a TEY is highly linked to a chosen historical to represent the electricity system conditions. For example, the year 2022 is not similar to the year 2021, with events such as the Ukraine war and the

gCO2eq/kWh of swiss electricity, consumer mix	2021		2022	
	Annual average	% difference of annual average to “Nearest”	Annual average	% difference of annual average to “Nearest”
Nearest TEY	124	-	141	-
Min TEY (min GHG value from 5 Nearest days)	101	-18%	120	-15%
Max TEY (max GHG value from 5 Nearest days)	153	+23%	166	+18%

Figure 9: Annual average GHG emissions of the TEY profiles generated: Nearest profile, min profile and max profile selected among 5 nearest days selected in the process.

low availability of French nuclear power plants that have altered electricity production and exchange patterns throughout Europe. These differences are visible on Figure 10 which represents the real GHG emissions profiles of 2021 and 2022 : the carbon footprint in March, April and during the summer of 2022 are significantly higher than in 2021.

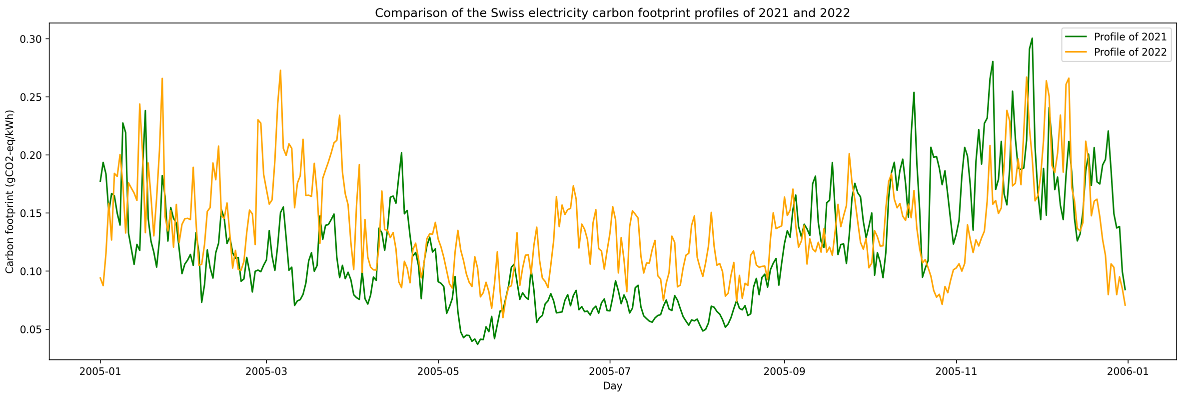

Figure 10: Comparison of the Swiss electricity carbon footprint profiles of 2021 and 2022

3.2 Development of modeling and optimization environment (WP2)

In order to realize the goals of this project, final developments in the optihood framework were made. The work carried out within each task of WP2 is presented in the following subsections.

3.2.1 Energy system component models (Task 2.1)

PVT collector

PVT class was implemented within the converters module, which defines the energy conversion technologies supported by optihood. The collector output is modelled based on the characteristic curve model reported in the SwissEnergy sponsored project PVT Wrap-Up (Zenhäusern et al. (2017)). The thermal output of a PVT collector, $\dot{Q}$, highly depends on the surrounding environment and the operating conditions. The most significant influencing factors are the solar irradiation per collector surface area (G), ambient air temperature (T_{amb}) and the mean temperature of the collector fluid (T_{m}). The characteristic equation of thermal output of the PVT collector is given by:

$$\frac{\dot{Q}}{A} = \left(G - \frac{P_{el}^{DC}}{(\alpha\tau) \cdot A}\right) \cdot \eta_o - a_1(T_m - T_{amb}) - a_2(T_m - T_{amb})^2 \tag{1}$$

where A stands for the gross area of the collector surface, P_{el}^{DC} stands for the DC electrical output of the collector, $(\alpha\tau)$ is the transmission absorption product of the collector, η_o is the maximum thermal efficiency, a_1 is the linear heat loss coefficient and a_2 is the quadratic heat loss coefficient of the collector.

A corresponding label *PVT* was added to the energy conversion technology processing function, to allow the definition of a PVT collector in the input excel/config file while preparing the optimization problem.

Layered thermal energy storage and discrete temperature levels

A discretized thermal energy storage with several predefined discrete temperature levels was implemented. Moreover, the heat production technologies such as heat pumps, CHP, solar thermal collectors, etc. were extended to allow multiple output flows (at different temperature levels). It should be noted that the temperature levels are predefined and each heat production technology, therefore, has a predefined hourly efficiency related to a specific temperature level. The number of discrete temperature levels is parameterized and can be defined in the input scenario excel file. In order to use discrete temperature levels, the `temperatureLevels` parameters has to be True when the `EnergyNetwork` class is instantiated:

```
import EnergyNetworkGroup as EnergyNetwork

# set a time period for the optimization problem
timePeriod = pd.date_range("2021-01-01 00:00:00", "2021-12-31 23:00:00", freq="60min")

# create an energy network and set the network parameters from an excel file
network = EnergyNetwork(timeperiod, temperatureLevels=True)
```

The discrete temperature levels defined in the input scenario (excel) file, set the temperatures of the output flows of the heat conversion technologies. Depending on the time resolution of the optimization problem, it may not be acceptable for a heat conversion technology to produce heat at more than one temperature levels in a single time step. Therefore, `limit_active_flow_count` constraint of oemof solph package (Hilpert et al. (2018)) was used to permit only one of the heat output flows to remain active at a given time step.

A class `ThermalStorageTemperatureLevels` was developed to represent a discretized thermal energy storage. The model of a layered thermal energy storage is a combination of dual temperature zone storages from oemof thermal python package (Hilpert et al. (2018)). The dual temperature zone storages include predefined calculations for top/bottom and lateral surface losses. While the lateral surface losses are preserved for the storage layers at each temperature level, the top and bottom surface losses should only be considered for the topmost (i.e. at the highest temperature level) and the lowest (i.e. at the lowest temperature) layers. The fixed one-time investment cost of the discretized thermal energy storage should be added to the objective function only once (instead of being added for each layer separately). These functionalities are implemented within the `ThermalStorageTemperatureLevels` class. Moreover, the total storage volume V_{stor} is calculated as the sum of individual layer volumes (v_i), as follows:

$$\sum_{i=1}^{n} v_i = V_{stor} \tag{2}$$

where n denotes the number of discrete temperature levels.

A constraint called `multiTemperatureStorageCapacityConstaint` was developed to implement the following rule on the storage volume capacity:

$$V_{stor,min} \leq V_{stor} \leq V_{stor,max} \tag{3}$$

where $V_{stor,min}$ and $V_{stor,max}$ represent the minimum and the maximum limits for the storage volume.

Figure 11 shows a graphical representation of a layered thermal energy storage with three discrete temperature levels. The DHW demand is met using the topmost temperature level at 65 °C i.e. highest temperature, while the lowest temperature level at 35 °C is used to cover the SH demand. A rule for charging the thermal energy storage was implemented, such that the energy inflow at a given storage layer (except the lowest layer), equals the energy outflow from the preceding storage layer. Therefore, in order to supply thermal energy at 50 °C to the storage, the same volume added at the 50 °C layer should be displaced from layer below, i.e. from the 35 °C storage level (as shown in Figure 11). This means that the energy conversion technologies can heat water from 35 °C to 50 °C and from 50 °C to 65 °C, in that order.

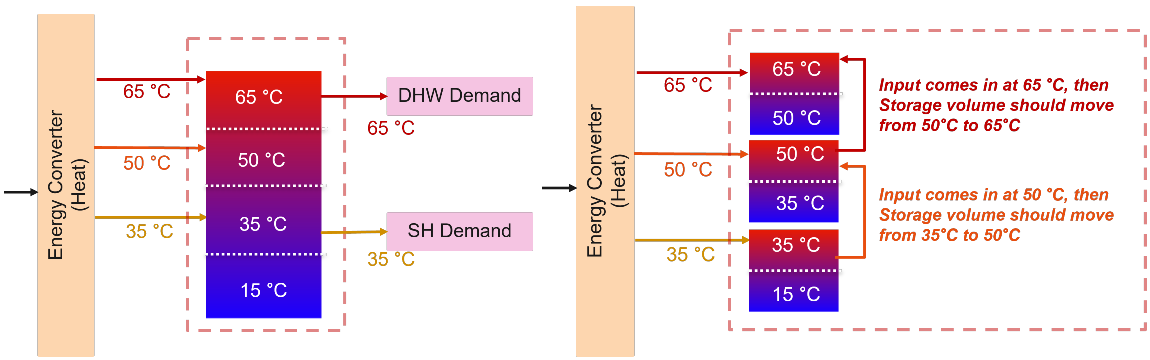

Figure 11: Graphical representation of a layered thermal energy storage model with three discrete temperature levels at 35°C, 50°C and 65°C, and a return temperature of 15°C.

Ice storage

The `IceStorage` class was implemented within the storages module of optihood. The formulation of the ice storage model is based on the solution of the energy conservation law applied to the water of the storage as per Carbonell et al. (2015). It is basically the same as the energy conservation law for hot water storage with the inclusion of the latent heat term for ice formation $\frac{h_f}{V}\frac{\partial M_{ice}}{\partial t}$:

$$\rho c_p V \frac{\partial T_{stor}}{\partial t} = -(UA)_{tank} \cdot (T_{stor} - T_{amb}) + \frac{h_f}{V}\frac{\partial M_{ice}}{\partial t} + \sum_{i=1}^{n} \dot{Q}_{hx-port}(i) \tag{4}$$

where, ρ and c_p stand for the density and specific heat capacity of water, respectively. V is the storage volume, T_{stor} is the average temperature of the storage, T_{amb} is the ambient air temperature, $(UA)_{tank}$ is the product of overall heat transfer coefficient and the external area of the storage tank, M_{ice} is the mass of ice and h_f the latent heat of fusion. $q_{hx-port}$ are the heat fluxes between the heat exchanger and the direct ports, and can be represented as:

$$\sum_i \dot{Q}_{hx-port}(i) = \sum_i \dot{Q}_{in}(i) - \sum_i \dot{Q}_{out}(i) \tag{5}$$

here Q_{in} and Q_{out} are the heat inflows and outflows to/from the ice storage tank, respectively.

The term for heat of solidification and melting appearing in Eq. 4 can be discretized as:

$$\dot{Q}_{lat} = h_f \frac{M_{ice}^{t+1} - M_{ice}}{\Delta t} \tag{6}$$

The complete discretized equation for ice storage model is represented as:

$$\rho c_p V \frac{T_{stor}^{t+1} - T_{stor}^{t}}{\Delta t} = -(UA)_{tank} \cdot (T_{stor}^{t} - T_{amb}^{t}) + h_f \frac{M_{ice}^{t+1} - M_{ice}}{\Delta t} + \sum_{i=1}^{n} \dot{Q}_{hx-port}(i)^t \tag{7}$$

In order to solve this equation one can split the formulation in two parts. One considering only the sensible part where the $M_{ice} = 0$ kg and a second formulation for the latent part assuming $T = 0$ °C. The equation with ice formation is reduced to:

$$0 = (UA)_{tank} \cdot T_{amb}^{t} + h_f \frac{M_{ice}^{t+1} - M_{ice}}{\Delta t} + \sum_{i=1}^{n} \dot{Q}_{hx-port}(i)^t \tag{8}$$

In addition, the following constraints were implemented. The constraint to set up the initial conditions such as initial storage temperature and initial mass of ice is given by:

$$\begin{bmatrix} T_{stor}^{0} \\ M_{ice}^{0} \end{bmatrix} = \begin{bmatrix} T_{stor}^{init} \\ 0 \end{bmatrix} \tag{9}$$

The constraint for the temperature of storage during ice formation is given by:

$$T_{stor}^{i} \geq 0 \quad \forall i \in t \tag{10}$$

The mass ice fraction, also known as ice packing factor, f^t, is calculated as:

$$f^t = \frac{M_{ice}^{t}}{M_{water,max}} \tag{11}$$

where, $M_{water,max}$ denotes the overall amount of water and ice in the storage tank. The constraint on the maximum allowed value of f^t is represented as:

$$f^t \leq f_{max} \tag{12}$$

Depending on the ice storage design, the f_{max} can be in the range of 0.5 to 0.8.

Low temperature source of heat pump

A second input energy flow, i.e. low temperature heat, was added to the evaporator side (or source side) of the ASHP and GSHP to enable a representation of a low temperature thermal grid within the optihood framework. The low temperature heat flow was added as an optional input flow within the heat pump implementation class. The magnitude of the low temperature heat input of the heat pump, Q_{evap}, is evaluated based on the law of energy conservation:

$$P_{hp} + Q_{evap} = Q_{cond,sh} + Q_{cond,dhw} \tag{13}$$

where, P_{hp} is the electrical energy used by the heat pump, while $Q_{cond,sh}$ and $Q_{cond,dhw}$ represent the heat produced by the condenser for space heating at 35°C and domestic hot water at 65°C, respectively.

The relation given by Eq. (13) was implemented within the constraint group of the heat pump implementation base class `CombinedTransformer`.

3.2.2 Dynamic building model (Task 2.2)

When a building model is used, the optimizer can use the thermal mass of a building as a thermal storage by allowing to vary the indoor air temperature within a predefined comfort range (between $T^t_{ind,min}$ and $T^t_{ind,max}$). A comfort violation indicator variable, ε^t, is present in the building model to allow a violation of this comfort range in order to reach optimization feasibility in unavoidable cases. The indoor comfort temperature rule is represented by the equation:

$$T^t_{ind,min} - \varepsilon^t <= T^t_{ind} <= T^t_{ind,max} + \varepsilon^t \tag{14}$$

where T^t_{ind} denotes the indoor air temperature (°C) at time t.

In order to keep the indoor air temperature within the range ($T^t_{ind,min}$, $T^t_{ind,max}$) whenever possible, the value of ε^t chosen by the optimizer should be as low as possible. To account for this, the constraint group of `SinkRCModel` class, i.e. linear RC model (proposed in Péan et al. (2019)) describing the thermal behavior of a building, in optihood was modified. We included a penalty factor (`penaltyComfortViolation`) linked to the variable ε^t in the objective expression of optimization. The updates made to the objective expression are shown in Figure 12. This penalty factor for comfort violation, needs to be provided when formulating the optimization problem. As a general suggestion, the chosen penalty factor should be higher than the cost of providing heating (or cooling) energy i.e. it is more expensive to violate the indoor temperature range than to provide the necessary heat to the rooms (or to extract the excess heat from the rooms). A default value of 1 is assumed, if this factor is not defined in the input excel/config file.

```
def _objective_expression(self):
    r"""Objective expression to add costs to high values of self.epsilon"""
    m = self.parent_block()
    variable_costs = 0
    fixed_costs = 0

    for g in self.sinkrc:
        for t in m.TIMESTEPS:
            variable_costs += self.epsilonIndoor[g,t]*self.penaltyComfortViolation

    self.cost = Expression(expr=variable_costs + fixed_costs)
    return self.cost
```

Figure 12: Update in the objective expression of the building model class `SinkRCModel`.

Furthermore, the building model class `SinkRCModel` allows both heating and cooling. Cooling is implemented as a possibility of heat rejection, for example by means of a chiller with a fixed efficiency. The state space equation respective to the distribution temperature of the building model is given as:

$$C_{dis} \cdot \dot{T}^{dis} = \frac{1}{R_{dis}}(T^{ind} - T^{dis}) + Q^{heat}_t - Q^{cool}_t \tag{15}$$

where R_{dis} and C_{dis} denote the thermal resistance (in K/kW) and heat capacity (in kWh/K), respectively, of the distribution system. T_{dis} and T_{ind} are the temperatures of the distribution system and indoor air space, respectively, in °C. Q^{heat}_t and Q^{cool}_t represent the heating power and the cooling power (in absolute terms) of the distribution system, respectively, in kW at time t.

Moreover, the means for setting up the building model parameters was included and a simple fitting method was implemented to determine the building model parameters. In the developed fitting method, different indoor air temperatures could be set during the day and night, for example 22 °C during the day and 20 °C at night. The following simplified equation is used to calculate the heating power Q^{heat}_t, in kW, at time t:

$$Q^{heat}_t = U_{dis}(T^{dis} - T^{ind}) = U_{building} \cdot (T^{ind} - T^{amb}) - gA \cdot I^H_t - Q^{occ}_t \tag{16}$$

where T^{dis}, T^{ind} and T^{amb} denote the distribution system, indoor air mass and ambient air temperatures, respectively, in °C. The term gA represents the product of transmittance of glass, lumped factor for considering window surfaces at different orientations and the total aperture area of the windows in m^2. I_t^H and Q_t^{occ} are the total horizontal solar irradiation (kW/m^2) and heat gain from occupancy (people, electrical equipment, lights, etc.) in kW, respectively, at time t. U_{dis} is the thermal transmittance of the distribution system in kW/K. $U_{building}$ is the thermal transmittance of the building, in kW/K, and is given by the following relation:

$$\frac{1}{U_{building}} = \frac{1}{U_{ind}} + \frac{1}{U_{wall}} \tag{17}$$

here, U_{ind} ad U_{wall} denote the thermal transmittance of the indoor air mass and of the wall and building mass, respectively.

The effective thermal transmittance of a building $U_{building}$ is determined by fitting the heating demand calculated by Eq. (16) to the actual heating demand of the building using the minimization method of Scipy (Jones et al. (2001)) in Python.

An excel file was introduced for defining the building model parameters, the location of this file needs to be specified when defining the optimization problem (within the input scenario file described in section 2.2.2). A snapshot of this file is shown in Figure 13. The thermal resistance, R (in K/kW), and thermal capacitance, C (in kWh/K), of each thermal state space of the building model (distribution system, indoor air mass and wall and building mass) are defined for each building. In addition, the lumped product respective to the aperture area of the windows, gA and the initial values of the indoor air temperature (°C), distribution system temperature (°C) and wall temperature (°C) are listed. The allowed range of indoor air temperature is also specified in this file, by means of the minimum (`tIndoorMin`) and the maximum (`tIndoorMax`) allowed temperatures in °C. Lastly, the minimum and maximum power limits (in kW) delivered by the distribution system are also defined here.

Building Number	gAreaWindows	rDistribution	cDistribution	rIndoor	cIndoor	rWall	cWall	tIndoor Min	tIndoor Max	tIndoor Init	tDistribution Init	tWallInit	qDistribution Min	qDistribution Max
1	158.9	81.89	0.00116	9.83	0.00431	185.62	0.8040	20	24	23.5	31.9	22.1	0	1.00E+03
2	474.0	24.56	0.00269	2.95	0.01002	55.66	1.8677	20	24	21.8	21.0	21.8	0	1.00E+03
3	62.4	51.17	0.00066	6.14	0.00247	115.97	0.4593	20	24	22.4	22.5	22.3	0	1.00E+03
4	185.3	51.80	0.00180	6.22	0.00672	117.40	1.2519	20	24	23.4	34.9	21.7	0	1.00E+03
5	154.3	31.56	0.00209	3.79	0.00779	71.54	1.4517	20	24	21.9	21.9	21.7	0	1.00E+03
6	185.0	27.94	0.00213	3.35	0.00796	63.32	1.4826	20	24	22.4	22.4	22.3	0	1.00E+03
7	69.3	77.85	0.00061	9.34	0.00226	176.45	0.4208	20	24	22.3	22.3	22.2	0	1.00E+03
8	206.1	28.52	0.00148	3.42	0.00553	64.65	1.0304	20	24	21.4	21.4	21.3	0	1.00E+03
9	211.3	35.11	0.00189	4.21	0.00705	79.59	1.3134	20	24	22.1	22.1	21.9	0	1.00E+03
10	653.5	15.28	0.00403	1.83	0.01502	34.63	1.8655	20	24	22.4	22.4	22.2	0	1.00E+03

Figure 13: Input file defining the parameters of the building model represented by `SinkRCModel` class in optihood.

3.2.3 Solar radiation processing (Task 2.3)

In 2022, the "weather" class was introduced to facilitate the calculation of the solar radiation impinging on a tilted surface located at a given site defined in terms of longitude and latitude coordinates. Building on this, in 2023, a complementary class named "calepinage" was developed. This class serves the purpose of determining the optimal number of solar collectors that can be accommodated on a rectangular roof with arbitrary orientation.
Leveraging the capabilities of the Python package "Shapely," tailored for set-theoretic analysis and manipulation of planar features, the projection of the reference panel onto the horizontal plane is employed. This projection dynamically populates the specified geometry until further placement of panels is precluded by the geometric constraints defined by reciprocal shadowing distances and roof features, such as orientation, latitude, and safety distances to the roof edge. This method ensures an efficient and optimized arrangement of panels within the given spatial constraints, maximizing solar collector coverage on the roof.
Upon completion of the computations, the class provides the maximum number of panels that can be accommodated on the provided rectangular-shaped roof, factoring in the assumed orientation and tilt.
For a more in-depth understanding of the "Calepinage" class and its functionalities, additional details are outlined in Appendix A.

Class use-case example

Figure 14 shows the district Im Lenz in Lenzburg, one of the "2000 Watt" sites chosen as an example of Swiss typical district. The highlighted building features an 11 m by 50 m rectangular shaped roof and it is located at Niederlenzer Kirchweg 8 in Lunzburg. The building has its short axis oriented towards 10° West and according to the adopted convention, it has an azimuth of 190°. It is assumed that solar panels of rectangular shape with dimensions 2 m by 1 m are installed, either in portrait layout or East west arrangement (see Figure 15). Collectors can be installed aligned with the building or facing south, if in portrait arrangement, or along the North-South direction, if in East-West arrangement.

Figure 14: "2000 Watts" site Im Leinz in the city of Lenzburg: google map aerial view (left pane) and site representation under City Energy Analyst (right pane).

Figure 15: Panel arrangement according to portrait layout (left pane) and east-west structures (right pane).

The python instruction to create a class named roof_1 of type "Calpinage" in the case of the building in

Lenzburg (i.e., latitude of 47.39°N) with solar panels in portrait layout, facing south and featuring a tilt of 30°, and with a minimum row distance of 0.6 m, is the following:

$$roof\_1 = Calpinage(orientation = 190, lat = 47.39, w = 1, l = 2, W = 11, L = 50, tilt = 30, f\_EW = False, f\_plot = True, f\_orient = True, d\_rows = 0.6) \quad (18)$$

while the one to perform the same calculation in the case of east-west arrangement would be the following:

$$roof\_1 = Calpinage(orientation = 190, lat = 47.39, w = 1, l = 2, W = 11, L = 50, tilt_E W = 20, f\_EW = True, f\_plot = True, f\_orient = True, d\_rows = 0.6) \quad (19)$$

The graphical output for the previous instructions is shown in Figure 16 and Figure 17 for portrait and east-west layout, respectively. Table 3 shows the number of panels that can be installed on the same roof in portrait layout and in East-west arrangement for several tilt values, together with the fill-in ratio calculated assuming the default distance between collector and roof edge (i.e. d_L = d_W = 0.5 m), and default minimal spacing between neighboring rows (i.e., 0.6 m).

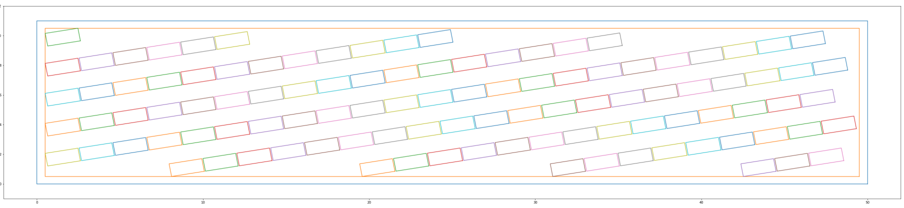

Figure 16: Panel placement on the roof according to South alignment and in portrait layout.

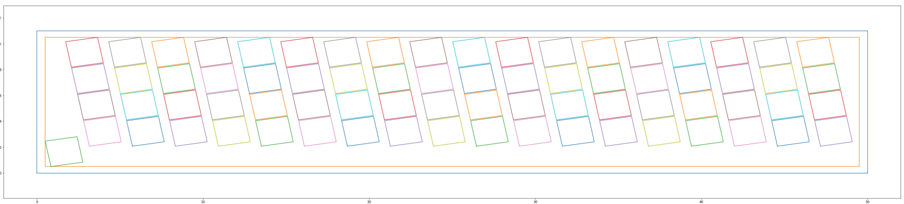

Figure 17: Panel placement on the roof according to North-South alignment in East-West layout.

Panel tilt	Number of panels		Fill-factor	
	Portrait	EW	Portrait	EW
20	120	146	48.9%	59.6%
30	105	154	42.8%	62.8%
40	95	170	38.8%	69.4%

Table 3: Number of panels and fill-factor for the building roof under study for several values of panel tilt installation.

3.2.4 Data and parametric functions for cost and environmental impact (Task 2.4)

In 2023, activities were carried out to add the data for two new technologies (PVT collectors and ice-storage tanks). Detail are given in the sections below. Moreover, GES emission for borehole heat exchangers was updated from 39.9 gCO_2eq/m to 23.2 gCO_2eq/m according the the latest KBOB dataset[6].

Cost parametric functions for PVT and ice-storage

Two types of PVT have been defined (data given in project project HiPer-PVT[7]): i) "uncovered" are PVT collectors without (second) cover glazing, i.e. like standard PV panels, but with a heat absorber (typically) glued to their rear side and ii) "covered" are similar to thermal flat plate collectors, but where the absorber plate is equipped with PV cells. As solar collectors, they have heat insulation on the rear side and a glazing to prevent convection losses on the front side. Cost functions for the two types PVT collectors were derived by offers for surfaces between 1 m^2 to 50 m^2.

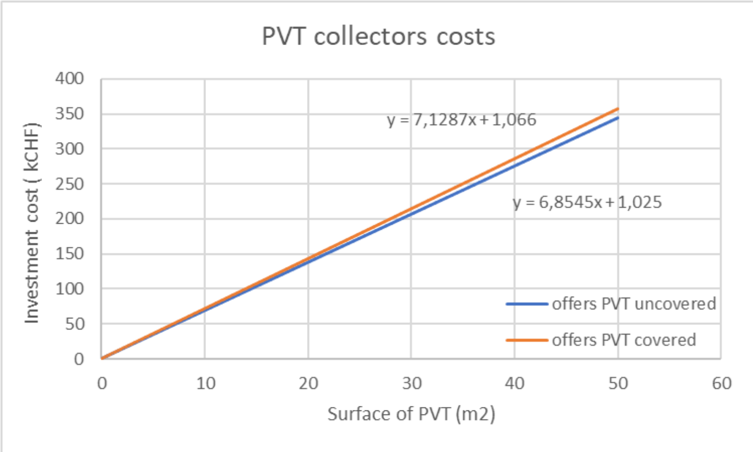

Figure 18: linear regression for the two types of PVT.

Costs between the two types of collector are very similar. The offers include the costs of installation and planning, transport and the accessories. Installation costs include labor to install all the components (accumulator, expansion vessels, etc.), the cost of the electrical connection and the cabinet, hydraulics, and commissioning. The cost of OPEX are similar of photovoltaic panel, an average annual cost of 2 % of the CAPEX will be taken into consideration.
Cost estimations for the ice storage are taken from the BigIce project conducted by SPF-OST (Carbonell et al., 2021). The cost is split into two parts, namely the casing and the heat exchangers. It is assumed that the casing is made of concrete and also that excavation is needed to accommodate the ice storage in the cellar of the building or for placing it underground. The cost of the ice storage casing and excavation is shown in Fig. 19.
For the heat exchangers inside the storage several offers have been collected with a price range that depends on the technology used. The cost is provided as a function of the ice storage volume including an uncertainty range which depends on heat exchanger and supplier used:

$$\text{cost Hx ice storage} = 352^{+124}_{-152}\ \text{CHF}/\text{m}^3 \tag{20}$$

LCA parametric functions for PVT and ice-storage

The environmental impact data for the ice storage system is retrieved from the output of the project "High-Ice" carried by SPF-OST (Philippen et al., 2015). The GHG emissions for production is 350 $kgCO_2eq/m^3$ of ice storage made of concrete and built in the ground, and with de-iceable plate heat exchangers.
The environmental impact data for the solar hybrid photovoltaic and thermal system is retrieved from the KBOB 2021 database. The GHG emissions for the production of a system with a photovoltaic efficiency of

[6] https://www.kbob.admin.ch/kbob/fr/home/themen-leistungen/nachhaltiges-bauen/oekobilanzdaten_baubereich.html

[7] https://www.aramis.admin.ch/Grunddaten/?ProjectID=40732

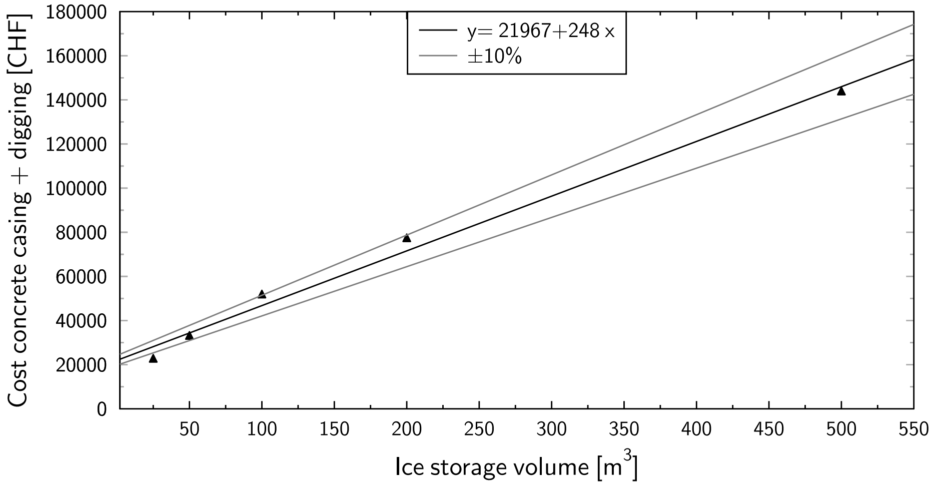

Figure 19: Costs of concrete casing for a conventional ice storage on a new building including excavation.

0.167 kWp/m^2 is 370 kgCO_2eq /m^2 or 2220 kgCO_2eq /kWp, the installation including the panels, inverter, mounting system, exchanger and pipes.

3.2.5 Optimization framework (Task 2.5)

As the number of buildings increase, formulating an optimization problem using an Excel file could become rather cumbersome. As an example, a snapshot of an input excel file with 28 buildings is shown in Figure 20. In the Excel file, a choice of available technologies is added separately for each building. This offers flexibility when defining the energy systems of different buildings, where each building could have different available technologies with different limits on the minimum and maximum permissible capacities. However, if each building has a similar list of available technologies this would require the same Excel row to be repeated over and over again for every building. Moreover, optihood provides a high level of flexibility in terms of how the individual system components are connected. This information has to be defined within the Excel file for each component. Nonetheless, this could increase repetitive work during the preparation of the Excel file when typical connections are used. In order to address these issues and make the problem definition more intuitive, a configuration (or config) file was introduced as an alternative method for formulating an optimization problem.

In a config file, one could provide the same information as in the input Excel file but for a case where all the buildings have an identical setup (technologies, limits on capacities, costs, etc.). Figure 21 shows an example of a config file where grid electricity is used as a primary energy source and heat is produced using air-source and ground-source heat pumps (ASHP and GSHP). Each building would have the same available energy sources and technologies. Paths to the weather file, electricity impact and demand profiles are also specified within this config file. Moreover, the connections between energy sources, conversion and storage technologies and demands are fixed to default system connections when a config file is used. The default system connections for different system components supported by the config file are shown in Figure 22. Note that the specific connections would realize only when the corresponding technologies/sources/sinks are selected. As an example, the connection between natural gas resource and CHP would be realized only if the optimizer chooses CHP as an optimum solution in the optimization results.

A new method called `createScenarioFile()` was implemented within the `EnergyNetworkIndiv` and `EnergyNetworkGroup` classes. This function reads a config file and derives the equivalent Excel file based on the default system component connections. The equivalent Excel file includes the same energy sources,

	A	B	C	D	E	F
1	label	building	active	from	to	efficiency
2	GWHP	1	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
3	GWHP	2	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
4	GWHP	3	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
5	GWHP	4	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
6	GWHP	5	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
7	GWHP	6	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
8	GWHP	7	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
9	GWHP	8	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
10	GWHP	9	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
11	GWHP	10	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
12	GWHP	11	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
13	GWHP	12	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
14	GWHP	13	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
15	GWHP	14	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
16	GWHP	15	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
17	GWHP	16	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
18	GWHP	17	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
19	GWHP	18	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
20	GWHP	19	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
21	GWHP	20	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
22	GWHP	21	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
23	GWHP	22	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
24	GWHP	23	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
25	GWHP	24	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
26	GWHP	25	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
27	GWHP	26	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
28	GWHP	27	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5
29	GWHP	28	1	electricityInBus,heatSourceBus	shDemandBus,dhwDemandBus	4.5

Figure 20: Input excel file for defining an optimization problem for a neighborhood with 28 buildings.

conversion and storage technologies (including same costs, minimum/maximum capacities, etc.) for each building. It is worthwhile to note that the `createScenarioFile()` could still be used to prepare a first version of the Excel file if system components for all the buildings are not identical. The prepared Excel file could then be adapted later on instead of creating it from scratch.

3.3 Advanced energy management strategies (WP4)

3.3.1 Development of model predictive control (Task 4.1)

Plugin controller in Polysun

The optimization framework optihood was coupled with the Polysun simulation environment using the SimpleRpc plugin controller. This plugin controller passes commands from Polysun to an RPC server through a remote procedure call (RPC). A snapshot of the properties setup window for the RPC plugin controller in Polysun is shown in Figure 23. Here, we use JSON-RPC stream server for coupling the Polysun environment with optihood. The name of the control function needs to be specified in the controller properties window. This function reads the input parameters at every time step of the Polysun simulation and evaluates the output commands (or control signals) for Polysun. Therefore, a dispatch optimization using optihood has to be invoked from within this function to determine the next control decisions for Polysun.
Moreover, the RPC controller in Polysun has an associated config file " config.properties". Some of the parameters are displayed and can be changed in the properties window of the control in the Polysun GUI. However, not all of them, in particular the timeouts aren't displayed in the Polysun GUI. These have to be set directly in the config file (to 0 if no timeout is wanted, i.e. Polysun waits without time limit for the return of the function). In order to allow Polysun to wait for the optimization to finish and the return of the control function, readTimeout and connectionTimeout were set to 0.

Updates made to the optihood framework

The optihood code was updated with respected to the latest upgraded version of the oemof.solph package (i.e. v0.5.0). The v0.5.0 of oemof.solph supports non-convex investment flows and therefore, constraints such

```
##########################################################
# CONFIG FILE TO CREATE THE INPUT SCENARIO EXCEL FILE   #
##########################################################

# NOTE: UNITS FOR ALL PARAMETERS ARE IN PER KW

[CommoditySources]
# Set True or False for each possible commodity source
# The sources which are set to True should have an associated secti
# Weather data path is also set here
electricityResource=True
naturalGasResource=False
WeatherPath=.\data\weather.csv

[electricityResource]
# CO2 impact and cost per kW should be defined here
# Either a constant value or a path to the time series could be def
Cost=0.204
Impact=.\data\electricity_impact.csv
FeedinTariff=0.09

[naturalGasResource]
Cost=0.087
Impact=0.228

[Demands]
# The program expects all the three demands (EL, SH and DHW) to be
# Path to demand profiles and whether demand profiles are fixed or
# Fixed is set to 0 if building model is used for space heating (1
# The path should contain all the demand profiles (all buildings)
Fixed=1
Path=.\data\profiles_noSH_summer_25DHW

[Transformers]
# Set True or False for each possible transformer (energy conversio
# The transformers which are set to True should have an associated
CHP=False
ASHP=True
GSHP=True
GasBoiler=False
ElectricRod=False
```

Figure 21: Example of a configuration file or config file for optimization problem definition.

as the minimum up and downtime, the minimum and maximum output power flows of an energy conversion technology. The following main updates were made to the optihood code to allow MPC functionality:

- The output flows of energy conversion technologies were defined as non-convex output flows, such that the constraints related to the minimum up and downtime, etc. can be applied. In the previous version of oemof.solph, a combination of non-convex flows with investment optimization was not possible.
- A constraint to avoid the production of both SH and DHW at the same time step by a heat pump was added. If one works with long time intervals (e.g. hours or longer), then this constraint might not be needed. However, for control optimization (i.e. MPC), where one needs to work with smaller time intervals, it is necessary. This constraint was formulated based on the `limit_active_flow_count` constraint from the upgraded oemof.solph version.
- The changes corresponding to the renaming and restructuring of modules within the oemof.solph v0.5.0 were made.

Example system for a single building (application of MPC)

The MPC control with optihood connected to Polysun is demonstrated for the case of the system represented in Figure 24. Here we have a single family house with a 12 kWp PV for the generation of electricity (in addition to the electricity grid) and a 15 kW air-water heat pump. In addition, two thermal energy storages are available: 600 L for space heating and 300 L for domestic hot water. The heat pump in the given example is non-modulating, while optihood has a modulating heat pump model by default. Therefore, a non-modulating heat pump was configured in optihood by setting the minimum and maximum power output limits in the

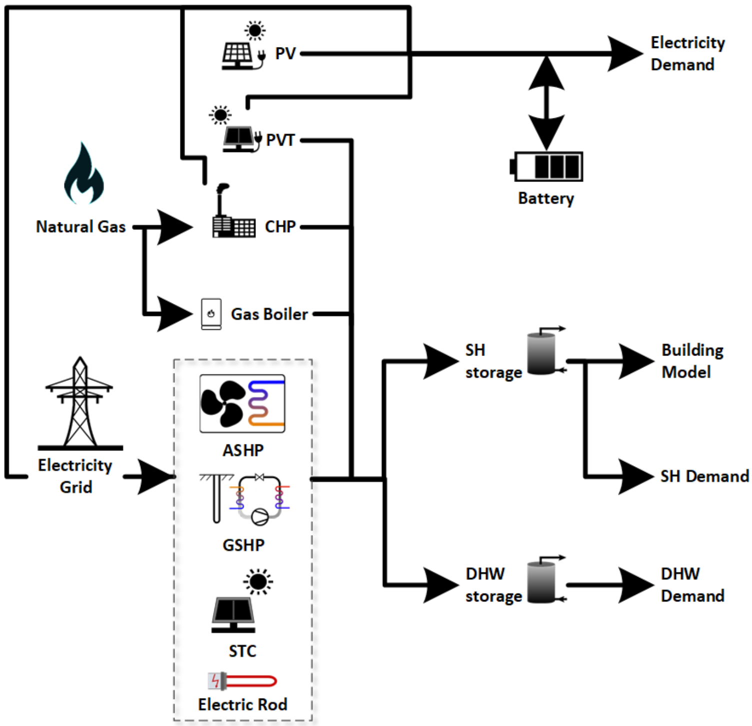

Figure 22: Default connections between different system components when a config file is used for optimization problem definition.

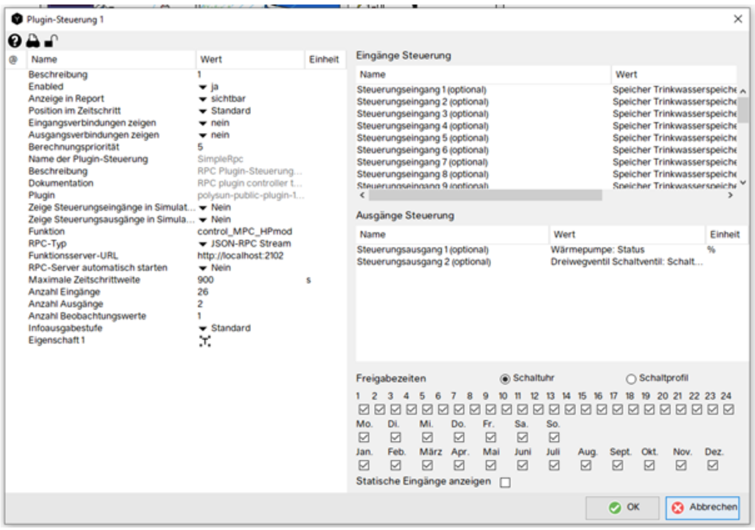

Figure 23: Snapshot of the properties window of the RPC plugin controller in Polysun.

HeatPumpLinear class to 0.99 and 1, respectively. One could easily make the heat pump modulating, by relaxing these limits, and by adding a control variable corresponding to the power of the heat pump to be used by the Polysun controller. The input scenario file for optihood is adapted by the control function before every optimization run (i.e. initial states of the storages as well as paths to weather and demand profiles are updated). The prediction files for weather and demand profiles with two-day-horizon (in 15 minute time intervals) were generated for the complete year. It would need much less input data if instead of having a new file for each 15 minute interval, we would parse a file that contains all data. However, this way was simpler to implement and is anticipated to be faster in execution. In our method, we assume perfect predictions, however, if at some point one wants to work with real (and not perfect) predictions, then there will also be a new file every 15 minutes, that will have different (updated) predictions for the same points in the future.

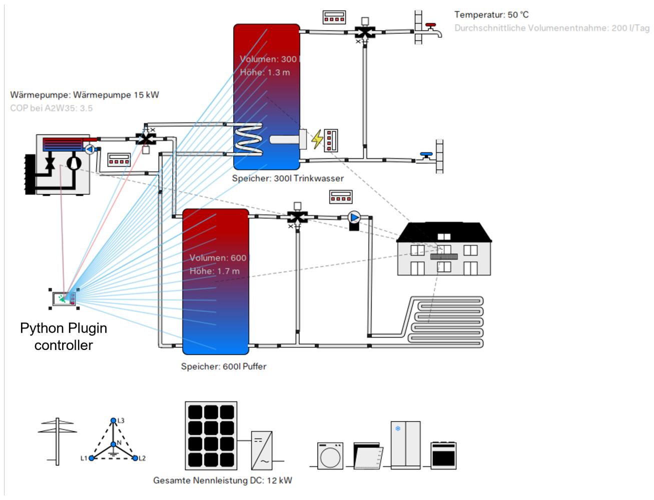

Figure 24: Schematic representation of an example system with PV, air-water heat pump, storages for space heating and domestic hot water. This system represents the space heating, hot water and electricity demands of a single building

The RPC plugin controller runs an optimization using optihood every 15 minutes. It further has exception rules, like "don't turn on the heat pump when the storage is too hot" or "do turn on heat pump when level drops below a critical level". The optimizer (optihood) works with the state of charge of the storages (here defined using the mean temperature of the storage). In this example, the optimizer runs with the goal of minimizing the energy production cost, i.e. in this case the same as minimizing the grid electricity consumption.

Figure 25 demonstrates the operation of the heat pump for the production of DHW using MPC. It can be seen that the DHW storage is charged only as soon as PV electricity is available. Moreover, the storage is fully charged around noon each day, when the available PV electricity is the highest. Grid electricity is used mainly for household electricity consumption. The use of MPC in this case results in more than 20% reduction in the total yearly grid electricity consumption, compared to a standard rule based control.

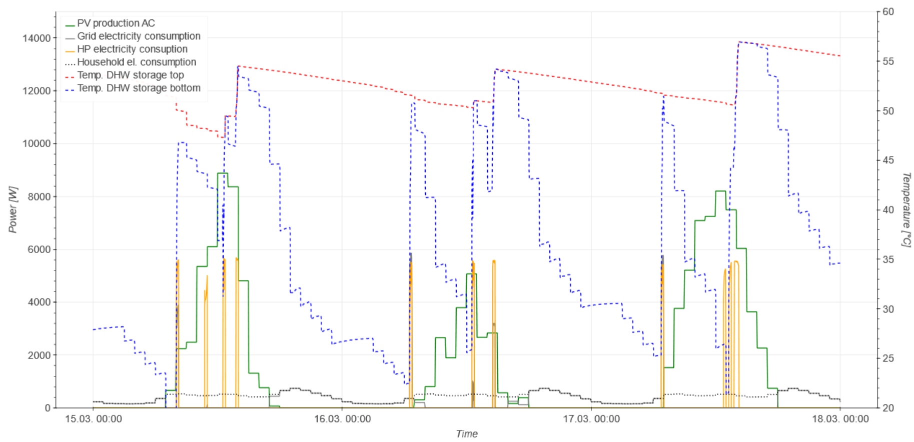

Figure 25: Operation of heat pump for DHW production using MPC control, where optihood is coupled with Polysun.

4 Evaluation of results to date

4.1 Boundary conditions and evaluation methods (WP1)

The task 1.3 provided "typical electricity year" data representing typical hourly GHG emissions profile for the swiss electricity that were generated based on weather TMY data from 24 stations in Switzerland, and from historical GHG emissions profiles of swiss electricity mix for the years 2021 and 2022 generated with EcoDynElec. The TEY data are useful in building performance assessment to assess the GHG emissions of electricity load profiles ensuring consistency between weather conditions of a TMY dataset and electricity system conditions of an historical year. The results can't be validated to historical year because they are meant to be realistic in regards to synthetic conditions from the TMY. The quality of the TEY data has been assessed through comparison with annual average GHG emissions of their respective historical years. The global representativeness is good with annual average GHG emissions coherent with observed values between 2016 and 2022. The method to generated TEY bring another positive output that was not initially planned which is the ability to generate "min" and "max" TEY profiles in a certain range of variation compared to the most representative (or "nearest") profile. The "min" and "max" TEY profile correspond respectively to -15 % to - 20 %, and +15 % to +20 % of annual average GHG emissions compared to a 6-year historical average over 2016 and 2022. Those "min" and "max" TEY profiles are practical to be used for uncertainty and sensitivity analysis in building performance assessment and optimization.

4.2 Development of modeling and optimization environment (WP2)

The optihood framework was further extended, in particular by implementing the missing energy system components namely PVT collector, discretized thermal energy storage and ice storage, improvements in the dynamic building model (including development of a simple fitting method and parameter input method), and introducing a config file for defining common optimization problems. The list of implemented technologies is now complete. In particular, the implementation of the discretized thermal energy storage with discrete temperature levels (which is a major extension to the already existing features of oemof) was highly relevant for thermal technologies to account for the temperature dependence of efficiencies. Moreover, the updated framework was maintained open source on GitHub. The optihood framework is fully functional, has been thoroughly tested (with new features being added on the go when needed) and the results are encouraging.
As a part of MS 2.2, data for GSHP was updated from the dataset of the KBOB. Moreover, data for cost and GHG emissions were gathered for PVT collectors and ice storage tanks.

4.3 Advanced energy management strategies (WP4)

The optihood framework was successfully coupled with the Polysun environment, along with passing the initial states of storage technologies, weather and demand profiles to optihood and receiving the control signals based on the optimization results in Polysun. A first test of the MPC using optihood was performed using an example of a single family house with PV, ASHP and storages for DHW and SH. In the example, we assume a fixed price of grid electricity. We anticipate that a scenario with dynamic grid electricity prices would better demonstrate the potential of MPC, with even higher savings compared to a conventional rule based control.

Tuning/matching of component models (heat pump efficiencies, storage capacities, building behaviour, etc.) between the simulation environment and the optimizer is critical. The optimizer otherwise might take wrong decisions, e.g. the optimizer thinks heat pump takes less electricity than it actually does and then it turns it on when not enough PV is available or the optimizer thinks storage is full even though it is not and decides not to charge it further, even though PV would be available. Speed of optimization is quite critical. Optimization of the system depicted in Figure 24 with a 2-day-horizon takes roughly 1 second (on simple laptop). A simulation of this system over a year now takes 10 hours on a simple laptop (the calculation time of polysun simulation is negligible). More complex systems will take considerably more time, but as a real controller it could still be fast enough.

5 Next steps

The following points will be addressed next within the specified WPs:

- WP4 (advanced energy management): Apply MPC control via optihood to small neighborhood configurations including solar thermal components and show its benefits.
- Start WP3 (system design optimization):
  - Generate load profiles for the reference neighborhoods
  - Use the framework to design optimal solar neighborhood solutions and further develop it if new functionalities are needed
- WP5 (case studies):
  - Documentation of the optimization results for the case study defined in Task 5.1.
  - Start the case study in Task 5.2.

6 Dissemination and communication

The dissemination activities of the second project year include the following:

- We presented the optihood framework at the SPF Industrietag (Industry day) on 08 March 2023. This annual event organized by SPF brings together several industry professionals and provided us with a platform for knowledge exchange/networking with industries.
- We participated in the CISBAT 2023 conference held at EPFL Lausanne, with a poster presentation, on 14 September 2023. A research paper on the optihood framework will be published in the upcoming CISBAT 2023 Special Issue of Journal of Physics: Conference Series (to be published in November).
- We secured a mandate from Energie 360° for the use of optihood to study the flexibility potential in a district heating network (which is currently in the planning stage).
- The developed framework *optihood* was maintained open-source on GitHub.

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A Appendix A

A.1 The "calepinage" class

The "Calepinage" class, implemented in Python and utilizing the "Shapely" package, offers a robust method for calculating the optimal number of panels that can be accommodated on a rectangular-shaped roof with arbitrary orientation. Specifically tailored to the geometric characteristics of a reference solar panel of width w and length l, the class employs a sophisticated algorithm. This algorithm first computes the optimal distance between rows, strategically minimizing shading during the winter solstice at the latitude of installation. Subsequently, it maximizes the utilization of available space by efficiently filling the roof with the greatest possible number of panels.

The class takes as input the following series of data, with default values provided in parentheses:

- $orientation$ (180): the orientation of the building in degrees, following the convention where 180° represents South, 90° corresponds to East, 270° indicates West, and 360°/0° denotes North;
- lat (42.6): the latitude at the center of the building roof; used to determine the optimal row distance to avoid reciprocal shadowing of the panel rows at noon on Winter solstice;
- W (10): width of the rectangular shaped roof, in $[m]$;
- L (10): length of the rectangular shaped roof, in $[m]$;
- w (1): panel width, in $[m]$;
- l (2.05): panel length, in $[m]$;
- $tilt$ (20): panel tilt, used to compute the horizontal projection of the panel in a portrait installation arrangement, in [°];
- $tilt\_EW$ (20): tilt of individual panels in an East-West installation arrangement, in [°];
- d_W (0.5): distance from the roof edge on the short side of the building, in $[m]$;
- d_L (0.5): distance from the roof edge on the long side of the building, in $[m]$;
- d (0.6): minimum distance between rows, to ensure a pathway for operational and maintenance activities, in $[m]$;
- off_pnl (0.07): collector spacing along each collector row, in $[m]$;
- f_orient (False): boolean to consider collectors oriented towards South (True) or orient them parallel to the main building axis (false);
- f_EW (False): boolean to enable (True) or disable (False) E-W installation arrangement calculations;
- f_plot (False): boolean to enable plotting the collector arrangement on the rectangular shaped roof.

The use to create an instance "Roof" of class "calpinage" for a 20 m by 10 m roof oriented 45° East to retrieve the maximum number of 2 by 0.75 m collectors that can be installed with a tilt of 33°, facing south in portrait arrangement, is as follows (see Figure A1):

$$\begin{aligned} Roof = Calpinage(orientation = 90 + 45, w = 0.75, l = 2, W = 10, L = 20, tilt = 33, \\ f\_EW = False, f\_plot = True, f\_orient = True) \end{aligned} \tag{21}$$

While the use to create the same instance for a roof oriented 15° West in East-West arrangement would be the following (see Figure A2)):

$$Roof = Calpinage(orientation = 180 + 15, w = 0.75, l = 2, W = 10, L = 20, tilt = 33, \\ f\_EW = True, f\_plot = True, f\_orient = True) \quad (22)$$

The "calpinage" class, besides providing the option to plot the surface studied, e.g. roof, and the collector arrangement, outputs the total number of panels and the ratio of roof surface covered by the collectors. It has to be noted, that each E-W collector arrangement corresponds to 2 collectors installed side-by-side at a customized tilt. As an example, in the case of Figure A1, 36 panels can fit the roof with orientation 45° E in portrait arrangement, while in the case of Figure A2, 50 panels can be installed on the 15° W oriented roof in E-W layout, featuring a coverage ratio of 31.6 % and 43.8 %, respectively.

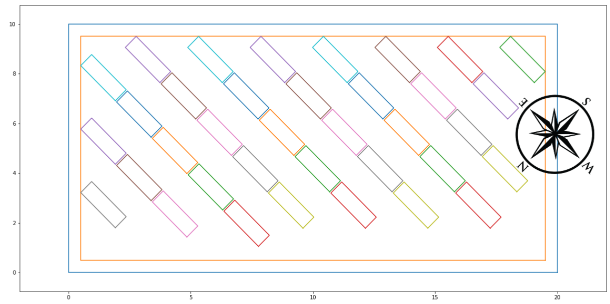

Figure A1: Graphical output of the *"Roof"* instance of class *"calpinage"* for a 20 m by 10 m roof oriented 45° East filled with 2 m by 0.75 m collectors installed with a tilt of 33°, facing south and in portrait arrangement.

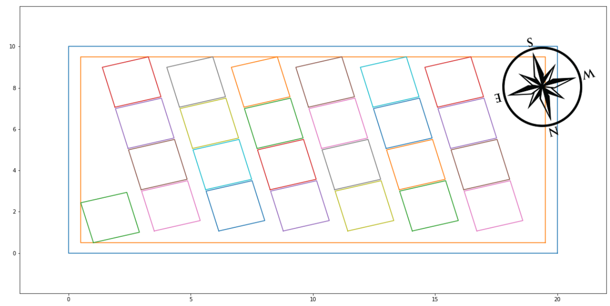

Figure A2: Graphical output of the *"Roof"* instance of class *"calpinage"* for a 20 m by 10 m roof oriented 15° West filled with 2 m by 0.75 m collectors installed in an East-West structures with default tilt.