PUSH-IT

Piloting Underground Seasonal Heat Storage In geothermal reservoirs

Deliverable 2.2

Open-source framework for LCOE and CRS assessment code and documentation

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List of Abbreviations

ATES	Aquifer Thermal Energy Storage
BTES	Borehole Thermal Energy Storage
CAC	Carbon Emission Abatement Cost
CapEx	Capital Expenditures
COP	Coefficient of Performance
DH	District Heating
EC	European Commission
HT-ATES	High-Temperature Aquifer Thermal Energy Storage
LCOE	Levelized Cost of Energy
MTES	Mine Thermal Energy Storage
MWh	megawatt-hours
NPV	Net Present Value
OpEx	Operational Expenditures
PVGIS	Photovoltaic Geographical Information System
STES	Seasonal Thermal Energy Storage
UTES	Underground Thermal Energy Storage
TVP	True Vertical Depth
WP	Work Package

1. Introduction

1.1. The PUSH-IT project

The Piloting Underground Storage of Heat In geoThermal Reservoirs (PUSH-IT) project is a four-year initiative funded by the European Union's Horizon Europe research and innovation program launched in January 2023. The project aims to showcase the full-scale applications of heat storage (up to 90°C) of three different technologies in geothermal reservoirs at six different sites with various societal, heat networks, and geologic conditions relevant across Europe.

The project will implement, develop, and test the ability of the following thermal energy technologies to store and recover heat:

1. **Aquifer Thermal Energy Storage (ATES):** This technology involves storing and recovering thermal energy in aquifers - permeable underground layers containing groundwater.
2. **Borehole Thermal Energy Storage (BTES):** BTES systems consist of a set of tubes installed vertically in boreholes, creating a large underground heat exchanger.
3. **Mine Thermal Energy Storage (MTES):** MTES utilizes water present in abandoned mines as a medium for transporting and storing heat.

PUSH-IT will implement these technologies across six European sites:

- **Delft, Netherlands:** Demonstration of ATES at depths of 200-300 meters, storing heat from a geothermal doublet (up to 80°C) integrated into a heat network for the built environment.
- **Darmstadt, Germany:** Demonstration of BTES at a depth of 750 meters in a crystalline granodioritic reservoir, connected to a university campus to store excess heat (above 50°C) from a supercomputer and summer heat surplus.
- **Bochum, Germany:** Demonstration of MTES at a depth of 120 meters, reusing summer surplus heat from a university campus (up to 80°C) to supplement the district heating infrastructure.
- **Berlin, Germany:** Follower site for ATES at a depth of 400 meters, integrating surplus heat (up to 90°C) from a wood-fired power plant into a heating network.
- **Litoměřice, Czech Republic:** Follower site for BTES at a depth of 500 meters, combining heat sources such as deep geothermal and cooling of photovoltaic panels into a field of deep boreholes, integrated into the existing heat network.
- **United Downs, United Kingdom:** Follower site for MTES at a depth of 500 meters within an abandoned mine complex, adjacent to a drilled fractured geothermal reservoir with fluid temperatures around 180°C.

With these implementations, PUSH-IT addresses societal engagement, governance, and policies, ensuring underground heat storage's safe, reliable, and economically viable integration into existing and future regulatory frameworks. It promotes the reduction of environmental impacts, levelized cost of energy (LCOE) and risks, and improved performance and robustness via developing and demonstrating several enabling technologies for seasonal heat storage.

1.2. Purpose of this document

Seasonal thermal energy storage (STES) (up to 90°C) in geological reservoirs can supply heat directly to meet the demand or be boosted in temperature with the help of a heat pump. It allows the balance of heat supply and demand by using sustainable excess heat and reduces the need for large backup capacity. It has the potential benefits of meeting heat demand, reducing LCOE, and decarbonization.

Generic, open-source, and high-performance tools are needed to assess the techno-economic performance from both storage technology and system perspectives. This document reports on the development of two tools.

1. The thermal storage tool presented here assesses the LCOE delivered from storage and quantifies its reduction due to the implementation of enabling technologies.
2. The heating system tool quantifies the potential economic benefits of adding thermal storage in a district heating system and optimize the economic performance via the dynamics among components of the heating system, e.g., supply, storage, and demand units. The tool should also allow for calculating thermal storage's carbon abatement costs (CAC) and allow for comparison with other sustainable heat technologies.

The development of the pre-mentioned tools is the key task for Deliverable 2.2. In addition to the code, this document presents the methods, process, and results of the models' development. It starts with a brief introduction to Work Package 2 and Task 2.3 and further elaborates on Deliverable 2.2. The focus of this document is on the methods and the results of tool development. It records the modelling purpose, model design, scope, mathematic equations, and required input and outputs as part of the methods. For the results, the document presents the model structure, expected outcomes, application, and limits.

2. Description of the work

2.1. WP2: General Overview and Objectives

Work Package Two (WP2) combines a dedicated application of generic methods required for the societal engagement activities (stakeholder engagement, legal framework reviewing, and LCOE reduction) at the demo and follower sites. The results from these activities will be analysed/assessed to generate general, widely applicable tools, workflow insights, and information that can be applied in future geothermal storage sites elsewhere in Europe.

The goal of WP2 is to create societal conditions that can help realize demonstration technologies as a pathway for achieving a just and sustainable energy transition. These societal conditions include stakeholder engagement, insights from the legal framework, and LCOE reduction optimization.

2.2. Task 2.3: General Overview and Objectives

The overarching objective of Task 2.3 is to develop generic, open-source, high-performance, and scalable tools to assess the LCOE reduction and carbon emission abatement costs (CAC) of heat storage in geothermal reservoirs in combination with different heat supply sources. The tools include both subsurface processes and surface systems. The following steps were established:

- Calculate the LCOE and carbon emissions level of the existing heating system without heat storage (reference to the existing heating system).
- Develop a simulation and optimization tool (open-source) to simulate the techno-economic performance of heat storage in geothermal reservoirs and optimize the LCOE and CAC of the heating system with storage. The latter should be able to capture the system dynamics of heat supply, storage operational performance, techno-economic parameters, and uncertainty of future heat demand.
- Apply the tool to the demo sites to validate the predictive capacity for LCOE and propose LCOE and CAC reduction measures based on the optimization results.
- Assess quantitative risks in business case developments. Based on the range and probability of technical and economic parameters. The probability distribution of LCOE will be provided to generate in-depth details on economic performance and facilitate risk management.
- Re-evaluate the LCOE and CAC of each demo site after the implementation. Identify the impacts of local energy policies on further reducing LCOE, e.g., tax and subsidies, with input from Task 2.2. Proposing alternative policies to reduce LCOE further.

2.3. Deliverable 2.2: Objective

Deliverable 2.2 aims to develop generic, open-source (Python), high-performance, and highly scalable tools to simulate and optimize the LCOE and cost of emission reduction. This comprises two models:

The thermal storage model is able to simulate the techno-economic performance (LCOE) of high-temperature heat storage in geothermal reservoirs at any time interval. It is highly performant and scalable to quantify uncertainties comprehensively using probability.

The heating system model includes both subsurface processes and surface systems. It captures the system dynamics of heat supply, storage operational performance, techno-economic parameters, and uncertainty of future heat demand. It simulates existing heating systems and future sustainable heating systems with and without heat storage in geothermal reservoirs as the current and future reference. The LCOE of future sustainable heating systems with heat storage is optimized, and the CAC is quantified by comparing it with the reference.

The main difference between the two models is the application scope and level of detail. The *thermal storage model* focuses on the STES and provides techno-economic details for calculating the LCOE, while the *heating system model* focuses on a heating system and provides more details on the interaction between the STES and the other components in the heating system. It calculates LCOE and CAC of the STES as well as LCOE of the heating system.

The developed tools will be applied to the project sites for LCOE reduction and risk assessment. The tools can also be used to simulate and assess ATES, BTES, and MTES applications in other locations. A simplified user interface is developed to make the interaction with the underlying code more user-friendly and accessible.

2.4. Methodology

2.4.1. Levelized Cost of Energy

In many industries, accepted methodologies are used to calculate levelized unit costs [1,2]. The levelized unit cost is the cost of producing a unit of production over the lifetime of a project. Levelized cost of energy (LCOE) is defined as the ratio of the present value of the costs to the discounted amount of energy (electricity or heat) produced over the lifetime of the asset [3].

$$LCOE = \frac{\text{Total lifetime cost}}{\text{Total lifetime energy production}} = \frac{I + \sum_{t=1}^{n} \frac{O\&M}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E}{(1+r)^t}} \qquad \text{Equation 1}$$

Where:

- I: Investment costs
- O&M: Operation and maintenance costs during period t
- E: Energy production in the period t
- r: periodic discount rate for time period t
- n: Expected asset lifetime

The LCOE formula for the thermal storage component and the whole system is introduced in the equations below.

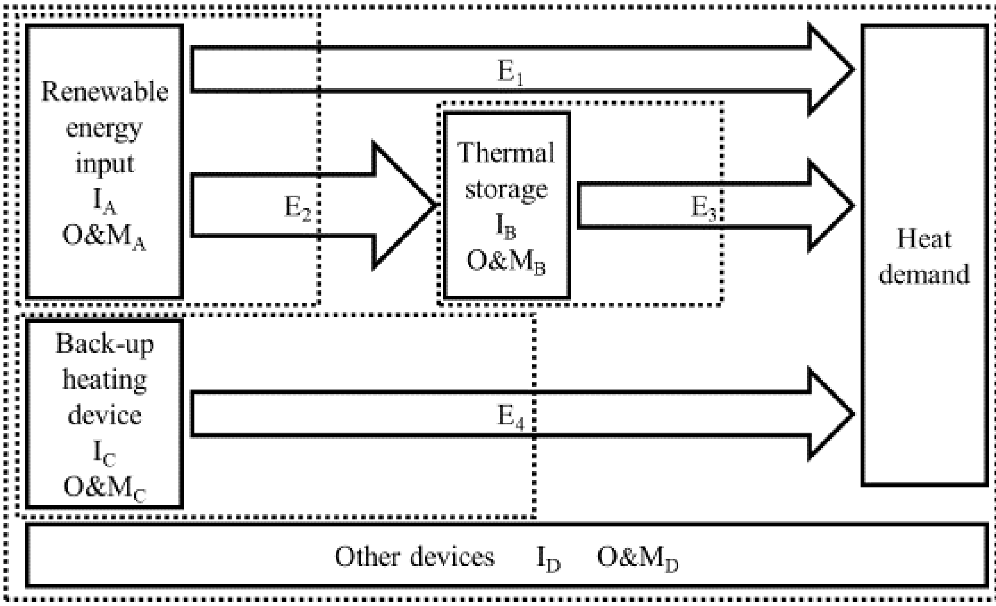

Figure 1: System boundaries for LCOE calculation in a heating system with heat storage [4]

$$LCOE_{thermal\ storage} = \frac{I_B + \Sigma_{t=1}^{n} \frac{O\&M_B}{(1+r)^t}}{\Sigma_{t=1}^{n} \frac{E_3}{(1+r)^t}} \qquad \text{Equation 2}$$

$$LCOE_{heating\ system} = \frac{I_A + I_B + I_C + I_D + \Sigma_{t=1}^{n} \frac{O\&M_A + O\&M_B + O\&M_C + O\&M_D}{(1+r)^t}}{\Sigma_{t=1}^{n} \frac{E_1 + E_3 + E_4}{(1+r)^t}} \qquad \text{Equation 3}$$

Where:

- I: the initial investment
- r: the periodic discount rate
- n: the lifetime
- O&M: the annual operation and maintenance cost
- E: the annual heat production. E1 is the heat production from the heat supply and directly goes to heat demand; E2 is the heat production from the heat supply and is stored in thermal storage; E3 is heat extraction from thermal storage, and E4 is heat production from backup units
- A, B, C, and D: the components of renewable energy supply, thermal storage, backup, and other devices, respectively.

Defining the system boundary is important to be able to apply the LCOE method to heat storage and a heating system with storage. Figure 1 shows different components in a heating system and their LCOE calculation boundaries. A sustainable heating system consists of key components, including sustainable heat supply, thermal storage, backup units, and other devices. When calculating the LCOE of thermal storage, heat production is E3, indicated in Figure 1. For LCOE of a heating system, heat production is the sum of E1, E3, and E4. The developed thermal storage model in this deliverable focuses on the storage LCOE estimation, while the heating system model estimates both storage and heating system LCOE.

2.4.2. Carbon Emission Abatement Cost

The carbon emission abatement cost (CAC) is a way to measure and compare the cost-effectiveness of decarbonization measures. In the model development, CAC quantifies the expense or financial investment associated with reducing, avoiding, or negating CO_2 emissions [5][6]. The CAC for heat storage is calculated as follows.

$$CAC = \frac{LCOE_{system1}}{EF_{system1}} - \frac{LCOE_{system2}}{EF_{system2}} \qquad \text{Equation 4}$$

Where $LCOE_{system1}$ and $LCOE_{system2}$ are the LCOE for the heating system with and without heat storage, respectively. As shown in Figure 1, system 1 is defined as the heating system with the components of heat supply units (A), thermal storage (B), backup units (C), and other devices (D), while system 2 is defined as the heating system without thermal storage, only components of A, C, and D.

EF is the emission factor, calculated as:

$$EF = \frac{\Sigma_{t=1}^{n} \frac{CO_{2,s,t}}{(1+r)^t}}{\Sigma_{t=1}^{n} \frac{E_{s,t}}{(1+\gamma)^t}} \qquad \text{Equation 5}$$

Where $CO_{2,s,t}$ are the total CO_2 emissions of the system in time period t, calculated by summing the CO_2 of the individual components. E is energy production in time period t, and r is the periodic discount rate for time period t. This calculation only takes into account the CO_2 emitted during the operation of the system.

As defined in the equation 5, CAC measures the cost-effectiveness of decarbonization measures from the system perspective. Therefore, the calculation of CAC only applies to the heating system model.

3. Techno-economic tool: thermal storage model

In the PUSH-IT project, several studies are underway to enhance the techno-economic viability of underground thermal energy storage (UTES) systems. These efforts include assessing alternative technologies, such as expanded well diameters and composite casings, exploring optimized control strategies for various designs, and dimensioning systems to meet seasonal heat demands efficiently. Additionally, evaluating carbon abatement costs within multi-component system designs will enable comparisons between UTES and other heating methods, thereby quantifying both economic and environmental benefits.

To effectively support these studies, a flexible, fast, and open-source software tool was developed. The techno-economic assessment tool for heat storage is implemented as an open-source Python code that integrates both technical and financial modelling to evaluate heat storage systems. The tool is designed to accommodate three heat storage technologies: Aquifer Thermal Energy Storage (ATES), Borehole Thermal Energy Storage (BTES), and Mine Thermal Energy Storage (MTES) (Figure 2). Each strategy fundamentally relies on well operations, making it essential to incorporate not only economic parameters but also key operational data of the wells.

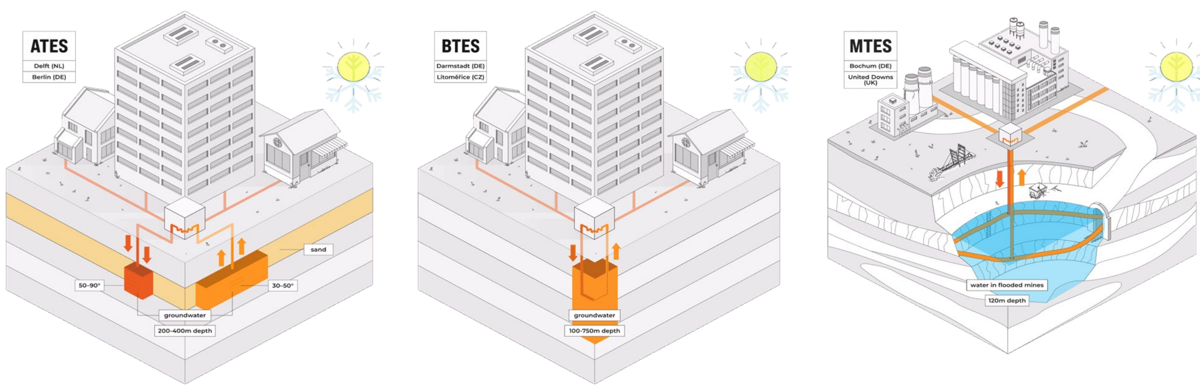

Figure 2: Heat storage strategies in the project.

(Each storage strategy relies on well operations, making it essential to incorporate both economic parameters and key operational data from the wells.)

The details of the code framework are provided in the following sections. In Section 3.1, the procedures for data pre-processing, including unit conversion and time interpolation, as well as the core physical calculations for pump power and heat production, are described. This section also details the economic analysis, which encompasses discounted cash flow, recurring cost calculations, and Monte Carlo simulations to assess uncertainty. In Section 3.2, the generic simulation outputs are presented, including time-series plots of key operational metrics and financial indicators such as Net Present Value (NPV) and Levelized Cost of Energy (LCOE), along with visualizations that demonstrate Monte-Carlo simulation.

3.1. Methods

The open-source geothermal techno-economic assessment code (GTEcon) for heat storage is structured into three primary modules: a default input module, a core computational module, and an execution module. These are organized respectively in the scripts "*default_input_class_GTEcon.py*", *"GTEcon_module.py"*, and *"run_GTEcon.py".* The code can be found on GitHub (https://github.com/taylan-akin/GTEcon.git).

The streamlined workflow of the code is illustrated in Figure 3.

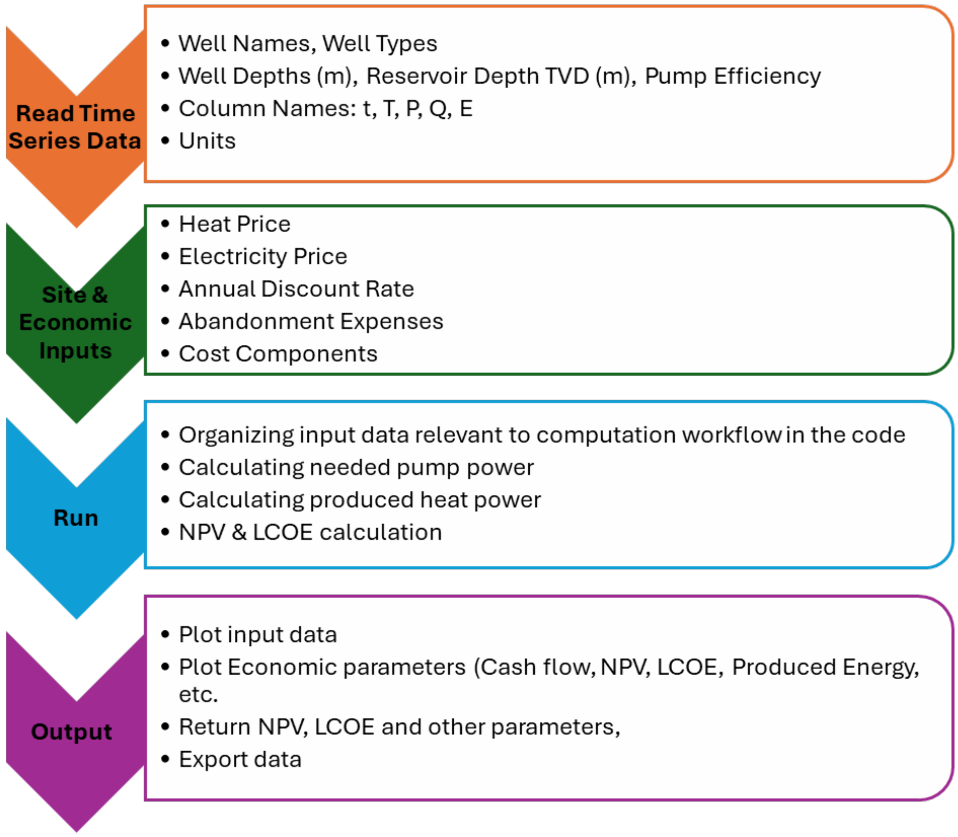

Figure 3: Workflow of the code

In the first step, time-series data of well operations (including well depths, reservoir depth, pump efficiency, and column headings for temperature, pressure, and flow rate) are read into the model. Next, site and economics-related parameters are assigned, such as heat price, electricity price, annual discount rate, and the appropriate cost components. Once these inputs are specified, the tool organizes and processes the data, computes the required pump power and heat production, and performs discounted cash flow analyses to determine key financial indicators such as NPV and LCOE. Finally, it generates both numerical and graphical outputs, including plots of the input and economic parameters, and generates an output file summarizing the results. The following subsections detail each stage of this process.

3.1.1. Data Handling and Pre-processing

Well Data

Well design and time series of operation data must be provided as input to the code. Specifically, pressure (P), temperature (T), and volumetric flow rate ($\dot{V}$) for each warm and hot well must be provided. These data can be retrieved from the Supervisory Control and Data Acquisition (SCADA) system of any UTES in operation or from predictive simulation results. In addition to the time series, well type (hot well: H, warm well: W), pump efficiencies, column names in the time series (P, T, $\dot{V}$) and the true vertical depth (TVD) of the reservoir section in each well must be assigned as well. An example template of well data is given in Table 1.

Table 1: Example of Well Data

Well Names	Well Type	Well Depth (m)	TVD (m)	Pump Efficiency	T	P	$\dot{V}$
H1	H	180	155	0.5	H1: temperature (K)	H1: BHP (bar)	H1 : water rate (m^3/day)
H2	H	180	155	0.5	H2: temperature (K)	H2: BHP (bar)	H2 : water rate (m^3/day)
H3	H	180	155	0.5	H3: temperature (K)	H3: BHP (bar)	H3 : water rate (m^3/day)
L1	W	180	155	0.5	L1: temperature (K)	L1: BHP (bar)	L1 : water rate (m^3/day)
L2	W	180	155	0.5	L2 : temperature (K)	L2 : BHP (bar)	L2 : water rate (m^3/day)
L3	W	180	155	0.5	L3 : temperature (K)	L3 : BHP (bar)	L3 : water rate (m^3/day)
L4	W	180	155	0.5	L4 : temperature (K)	L4 : BHP (bar)	L4 : water rate (m^3/day)

The code reads time-series data of well operation parameters from Excel files or direct arrays in Python. The user may have their own template for the well data. Assigning column names enables the code to identify the relevant data column in the input Excel file and preprocess the data for subsequent calculations.

Units

The model employs default units for all calculations. The code accepts inputs in any units for the appropriate variables and converts them internally to the default units: time in years, temperature in degrees Celsius, pressure in bar, and flow rate in cubic meters per day (m^3/day). Since the code is flexible and can read time series data in any order, the units in the input files need to be defined. If the defined units differ from the default ones, they are automatically converted to ensure consistency in data processing and accurate unit conversion throughout the analysis. The units of the input data can be specified by the user in the well-input settings.

Economic Inputs

The next stage involves the assignment of economic parameters. Key values such as the heat price, electricity price, and annual discount rate are specified. In addition, a detailed breakdown of cost components can be entered. Each cost component is defined by its unit cost, quantity, and replacement interval. If the cost parameter is an OpEx item, its recurrence frequency (replacement interval) must be greater than zero, indicating the interval after which the cost will occur again. If a value of zero is assigned to any cost item, it is classified as CapEx. This detailed economic input framework allows the model to automatically categorize expenses as either capital expenditures (CapEx) or recurring operating costs (OpEx) based on their replacement intervals. These inputs serve as the basis for calculating discounted cash flows and for deriving key financial indicators, including Net Present Value (NPV) and Levelized Cost of Heat (LCOE).

3.1.2. Pump Power Calculation

For each well, the required pumping power is determined by calculating the pressure differential between the reservoir pressure and the sum of the water column in the well, friction loss, and surface pipeline pressures.

$$\Delta p = p_{wc} + p_{fric} + p_{pl} - p_{reservoir} \qquad \text{Equation 6}$$

This equation defines the net pressure difference (Δp) that the pump must overcome. $p_{reservoir}$ represents the undisturbed pressure in the reservoir, p_{wc} is the water column in the well, p_{fric} accounts for pressure losses due to friction, and p_{pl} is the desired pipeline pressure.

$$p_{wc} = \rho g TVD \qquad \text{Equation 7}$$

This equation calculates the hydrostatic pressure (p_{wc}) exerted by the water column in the well. Here, ρ represents the density of water, which may vary with temperature, g is the acceleration due to gravity (typically ≈9.81m/s²), and TVD (True Vertical Depth) is the vertical distance from the surface to the reservoir section of the well. The hydrostatic pressure is a function of the water column's height and density, assuming a uniform gravitational field.

The friction pressure loss in the well is calculated using the Darcy–Weisbach equation, which quantifies the pressure drop due to friction in a pipe. The friction loss is given by:

$$p_{fric} = f\frac{8\dot{m}^2 L}{\pi^2 D^5 \rho} \qquad \text{Equation 8}$$

where $\dot{m}$ represents the mass flow rate (kg/s), L denotes the well length (m), D is the diameter of the well (m), ρ corresponds to the fluid density (kg/m³), f is the friction factor.

The friction factor f is determined by solving the Colebrook–White equation:

$$\frac{1}{\sqrt{f}} = -2\log_{10}\left(\frac{\varepsilon}{3.7D} + \frac{2.51}{Re\sqrt{f}}\right) \qquad \text{Equation 9}$$

with the Reynolds number defined as:

$$Re = \frac{4\dot{m}}{\pi D\mu} \qquad \text{Equation 10}$$

where ε is the pipe roughness (m), and μ is the dynamic viscosity of the fluid. The Colebrook–White equation is solved iteratively using SciPy's solve, which yields the friction factor f. With f determined, the friction loss (p_{fric}) is computed using the Darcy–Weisbach formula.

The pumping power is then calculated by:

$$P_{pump,\ well} = \frac{\Delta p\dot{V}}{\eta} \qquad \text{Equation 11}$$

where, $\dot{V}$ is the volumetric flow rate (m³/s), and η is the pump efficiency (-) which can be assigned separately to each well.

Total power required by the pumps is calculated by:

$$P_{pump,\ total} = \sum_{i=1}^{n_{well}} P_{pump,\ i} \qquad \text{Equation 11}$$

Thermal Power Calculation

In order to calculate the heat power at each well, the code first determines the thermodynamic energy carried by the flowing water. Using the IAPWS97 formulation [7], the tool calculates water density and enthalpy based on the temperature and pressure at each well. These thermodynamic properties, together with the flow rate, are used to compute the instantaneous heat power at each well for each time step. The instantaneous heat power in each well is computed according to the following equation:

$$P_{heat,\ well} = \dot{V}\rho h \qquad \text{Equation 12}$$

where $\dot{V}$ is the volumetric flow rate (m³/s), ρ is the water density (kg/m³), and h is the enthalpy (J/kg). The default unit of the calculated heat power ($P_{heat,\ well}$) is in MW.

After well heat powers are computed, the code aggregates the thermal power for each well classified as hot and warm. Specifically, the total heat power for hot wells is calculated as

$$P_{hot,\ total} = \sum_{i=1}^{n_H} P_{heat,i}^{hot} \qquad \text{Equation 13}$$

and for warm wells as

$$P_{warm,\ total} = \sum_{j=1}^{n_W} P_{heat,j}^{warm} \qquad \text{Equation 14}$$

In these equations, n_H represents the number of hot wells and n_W represents the number of warm wells. The term $P_{heat,i}^{hot}$ denotes the heat power calculated for the *i-th* hot well, while $P_{heat,j}^{warm}$ represents the heat power for the *j-th* warm well.

We use the convention of a positive sign to mass inflow (representing injection) and a negative sign to mass outflow (representing production) as in reservoir modeling. During the charging phase, the calculated heat power is positive for a hot well and negative for a warm well due to the assigned flow rate sign. Conversely, during the discharging phase, the signs are reversed. The developed code requires users to input the flow rate according to this convention.

Since $|P_{hot,\ total}|$ is always greater than $|P_{warm,\ total}|$ in both charging and discharging modes, the net heat charge power (P_{charge}) and the net heat discharge power ($P_{discharge}$) can be derived as the difference of $|P_{hot,\ total}|$ and $|P_{warm,\ total}|$.

For charging mode;

$$P_{charge} = \begin{cases} |P_{hot,\ total}| - |P_{warm,\ total}|, & P_{hot,\ total} > 0 \\ 0, & P_{hot,\ total} < 0 \end{cases} \qquad \text{Equation 15}$$

For discharging mode;

$$P_{discharge} = \begin{cases} |P_{hot,\ total}| - |P_{warm,\ total}|, & P_{hot,\ total} < 0 \\ 0, & P_{hot,\ total} > 0 \end{cases} \qquad \text{Equation 16}$$

Using the absolute values is preferred to prevent errors in the calculation of the heat power when the sign convention is not strictly followed by the user in the input file.

Net Produced Power

The net power available from the system is defined as the effective thermal output after subtracting the energy consumed by the pumps from the total heat production. This quantity is represented by P_{net} and is calculated according to the following formula:

$$P_{net} = P_{discharge} - P_{pump,\ total} \qquad \text{Equation 17}$$

In the charging period P_{net} is negative, meaning that the UTES system consumes pump power without producing any heat power. This net power calculation, performed for each time step, provides a dynamic measure of the system’s effective energy output.

Coefficient of Performance (COP)

The COP is determined by taking the ratio of the heat production power to the pump power consumption. Mathematically, this is expressed as:

$$COP = \frac{P_{discharge}}{P_{pump,\ total}} \qquad \text{Equation 18}$$

where $P_{discharge}$ represents the heat power generated during production mode (in megawatts) and $P_{pump,\ total}$ denotes the total power consumed by the pumps (in megawatts). A higher COP indicates a more efficient system, as it means that a greater amount of thermal energy is produced for each unit of energy consumed by the pumps.

Net Produced Energy

The energy produced for each step is determined by multiplying the instantaneous heat production power by the duration of that time interval. This calculation yields the energy produced during each time step, expressed in megawatt-hours (MWh). Mathematically, the produced energy at the *i-th* time step is given by;

$$E_{produced,i} = P_{discharge,i}\ \Delta t_i \qquad \text{Equation 19}$$

where $P_{discharge,i}$ represents the heat production power (in MW) during the *i-th* time step and Δt_i is the duration of that time step (in hours).

3.1.3. Economic Analysis

The economic evaluation is carried out using a discounted cash flow approach to assess the financial viability of the heat storage system. In this process, the code integrates various economic inputs with operational data to compute key financial metrics. Initially, revenue is determined by multiplying the produced energy by the specified heat price. Capital expenditure is then established, and recurring costs associated with system components are incorporated based on user-defined replacement intervals.

Subsequently, the code assesses operating costs, particularly those related to pump energy consumption, by combining pump power data with the electricity price over each time step. The resulting cash flow is derived by subtracting these expenditures from the generated income. To account for the time value of money, the cash flows are discounted using the provided annual discount rate, which enables the computation of the Net Present Value (NPV).

Finally, the Levelized Cost of Energy (LCOE) is determined by comparing the cumulative discounted costs with the cumulative discounted energy production. This comprehensive approach yields crucial insights into the system's cost-effectiveness and financial risks, forming the foundation for further economic evaluation. Detailed descriptions and corresponding formulas are presented in the subsequent sections.

Income

The income generated from the system is determined by multiplying the total produced energy by the heat price. At each time step, the income is calculated as the product of the energy produced during that time step and the heat price. This is expressed by the formula

$$I_i = E_{produced,i}\ H_{price} \qquad \text{Equation 20}$$

where I_i is the income generated at the *i-th* time step, $E_{produced,i}$ represents the produced energy in megawatt-hours (MWh) during that interval, and the heat price (H_{price}) given by the user in euros per MWh. The total income over the entire simulation period is then obtained by summing the income across all time steps:

$$Income = \sum_{i=1}^{n} I_i = \sum_{i=1}^{n} \left(E_{produced,i}\ H_{price}\right) \qquad \text{Equation 21}$$

This calculation yields the overall revenue from thermal energy output, which is a key input for subsequent financial analyses, such as cash flow and net present value evaluations.

Recurring Cost Calculation

The economic model incorporates recurring costs to account for expenses that reoccur over the system's lifetime, such as maintenance or periodic component replacements. These costs are added to the cost parameter ($Cost_i$) at regular intervals defined by a recurring frequency, expressed in years. Costs are automatically classified as CapEx or OpEx based on their recurrence frequency. Recurring cost items are added at intervals corresponding to their specified replacement periods. A cost with a recurrence interval of 0 is treated as CapEx, while nonzero intervals trigger periodic additions to the cost stream of OpEx.

Pump OpEx

The operating expenditure associated with the pumping process is calculated at each time step. At the *i-th* time step, the pump operating expenditure is determined by multiplying the total pump power consumption for that interval, the duration of the time step, and the electricity price. This is expressed by the formula

$$OpEx\_pump_i = P_{pump,total,i}\, \Delta t_i\, E_{price} \qquad \text{Equation 22}$$

where $P_{pump,total,i}$ is the aggregated pump power (in megawatts) at the *i-th* time step, Δt_i is the duration of the *i-th* time step (in hours), and the electricity price (E_{price}) is provided in euros per megawatt-hour. The total operating expenditure for pumping is then obtained by summing $OpEx\_pump_i$ over all time steps.

Cash Flow

The model computes the net cash flow at each time step by combining the cash inflows and outflows associated with the system's operation. At the *i-th* time step, the cash flow is determined by subtracting the expenditures from the calculated income. This relationship is expressed as

$$CF_i = I_i - Cost_i - OpEx\_pump_i \qquad \text{Equation 23}$$

In this formula, $Cost_i$ represents the recurring expenditure allocated at the *i-th* time step. This per-interval calculation of cash flow is a crucial component in the overall financial analysis, serving as the basis for further metrics such as Net Present Value (NPV) and the Levelized Cost of Energy (LCOE).

Discount Factor Calculation

The periodic discount rate (r_{per}) is calculated based on the elapsed time. The discount factor is computed as:

$$r_{per}(t) = (1 + r)^{\frac{t}{365}} \qquad \text{Equation 24}$$

where r is the annual discount rate, and t is the elapsed time in days.

Net Present Value (NPV)

The cumulative NPV is determined by discounting the cash flow (CF_t) at each time step:

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{r_{per}(t)} \qquad \text{Equation 25}$$

Levelized Cost of Energy (LCOE)

The LCOE is computed as the ratio of cumulative discounted costs to the cumulative discounted energy produced. The equation is introduced in section 2.4.

3.1.4. Monte Carlo Simulation

The Monte Carlo analysis is designed to assess the sensitivity of the economic evaluation to uncertainties in key parameters. In this process, the code randomly samples constant values for the annual discount rate, heat price, and electricity price from normal distributions defined by user-specified means and standard deviations. For each Monte Carlo iteration, the sampled values are held constant over the entire period of assessment, and the model recalculates the economic performance, resulting in a corresponding NPV and LCOE

By performing a large number of iterations, the analysis generates a probabilistic distribution of both NPV and LCOE. In addition, a bootstrap-based convergence analysis is conducted to evaluate the stability of these metrics, with the 10^{th}, 50^{th}, and 90^{th} percentiles being computed for further insight into the range and reliability of the results. Visualizations, such as scatter plots of the input parameters and convergence plots for NPV and LCOE, are produced to facilitate risk assessment. These outputs allow decision-makers to understand the potential variability in the system's financial performance and to evaluate its economic robustness under different scenarios.

3.1.5. Visualization and Output

Comprehensive plotting routines are integrated to facilitate both input data review and output analysis:

- Input Visualization: Graphs display the time evolution of well temperatures, pressures, flow rates, and derived quantities such as pump power.
- Output Visualization: Detailed plots of the calculated financial metrics (e.g., NPV and LCOE) and their convergence during Monte Carlo simulations are generated.
- Export: Results are automatically exported to Excel files, ensuring that both numerical and graphical outputs are readily available for further analysis and validation.

3.2. Model application

The application of the thermal storage model yields comprehensive outputs that capture both the dynamic physical performance of the heat storage and its financial viability over time.

3.2.1. Input Data Overview

The code generates a set of visual summaries that help to validate and inspect the quality of the input data (Figure 4). In this stage, key parameters such as temperature, flow rate, pressure, and pump pressure differential are plotted against time. For each parameter category, the function produces a dedicated subplot where the continuous time series is displayed. Additionally, any data points that have been introduced via interpolation (to fill gaps in the original time series) are highlighted with distinct markers, enabling the user to easily identify and assess these adjustments. This graphical overview not only confirms that the necessary unit conversions and data pre-processing steps have been correctly applied, but it also provides an immediate visual check on the consistency and completeness of the well input data.

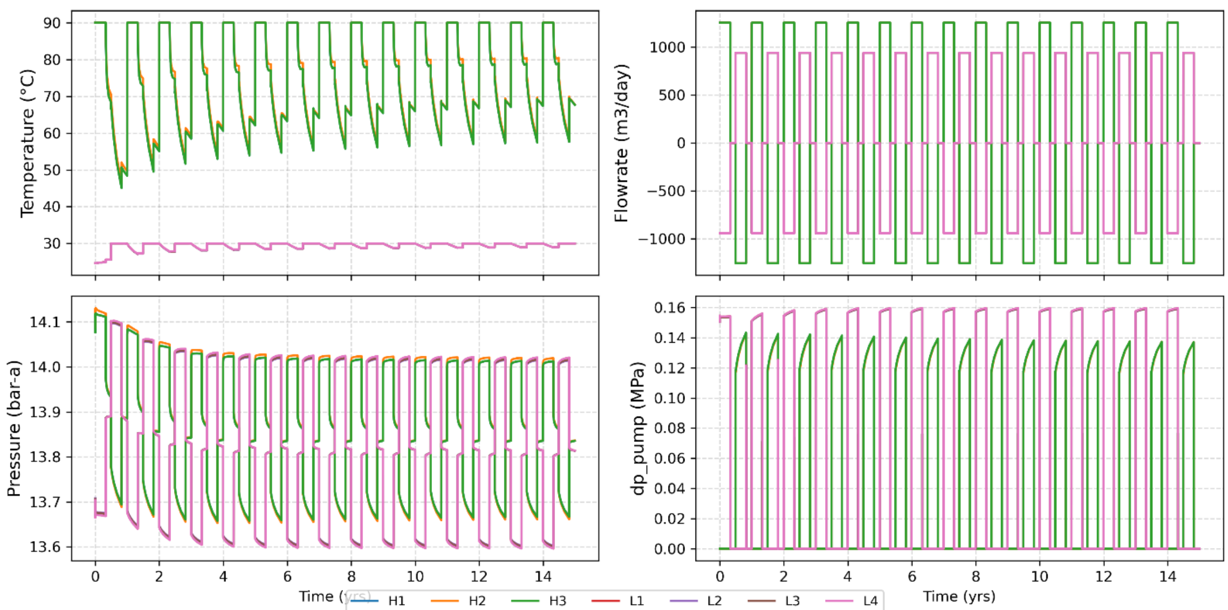

Figure 4: Overview of input data, demonstrated with time-series input from an HT-ATES system

3.2.2. Plotting Techno-Economic Parameters

The code provides a comprehensive visual summary of the simulation results, presenting key operational and financial indicators in a structured format (Figure 5). The code generates a multi-panel figure where each subplot focuses on a distinct performance metric. The first subplot illustrates the pump power for each well along with the aggregated total pump power, enabling a clear comparison between individual contributions and the overall system demand. The next subplot displays the produced net power, which is calculated as the difference between heat production and pump power consumption at each time step, thereby highlighting the system's effective energy output.

Further, the code generates subplots that show economic performance: one subplot presents the income generated from heat production over time, while another shows the cash flow, providing insight into the balance of inflows and outflows. In addition, the net present value (NPV) is visualized in a dedicated subplot, scaled appropriately to reflect its magnitude. The final subplot displays the LCOE, which is critical for assessing the cost-effectiveness of the storage system. Annotations, such as highlighting the final LCOE value at the last time step, are added to facilitate interpretation of the results.

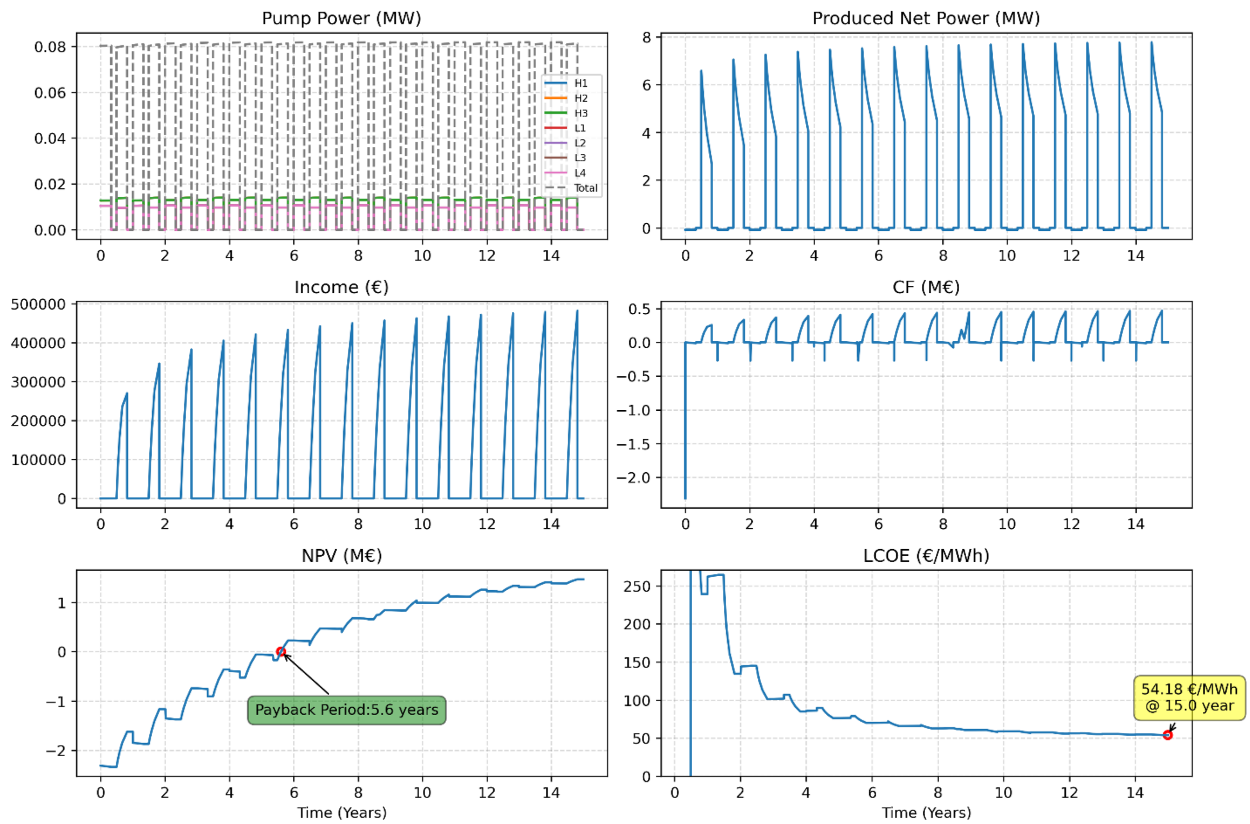

Figure 5: Overview plot of techno-economic parameters

Overall, these output plots serve not only as a validation tool for simulation but also as a means to communicate the system's performance in both physical and economic terms, thereby supporting a thorough evaluation of the techno-economic viability of the heat storage system.

3.2.3. Monte Carlo Simulation and Uncertainty Analysis

In the Monte Carlo simulation, the code generates a series of graphs that visually communicate both the variability of key economic inputs and the convergence of the resulting performance metrics. First, an overview plot is produced that consists of multiple subplots arranged in a grid. These subplots display scatter plots for each iteration, showing the randomly sampled values for the annual discount rate, heat price, and electricity price. In addition, scatter plots of the final LCOE and NPV are included, thereby illustrating how the uncertainty in the inputs translates into variability in the economic outputs (Figure 6).

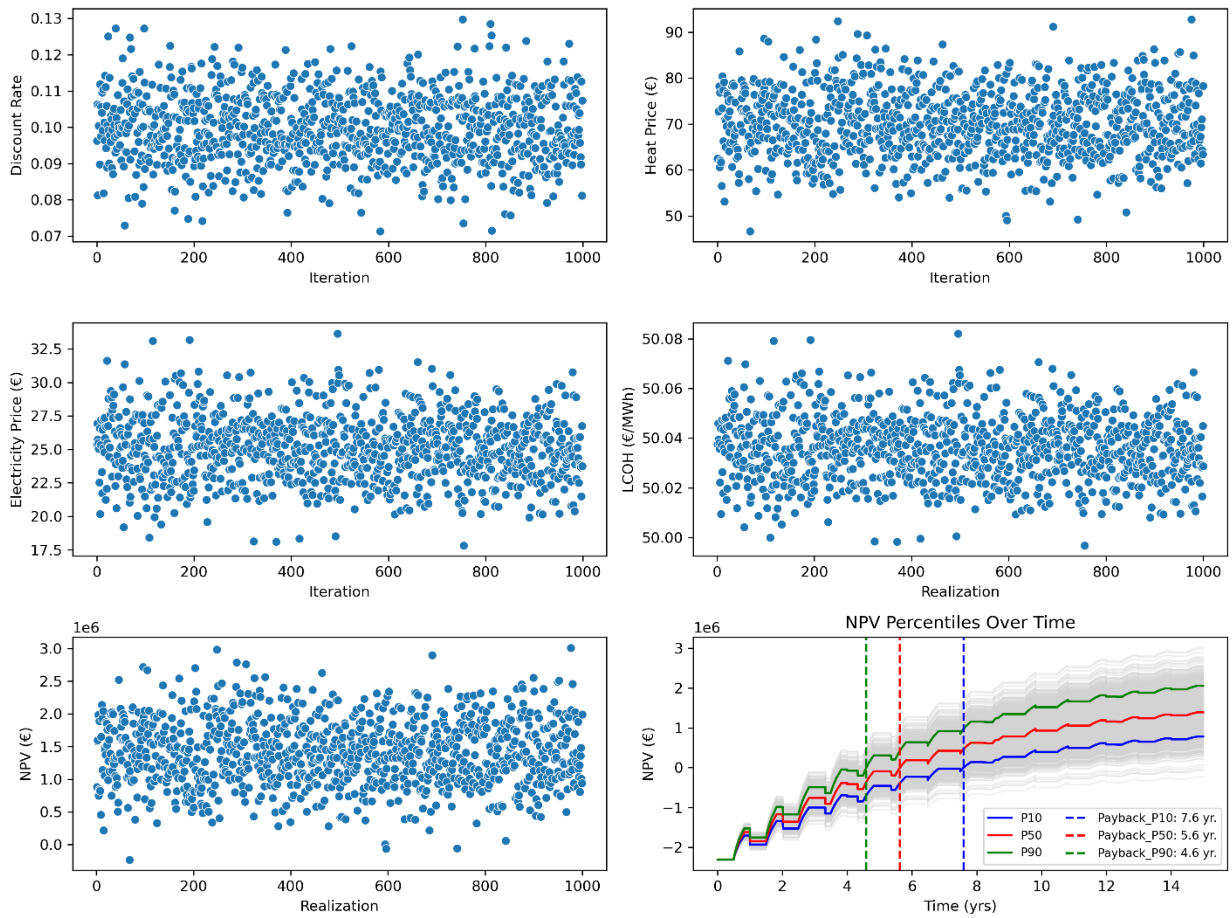

Figure 6: Scatter plots of key economic inputs (annual discount rate, heat price, and electricity price) along with the resulting LCOE and NPV for 1,000 Monte Carlo iterations.

(The lower-right subplot depicts how the NPV evolves over time for each realization, highlighting the variability in financial performance)

Following this, a convergence plot is generated to assess the stability of the simulation outcomes (Figure 7). In this plot, the bootstrap method is applied by repeatedly resampling the NPV and LCOE values, and calculating the cumulative averages as the number of iterations increases. The 10^{th}, 50^{th}, and 90^{th} percentiles of these cumulative averages are calculated and then plotted as functions of the iteration count. The convergence curves clearly demonstrate that as the number of iterations increases, both NPV and LCOE approach stable, reliable values. This convergence confirms the robustness of the simulation and provides confidence in the probabilistic estimates of the economic performance.

The graphical outputs of the Monte-Carlo Simulation serve a dual purpose: they act as a diagnostic tool to verify that the simulation is performing as expected and as a means to communicate the uncertainty and convergence behaviour of the key financial metrics.

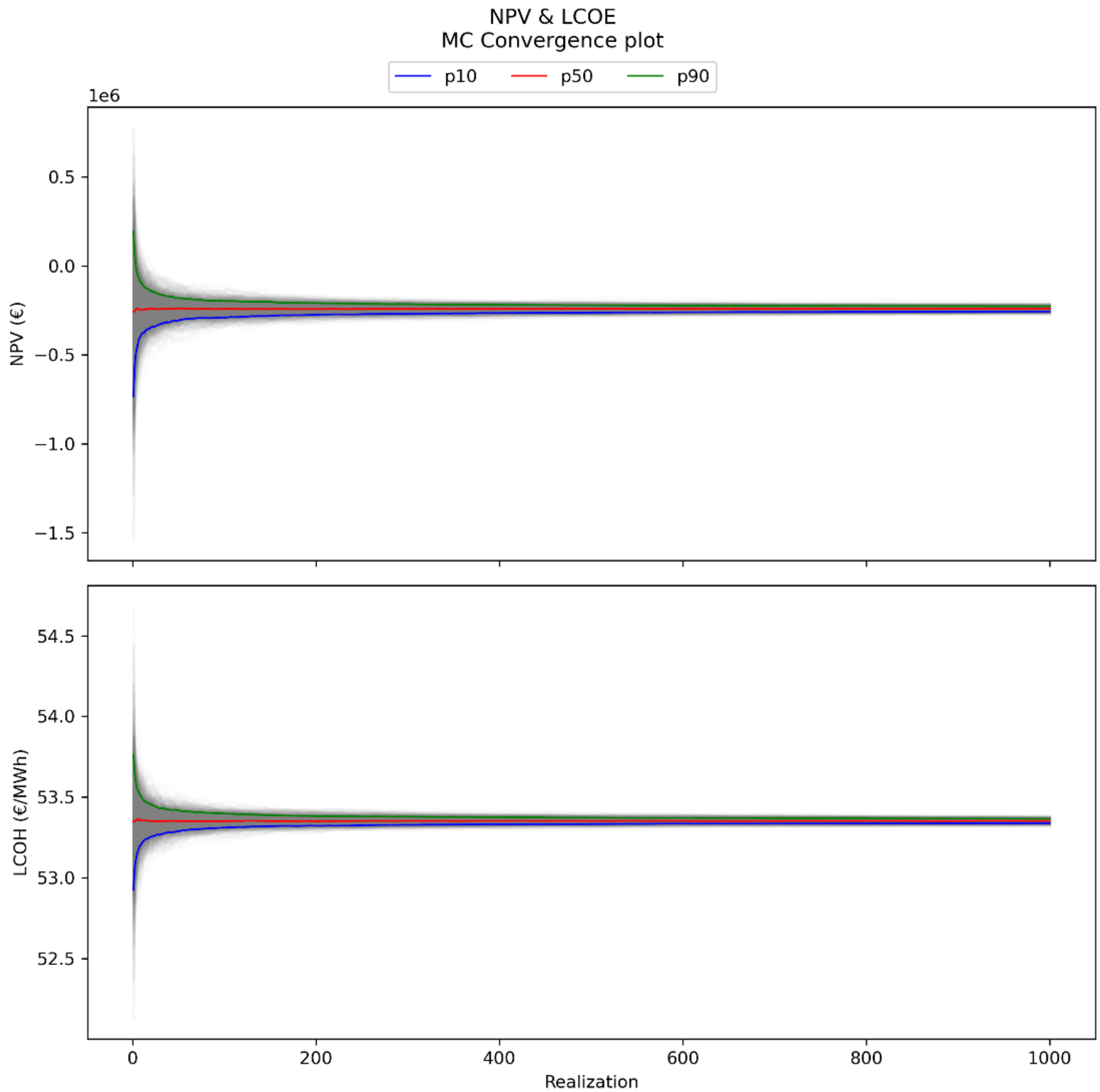

Figure 7: Convergence plots for NPV and LCOE based on Monte Carlo simulations.

(The P10, P50, and P90 lines show the progressive stabilization of these metrics as the number of iterations increases, providing confidence in the probabilistic estimates of the system's economic viability)

3.3. Limitations

In its current implementation, the code is highly dependent on the quality and resolution of the input data. Parameters such as flow rates, pressures, temperatures, and economic variables must be accurate and consistent since any inaccuracies or missing data points can propagate through the calculations and adversely affect the reliability of the results. The code includes internal control measures that verify the consistency of the input in terms of temperature and flow rate. This internal check logs any inconsistency to inform the user but does not terminate the calculation.

Another limitation stems from the thermodynamic assumptions. Although the code uses the IAPWS97 formulation to determine water properties, it assumes single-phase flow and does not account for more complex fluid behaviours, such as phase changes or non-ideal fluid interactions.

Consequently, the tool may not be suitable for applications where multi-phase flow or significant compositional effects are expected.

In addition, the current version does not simulate broad network interactions. It focuses on techno-economic metrics for an individual storage technology utilizing an arbitrary number of wells, but may not capture the complexities of a larger thermal network or district heating system with multiple components. Users requiring a more holistic assessment of network-level dynamics would need to couple this code with additional modelling tools.

The accuracy of the code outputs is also influenced by the temporal resolution of the user's input data. It inserts missing time points through interpolation, but if the original dataset has coarse time intervals, the computed results will also be relatively coarse. Conversely, a finer time interval can yield more detailed and potentially more accurate outcomes, although it may increase computational demands. Users should, therefore, balance data availability, computational efficiency, and the desired level of temporal detail when preparing input files.While the code can handle Monte Carlo simulations for moderate problem sizes, very large datasets or extremely fine time discretisations may lead to long run times in a standard Python environment. Additional optimization or parallelization might be necessary for users aiming to perform high-resolution analyses or a large number of stochastic simulations.

The modular design of the code allows users to integrate it seamlessly into their own algorithms and workflows. This flexibility means that the tool can be invoked repeatedly for different scenarios, enabling users to perform sensitivity analyses or parameter sweeps efficiently. Moreover, the design facilitates automated logging of results, so that outcomes from multiple runs can be compared or aggregated for further analysis. In addition, since the code creates outputs in standard data formats, users can readily apply their own custom templates and visualization tools to plot the results, thereby tailoring the analysis to meet specific reporting or research requirements. This capability significantly enhances the tool's versatility and applicability across a wide range of techno-economic assessments.

Overall, these properties of the code underscore the importance of carefully preparing input data and selecting suitable modelling assumptions for each specific scenario. By recognizing and addressing these constraints, users can make more informed decisions about the applicability of the code to their techno-economic assessments of underground heat storage systems.

4. Techno-economic tool: heating system model

4.1 Methods

The purpose of the open-source techno-economic code is to model a district heating (DH) system and assess the techno-economic performance and carbon abatement costs of the system. The model calculates the corresponding LCOE of both the system and the individual components. The scope of the model is one DH system. This DH system consists of components that produce or store heat. This heat is delivered to the heat demand. The conceptual idea of the heat flow within the DH system is shown in Figure 8. The model can be found on GitHub (https://github.com/dayfix/System-Modelling-HT-ATES).

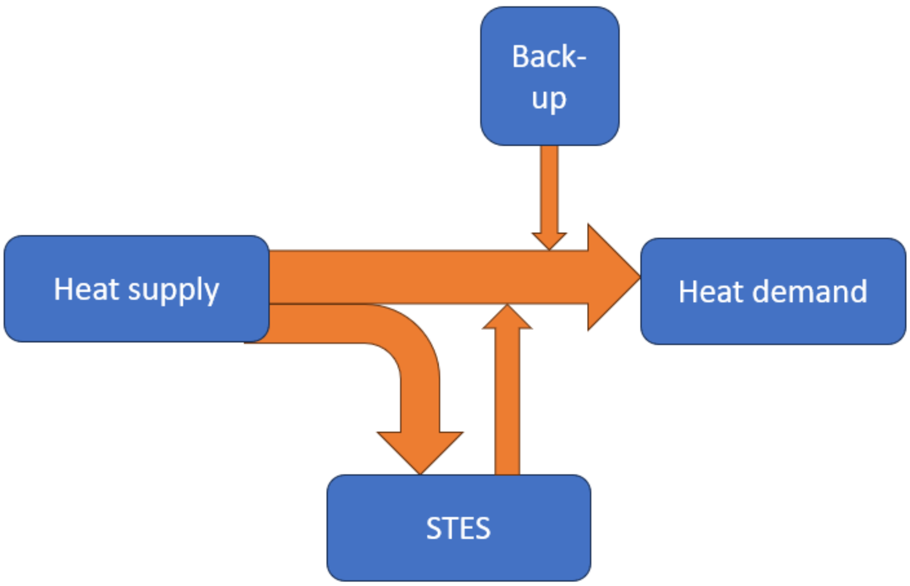

Figure 8: Conceptual heat flows in DH system

The objective of the DH system is to fulfil a certain heat demand with one or more heat supply systems (which can be further divided into main heat suppliers and back-up heat suppliers) and possibly a seasonal thermal energy storage (STES) component. Daily buffers and hydraulic pumps are out of scope for this model as these are very site specific (See also Section 4.3). The components of supply, demand, and STES are connected using the DH system pipes.

The basis for the model is that the heat demand always needs to be met. This demand is represented by an hourly heat load, which is assumed to have a set supply and return temperature (also called the cut-off temperature). The infrastructure connecting demand and supply in the DH system is not specified.

To meet this demand the different DH components are activated, using the control system explained below.

4.1.1. Control strategy

This heat demand is met by various heat supply technologies. A general control system is activated at each step. This control system ensures that all demand is met and is as follows:

1. The sustainable heat supply technologies are activated, which often have a lower operational cost compared to fossil fuel-based ones. Examples include deep geothermal and solar thermal collectors.
2. The STES is activated.
    - If the supply of heat exceeds the demand, the excess heat is stored up to the maximum amount of heat that can be stored. Any other excess heat is curtailed.
    - If the demand exceeds the supply, heat is extracted from the storage.
3. Any remaining unmet demand is covered by backup sources. An example is the gas boiler.

This is visually explained in Figure 9. Typically, time steps of one hour are taken, as heat demand is often defined on an hourly basis. The control system is applicable to a wide range of components, and any number of components can be added to this control system. This control system allows for the implementation of multiple sources and STES technologies.

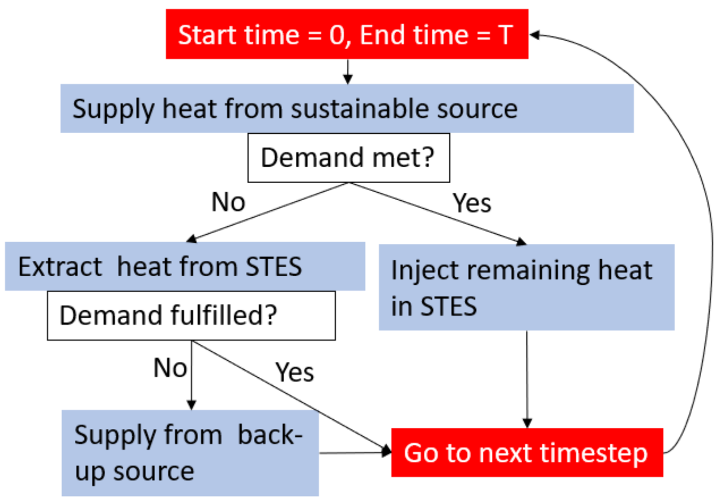

Figure 9: Control system for modelling the DH system.

4.1.2. Model components

The model components are divided into four categories: demand, sustainable heat supply, STES, and backup sources. Each category has its own requirements, inputs, and outputs.

Additionally, the network that connects the heat supply to the demand is not specified but is included in the system's LCOE. For this economic assessment, the required parameters are network length, cost per meter, and operational costs.

4.1.2.1. Heat demand

The heat demand in this system is represented by an hourly heat load, which fluctuates based on external factors such as weather conditions, building insulation, and occupancy patterns. This demand requires input from the user. An example of demand is shown in Figure 10.

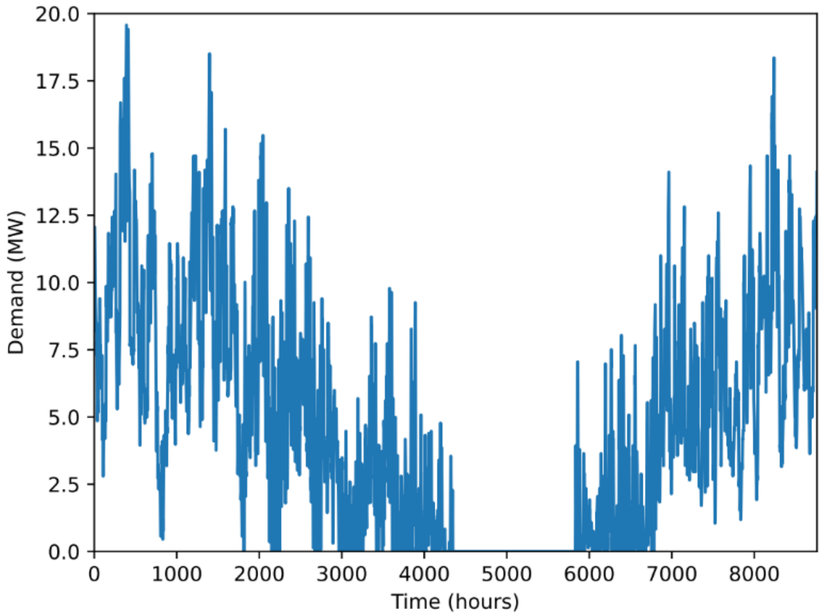

Figure 10: Example of a demand profile

To meet this demand, the heating system operates with a predefined supply and return temperature, called cut-off temperature. The supply temperature refers to the temperature at which heat is delivered to the distribution network, while the return temperature represents the water temperature after the heat is delivered to the user, based on which the delivered heat can be calculated using:

$$E = \dot{V}cdt \qquad \text{Equation 26}$$

where E is the heat delivered in Watt, $\dot{V}$ is the mass in kg/sec, c is the specific heat capacity in J/(kg℃), the used fluid is assumed to be water and dT is the difference between the supply and return temperature in ℃.

4.1.2.2. Sustainable heat supply technology

Sustainable heat supply technology forms the foundation of the control system, and examples include deep geothermal energy and solar collectors. Its heat output is determined by the specified input parameters. The primary outputs of these components are the heat generation per timestep (J/timestep) and the corresponding outgoing temperature (℃). Inputs vary depending on the technology used but should generally cover the heating power. For example, for deep geothermal, the required inputs are the flow rate and outgoing temperature, based on which the heating generated for each time step can be calculated (see Section 4.1.4.1). From the economic perspective, the user is required to give the CapEx and the variable and fixed OpEx to calculate the LCOE and CAC.

4.1.2.3. Seasonal Thermal Energy Storage (STES)

The STES in this project is specified to be one of HT-BTES, HT-ATES, and HT-MTES. The storage component stores heat from the sustainable source, which can be used later. The main input of this component is the recovery efficiency (η), defined as:

$$\eta = \frac{E_{out}}{E_{in}} = \frac{V_e \Delta T_e}{V_i \Delta T_i} = \frac{(T_e - T_g)}{(T_i - T_g)} \qquad \text{Equation 27}$$

where E is the energy injected into the aquifer (in) or extracted from the aquifer (out) (Joules). V is the yearly injected (i) or extracted (e) water volume (m³). T is the average temperature of the extracted (e) or injected (i) water (℃). T_g is the ambient ground temperature (℃). This equation assumes the injected and extracted volumes are the same on a yearly basis ($V_e = V_i$). This recovery efficiency reflects the amount of heat that can be recovered after storage. This equation calculates the efficiency based on the groundwater temperature.

For the DH system, the efficiency should be calculated based on the return temperature (or cut-off temperature) (called energetic efficiency), which is done using the following formula. (See Geerts et al. (2025) [12] for more information):

$$\eta_e = \eta * \frac{T_i - T_g}{T_i - T_c} + \frac{T_g - T_c}{T_i - T_c} \qquad \text{Equation 28}$$

where T_c is the cut-off temperature (℃) and η_e is the energetic efficiency. This energetic efficiency can be obtained from other models and input here to see the economic performance of the STES. Here again the assumption that $V_e = V_i$ remains and is valid for storage types that directly use the groundwater (ATES and MTES). While this assumption may also hold true for BTES, it is less meaningful due to the conduction-based nature of BTES, where the injected and extracted water primarily serves as a heat transfer medium. For BTES systems, the efficiency of heat storage and retrieval should be provided as an input parameter.

The output is the heat delivered from the storage component to the demand. The total heat stored is calculated using the control system combined with the output from the sustainable heat technologies, using the following formula:

$$E_{stored} = \sum_{t=0}^{t=N_{timesteps}} \max\left(0, \left(E_{sup,t} - E_{demand,t}\right)\right) \qquad \text{Equation 29}$$

where E_{stored} is the total stored energy in the STES (J), $E_{sup,t}$ is the energy produced by the supply technology at each timestep t (J), E_{demand} is the energy required by the demand at each timestep t (J). $N_{timesteps}$ is the number of timesteps in one year and $\max$ refers to taking the maximum value between the two options. This max value ensures that values below 0 are not subtracted from the injected energy.

The economic input factors are the CapEx and OpEx, which can be calculated using Section 3.1.3. The costs for the generation of the stored heat are calculated for the sustainable heat source and attributed to the HT-ATES.

4.1.2.4. Back-up source

The back-up source provides heat to all the demand that is not met after all other sources are supplied. Example sources are boilers that can be supplied by oil, gas, or diesel. These sources provide heat by burning their input and have a certain efficiency. The economic inputs are again the CapEx and OpEx, where OpEx can be defined in terms of burned mass and the price of that mass. The output is the heat delivered to satisfy the demand.

4.1.3. Parameter overview

A table of required input parameters is found in Table 2. The economic parameters can also be obtained from Section 3.1.3 where the cost of pumping can be calculated in units of €/MW. These values can be extracted from the previously discussed model and input here.

Table 2: Economic and environmental parameters required for the model

Component	Parameter	Unit
Sustainable heat supply technologies	CapEx	M€/MW or M€
	Fixed OpEx	€/MW per year
	Variable OpEx	€/MWh per year
	Lifetime	Years
	CO_2 emissions	$kgCO_2$/MWh
Back-up boiler	CapEx	M€/MW or M€
	Fixed OpEx	% of capex per year
	Gas price (including Tax)	€/MWh
	Lifetime	Years
	CO_2 emissions	$kgCO_2$/MWh
STES	CapEx	M€/(m^3 injection capacity) or M€
	Fixed OpEx	k€/(m^3 injection capacity)
	Electricity use	kWh/m^3 injected
	Lifetime	Years
	Electricity price	€/MWh
Network	Discount rate	%
	Network capex	€/m or €
	Network opex	% of capex per year
	Lifetime	Years

4.1.4. Example components

Some components have been predefined in the model. These are discussed below.

4.1.4.1. Sustainable source: Deep geothermal heat

This component is assumed to be a stable source of heat, which can provide the same amount of heat throughout the year. This component has a constant outgoing flow with a fixed temperature. The generated heat can be calculated by using (see section 4.1.2.1.)

$$E = \dot{V} c dt \qquad \text{Equation 30}$$

The outgoing temperature has to be inputted and either the flow rate or the heat output needs to be given, based on which the other one can be calculated. The economics can be obtained from the previously described model (see Section 3.1.3) or from other sources.

4.1.4.2. Sustainable source: Solar collector

The collector is treated as an uncontrollable heat source, producing heat based on irradiance. Its output is represented by a collector output curve, which indicates the heat generated at each timestep. This curve can be scaled according to the collector's size and is derived from the

European commission, PVGIS [8]. The solar collector is assumed to deliver a certain amount of kWh per kWp of installed capacity annually [9,10] with the heat distributed throughout the year proportional to the irradiance curve using the following equation:

$$E_{solar} = P_{kWp} * \theta \frac{E_e}{\sum_{t=0}^{t=N_{timesteps}} E_{e,t} dt} \qquad \text{Equation 31}$$

where E_{solar} is the energy generated at each time step by the solar collector in kW and subscript t refers to taking the value of one timestep. P_{kWp} is the peak power of the solar collector, θ is the amount of annual kWh per kWp installed, and E_e is the annual irradiance split into timesteps. dt is the length of one timestep.

Both the collector output curve and the heat delivered per kWp should be inputted by the user.

For example, obtaining the curve Photovoltaic Geographical Information System (PVGIS)for the location of Amsterdam and setting the solar collector size to 500 kWp and the heat delivered per kWp to 600 kWh per kWp (typical value for Amsterdam [8]), leads to the output seen in Figure 11.

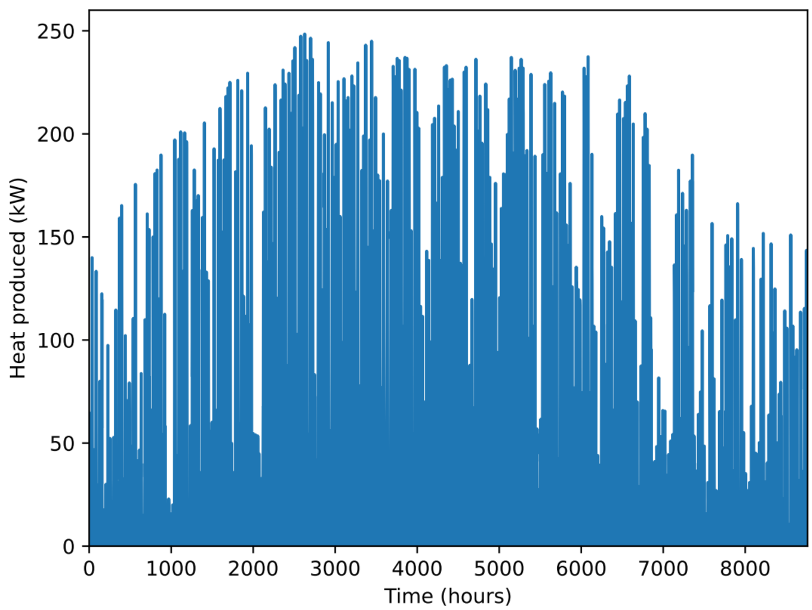

Figure 11: Example of solar collector output

4.1.4.3. STES: HT-ATES

An HT-ATES model was developed for this study, designed to be both accurate and computationally efficient for integration into a larger energy system model. The model is described in detail in Geerts et al. [11] and is briefly summarized here. A numerical MODFLOW model was created and used to generate a dataset that reflects how input parameters influence the temperature profile of the HT-ATES system. The temperature profile is defined as the temperature of the volume extracted from a well over time.

This model requires two operational parameters: total yearly injected volume and injected temperature. It also needs five aquifer parameters, which are porosity, aquifer thickness, horizontal hydraulic conductivity, anisotropy, and undisturbed ground temperature [11]. The output of the model is the temperature profile of the HT-ATES system, which shows the amount of energy that can be extracted from the HT-ATES. This model is constrained by the maximum pumping rate, which is assumed to be the same for injection and extraction, limiting the amount of heat that can be stored at any time step.

The HT-ATES model first predicts the system's recovery efficiency (η), defined in Section 4.1.4. This recovery efficiency is predicted using an extreme gradient boosting regression algorithm, which accurately estimates the HT-ATES recovery efficiency. Based on this prediction, a nearest-neighbour search is performed within the pre-generated dataset to identify the most accurate corresponding temperature profile. This approach ensures that the selected temperature profile remains consistent with the numerical model constraints.

This search is conducted using a distance metric that quantifies the similarity between newly inputted HT-ATES values and the dataset values. The following Euclidean distance definition is used:

$$d = \sqrt{\sum_{i=0}^{n} \left(x_i - x_{i,dataset}\right)^2} \qquad \text{Equation 32}$$

where d is the distance between the newly input HT-ATES values and dataset values, x_i represents the normalized newly inputted values, $x_{i,dataset}$ represents the corresponding values in the dataset. The set of n consists of ambient ground temperature, injected temperature, and recovery efficiency. Then, the temperature profile of the datapoint with the lowest d values is chosen.

The temperature profile was adapted to correct for the temperature of the injected water, which is the maximum temperature the temperature profile should reach. This was done by downscaling or upscaling the temperature profile using the injected temperature parameter. This temperature profile is the output of the model. More information and assessment of this model can be found in [11]. The HT-ATES is constrained by the user by giving a maximum flow rate, which is both for injection and extraction. This is the maximum rate that can be extracted during a single timestep and this constraint cannot be violated.

4.1.4.4. Back-up unit: Natural gas boiler

The gas boiler is used to cover all remaining unmet demand and burns natural gas with a certain efficiency to do so (in this study 93% [12]. The capacity of the gas boiler is scaled to provide 110% of its maximum load, ensuring that there is always enough capacity to meet the peak demand.

4.2 Model application

4.2.1 Working & Output model

Once the model is fully set up with the necessary input parameters, it proceeds with a structured three-step process to evaluate and visualize the system's performance and economic feasibility.

Step 1: Heat Flow Calculation

The model first simulates heat flows within the system, determining how thermal energy is transferred between components over a full year of operation, which is based on the previously explained control system and includes flows from the sources to the demand as well as from sources to the storage.

When considering a geothermal doublet, an HT-ATES, and a gas boiler, the calculation would be as follows:

Firstly, the heat generated by the geothermal doublet is determined by using the inputted values and calculating either the flow rate or the heat output, depending on the inputs given by the user, (see Section 4.1.2.4). The portion of the heat that can be directly supplied to meet demand at each timestep is then identified, while any excess heat is sent to the HT-ATES. Before storing heat in the HT-ATES, the maximum flow that can be injected at each timestep is assessed, ensuring that the injected heat does not exceed this limit.

Secondly, the HT-ATES is activated, provided that heat can be stored. At each timestep, the amount of heat that can be extracted is calculated using the HT-ATES (See Geerts et al. [10]) model and this heat is supplied to meet the remaining demand. If the heat demand, after accounting for the geothermal supply, is lower than the extractable heat, the HT-ATES output is adjusted accordingly. This process considers both the heat already extracted and the system's maximum extraction rate.

Finally, the gas boiler is activated to supply any remaining heat demand that is not met by the geothermal or HT-ATES systems.

Step 2: Visualization of Heat Contributions

To enhance interpretability, the model includes a built-in plot function that visualizes the following: The heat contribution of each component over time, which shows the balance between heat supply, storage, and demand throughout the year. These visualizations help identify bottlenecks, inefficiencies, and system optimization opportunities. An example plot is shown in Figure 12. A few observations from this figure are that the declining output from the HT-ATES from hour 7000 to hour 2500, which is due to the temperature decline of the HT-ATES during operation (see Geerts et al. [12] [10]). Furthermore the HT-ATES is mostly charged during summer, when there is an oversupply of heat from the geothermal well. Lastly, the heat demand is very intermittent and can change heavily, mainly based on the outside temperature.

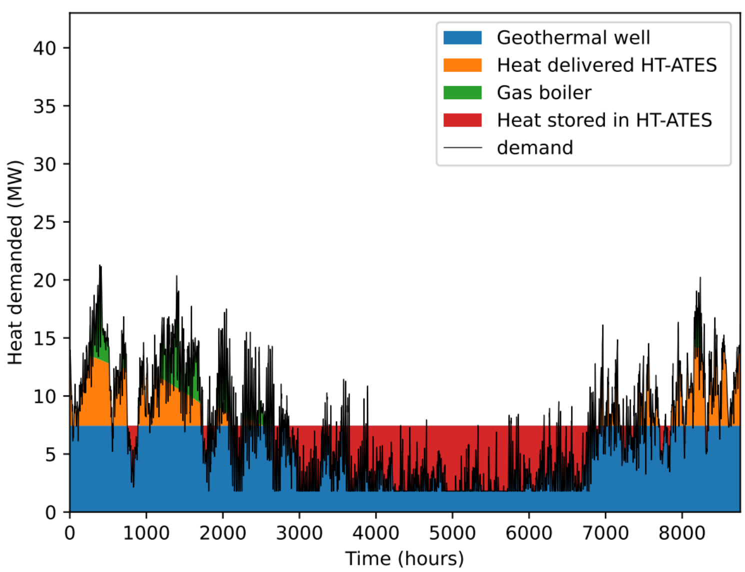

Figure 12: Example visualization of a system with a geothermal well, HT-ATES and gas boiler.

Step 3: Cost Calculations for Each Component

Based on the heat flow results, the model then calculates the costs associated with each component in the system and after calculating individual component costs, the model integrates these costs to determine the two key economic indicators: LCOE and CAC (See Section 2.4).

These economic calculations provide valuable insights into system affordability, return on investment, and environmental benefits, supporting decision-making for optimizing the heat supply strategy.

4.2.2 Application

The DH system simulation tool is designed for district heating (DH) networks of various sizes, with a primary focus on systems supplying heat to multiple buildings. It accommodates different heat demand sizes and patterns, allowing for a comprehensive analysis of system performance under various conditions. The tool calculates the levelized cost of energy (LCOE) and integrates multiple heat sources, including HT-ATES, solar collectors, deep geothermal heat, and gas boilers, while allowing for the incorporation of additional sources if needed.

This model can be used for multiple purposes. Firstly, the model can be used to optimize sizing and find cost-effective and energy-efficient solutions that balance supply and demand. These solutions can lead to CAC and LCOE reduction, which was the objective of Task 2.3. The model can also be used to design new DH systems or optimize existing networks by evaluating different supply and storage technologies and operational parameters.

Secondly, policy interventions can be assessed, the model can be used to compare the financial implications of policy changes, such as carbon taxes, subsidies, or regulations promoting renewable energy in DH systems.

Thirdly, the effect of demand-side management can be tested. The model enables the analysis of different heat demand patterns, including seasonal and daily variations, to optimize storage utilization and reduce peak loads. It helps evaluate the benefits of demand-side management strategies, such as thermal buffering in buildings or demand response programs.

4.3 Limitations

There are also limitations to consider. Firstly, the HT-ATES component is designed within the temperature range of 25-80°C; outside of this range, the model has not been tested, and this model likely has limited accuracy when used to model LT-ATES. This also implies that this model can only be used in DH systems that have an operating temperature around that range.

Secondly, the model simplifies some aspects of the DH network operation. It does not explicitly simulate hydraulic behaviour, such as pressure drops and flow balancing, focusing instead on thermal performance and economic evaluation. While these are key aspects of operating a DH system, they have less impact on the technical performance of the individual components.

Additionally, maximum flow rates within the DH pipes and daily buffer tanks and heat exchangers are omitted, which differ largely per DH system and require detailed simulation. Furthermore, the model assumes a set supply and return temperature, where in practice this supply and return temperature changes depending on the outside temperature and DH performance.

5. Conclusion and outlook

In this deliverable, the development and application of generic, open-source (Python), and highly scalable tools for simulating the LCOE and CAC are reported. Two models were created to accommodate the calculation of the metrics: LCOE and CAC. The first tool, the *thermal storage model*, described in Section 3, focused on the STES and calculating LCOE for this STES. The model was designed to be accurate and to contain all the necessary details to calculate the LCOE. The second tool, the *heating system model*, focused on the role of the STES within a heating system. It calculates LCOE and CAC for the STES as well as the other components of the heating system. The difference between the two models and their purpose mainly lies in the application scope and level of detail. The first model provides details on the technical and economic calculations of the STES, while the second model is simpler but expands its scope to the DH system and the other components included in this DH system.

So far, the *storage model* has been checked on ATES configurations with regard to technical performance. The *heating system model* has been applied to a simpler case of ATES. As soon as operational and cost data from the sites are available, further validation tests, as well as the LCOE reduction and business risk assessment, will be conducted. The tools can also be used to simulate and assess ATES, BTES, and MTES applications in other locations.

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The EU aims to have a net-zero greenhouse gas (GHG) economy by 2050, with 55% reduction on 1990 levels by 2030. At present, heating and cooling represent around 50% of the final energy demand in Europe and are mainly supplied by fossil fuel derived energy. It is therefore essential for heating and cooling to decarbonise to achieve EU ambitions.

A challenge for decarbonizing heat systems is the size of the seasonal mismatch between demand for heat and heat generation from sustainable sources – this mismatch is much larger than the equivalent intermittency in electricity supply and demand. The two main solutions to address this mismatch are: (i) to install a large capacity, so that peak demands can be met even at low production levels; or (ii) to store energy for later use if it is not needed at time of conversion. Many sustainable heat supply systems are characterised by high capital expenditure and low operational costs. Therefore, an installed capacity tailored at peak demand is not cost effective, while extending the annual operation period is advantageous for meeting energy needs, reducing levelised cost of energy (LCOE) and decarbonisation. Optimal utilisation of sustainable heat requires storing large amounts of heat to account for seasonal supply and demand fluctuations. Various technologies have been proposed for large-scale heat storage in geothermal reservoirs and low temperature storage is routinely applied. PUSH-IT focuses on extending storage temperature ranges to high temperatures. We will tackle remaining barriers, demonstrate applicability, increase public engagement, and optimise and de-risk operations. We will showcase three technology options that are fit for a wide variety of geological conditions covering most locations in Europe.

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