

Research papers

Numerical preprocessing of ground-coupled thermal impacts on seasonal ice energy storage systems for mixed-integer linear programming

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ABSTRACT

Mixed-integer linear programming (MILP) is widely applied for the optimization of complex energy systems due to its high computational efficiency. However, the requirement for linear formulations often leads to simplified thermal energy storage (TES) models, in which ambient heat losses are neglected or assumed. While acceptable for short-term storage, these simplifications can cause significant inaccuracies in seasonal applications. Ice energy storage (IES) poses an additional challenge due to its nonlinear phase-change behavior and its direct thermal interaction with the surrounding ground. This paper presents a computationally efficient approach to represent nonlinear, ground-coupled IES behavior within hourly resolved MILP-based operation optimization. The method is based on a numerical preprocessing strategy, in which the thermal behavior of the storage system is evaluated externally and subsequently incorporated into the MILP model in a linearized form. A key element of the methodology is the derivation of system-specific annual loss characteristics based on the physical properties of the storage and its geothermal coupling. The methodology is validated using a real-world trigeneration system, including a 500 m³ IES. Simulation results show good agreement with measurement data, capturing both temporal dynamics and energy quantities within a computation time of approximately 30 min. The simulated and measured annual IES temperature profiles exhibit a strong correlation, with a coefficient of determination of 0.77 for the reference year. Furthermore, the proposed preprocessing approach enables the integration of system-specific loss characteristics into design optimization and is transferable to other seasonal TES technologies, such as aquifer, cavern or pit thermal energy storage systems.

Nomenclature

Abbreviations	
AC	absorption chiller
CAD	computer-aided design
CC	compression chiller
CHP	combined heat and power
CPU	central processing unit
CS	cold storage
FC	free cooling
GB	gas boiler
HS	heat storage
HP	heat pump
IES	ice energy storage

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MILP	mixed-integer linear programming
MINLP	mixed-integer nonlinear programming
PV	photovoltaic
PVGIS	Photovoltaic Geographical Information System
SAPM	Sandia Array Performance Model
SOC	state of charge
TAO	Technology Alliance Upper Franconia
TES	thermal energy storage
ZET	Center of Energy Technology

Symbols

COP	coefficient of performance (—)
c	heat capacity (kJ kg ⁻¹ K ⁻¹)

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<i>D</i>	number of design days (–)
<i>d</i>	design day (–)
<i>E</i>	revenue (€)
<i>EER</i>	energy efficiency ratio (–)
<i>e</i>	specific revenue (€ kWh ^{–1})
<i>f</i>	ratio of high and radius (–)
<i>G</i>	geothermal gradient (K m ^{–1})
<i>$\dot{G}$</i>	gas consumption (kWh)
<i>H</i>	number of time increments (–)
<i>h</i>	specific enthalpy (kJ kg ^{–1})
<i>K</i>	costs (€)
<i>k</i>	specific costs (€ kWh ^{–1})
<i>l</i>	height (m)
<i>m</i>	mass (kg)
<i>n</i>	volume grading (–)
<i>P</i>	electrical energy (kWh)
<i>$\dot{Q}$</i>	thermal energy (kWh)
<i>R²</i>	coefficient of determination (–)
<i>r</i>	radius (m)
<i>SOC</i>	state of charge (kWh)
<i>T</i>	temperature (K)
<i>t</i>	time increment (–)
<i>UA</i>	heat transfer coefficient (W m ^{–2} K ^{–1})
<i>u</i>	hour of day (–)
<i>V</i>	volume (m ³)
<i>v</i>	volumetric increment (m ³)
<i>W</i>	number of calendar days (–)
<i>w</i>	calendar day (–)
<i>x</i>	binary variable (–)
<i>z</i>	depth (m)

Greek symbols

α	tilt angle (°)
γ	orientation (°)
Δ	gradient (–)
η	efficiency (–)
λ	thermal conductivity (W m ^{–1} K ^{–1})
μ	temperature coefficient (1K ^{–1})
ρ	density (kg m ^{–3})
τ	subincrement (–)
ϕ	loss factor (–)

Subscripts and superscripts

<i>amb</i>	ambient
<i>adopt</i>	adopted
<i>bottom</i>	bottom
<i>break</i>	break
<i>C</i>	storage ratio
<i>c</i>	cold
<i>ch</i>	charging
<i>co</i>	concrete
<i>d</i>	design day
<i>da</i>	damping
<i>dch</i>	discharging
<i>dem</i>	demand
<i>e</i>	end
<i>el</i>	electricity
<i>ex</i>	exergetic
<i>feed</i>	feeding
<i>g</i>	ground
<i>h</i>	heat
<i>i</i>	inside
<i>ice</i>	ice
<i>in</i>	input
<i>inv</i>	inverter
<i>L</i>	Lorenz
<i>liquid</i>	liquid
<i>loss</i>	loss
<i>m</i>	mean
<i>max</i>	maximum
<i>meas</i>	measured
<i>min</i>	minimum
<i>mix</i>	mix
<i>nom</i>	nominal
<i>O</i>	overall
<i>out</i>	output

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<i>pre</i>	predefined
<i>prim</i>	primary
<i>S</i>	supply components
<i>s</i>	start
<i>sec</i>	secondary
<i>shift</i>	shift
<i>side</i>	side
<i>sim</i>	simulated
<i>start</i>	start
<i>stop</i>	stop
<i>target</i>	target
<i>ref</i>	reference
<i>water</i>	water

1. Introduction

The accelerating integration of renewable energy sources is fundamentally transforming modern energy systems and increasing the relevance of energy storage technologies. In Germany, the share of renewable energy in gross final energy consumption reached 22.4% in 2024 and is expected to rise to 41% by 2030 [1]. While electrical energy storage has expanded rapidly in recent years [2], the deployment of thermal energy storage (TES) must increase substantially to achieve long-term decarbonization targets [3]. In particular, seasonal TES technologies are gaining increasing importance, as they enable the temporal decoupling of renewable heat and cooling generation from demand over extended time periods. Among these technologies, ice energy storage (IES) represents a promising solution due to its high energy density, the utilization of latent heat during phase transition and its applicability in heating and cooling grids. Furthermore, IES systems can provide seasonal flexibility by storing thermal energy over long periods while simultaneously interacting with the surrounding ground.

The increasing deployment of energy storage technologies not only expands the flexibility potential of future energy systems but also substantially increases their structural and temporal complexity. Especially the dynamic interaction between energy generation, storage and demand requires advanced simulation or optimization approaches capable of representing these interdependencies in a computationally efficient manner. Among available optimization approaches, mixed-integer linear programming (MILP) has proven to be a powerful framework for the techno-economic optimization of multi-energy systems due to its modularity, flexibility and favorable computational performance. This enables the integration into forecast models or web-based planning tools, as demonstrated by Wirtz [4]. Alternative optimization approaches, such as mixed-integer nonlinear programming (MINLP) or metaheuristic algorithms, are also capable of representing nonlinear system behavior directly. However, these methods often entail significantly higher computational effort, particularly for large-scale energy systems with high temporal resolution [5]. Therefore, MILP remains widely used when computational tractability is a primary concern.

Within MILP-based approaches, a distinction is observed between operational optimization and design optimization. Operational optimization assumes fixed component sizes and focuses on optimal scheduling. Conversely, design optimization additionally determines component capacities and includes investment costs, resulting in significantly higher model complexity [6]. In both cases, MILP requires linear or piecewise-linear relationships of all system components. Consequently, nonlinear physical processes must be simplified or reformulated [7]. For annual simulations with high temporal resolution, it is essential to balance model accuracy and computational efficiency to preserve the advantages of MILP. This challenge becomes particularly pronounced for TES technologies, whose thermal behavior is inherently nonlinear and strongly time dependent.

In many MILP studies, TES is frequently represented by an incremental energy balance of a perfectly stirred water tank, including charging energy, discharging energy, efficiencies and losses [8–13]. In

many cases, storage losses are either represented as a percentage factor proportional to the state of charge (SOC) or neglected entirely. While the assumed magnitude of losses has little impact for short-term TES, they are crucial for seasonal or long-term storage applications. In these applications, thermal losses accumulate over long periods and strongly influence storage performance. If similar factors to those used for short-term storages are applied here, such as 0.1%/h [14], the SOC drops to approximately (approx.) 50% of its initial state after one month of storage time. It is essential to note that the problem described is not caused by the different constant loss factors, but rather by the use of assumptions that are not specific to the system. For seasonal TES, loss behavior strongly depends on system characteristics such as geometry, storage temperature, insulation properties and geothermal boundary conditions. Therefore, the use of a system-specific loss representation is essential.

Several studies have proposed more detailed TES models that consider temperature stratification and temperature-dependent losses. Steen et al. [15] introduce a stratified storage model with a thermocline that shifts depending on the SOC. The configuration of the system results in perfectly separated temperature zones that correspond to the flow temperature and return temperature of the system. This methodology enables the calculation of losses associated with properties of the TES, the storage temperature and the ambient temperature for each increment. Lauinger et al. [16] apply this methodology to analyze a TES in a building. Given that the consideration of a variable building temperature would result in a nonlinear model, a constant building temperature is assumed in this study. However, such approaches significantly increase the computing time. Schütz et al. [17] show that even relatively simple stratified models can increase computing time by more than 200% compared to simplified SOC-based models, making them impractical for annual MILP simulations of complex energy systems.

As a result, most MILP-based studies of seasonal TES rely on simplified loss representations. These are often implemented using constant or time-dependent efficiency factors. Rojer et al. [18] utilize a similar MILP model to integrate a high-temperature aquifer TES into a district heating network. In this research the dissipation of heat is based on a time-related efficiency, which is defined as 70% of the initial SOC after 100 days. Mansoor et al. [19] concentrate their study on the optimal design of thermal energy systems in microgrids. In this instance, losses are incorporated into the long-term model using a fixed factor of 0.01%/h. As with the works of Renaldi et al. [20] and McKenna et al. [21], different assumptions regarding loss factors are applied in seasonal MILP models. In this context, Fig. 23 in the Appendix A provides an overview of various loss factors from the extant literature, considering the long-term storage behavior over a period of six months. It becomes evident that the selection of the constant loss factors from literature values has a significant influence on storage behavior, particularly regarding long-term and seasonal TES.

While these approaches provide valuable insights for seasonal TES modeling, they do not adequately capture the specific characteristics of IES systems, particularly the combination of phase-change behavior and ground-coupled heat transfer. IES systems constitute a distinct category of TES technologies due to their nonlinear phase transitions and direct thermal interaction with the surrounding soil. Furthermore, IES tanks are typically uninsulated, resulting in significant geothermal heat exchange over long storage periods. Consequently, IES represents a particularly challenging TES technology for MILP-based optimization, as both nonlinear phase transitions and long-term geothermal interactions must be represented within a computationally tractable framework.

Vetterli et al. [22], Karimi et al. [23] and Jalili et al. [24] have integrated an IES into a cooling system or a multi-supply system, designating this as short-term storage with daily intervals. In all scenarios, the losses are disregarded. Rafii-Tabrizi et al. [25] employ a more detailed IES model for MILP observations. Here, the phase transition is described using the temperature-enthalpy relationship established by Winteler et al. [26,27]. In addition, a thermal connection to the ground is

implemented via an extra layer between storage tank and soil. This study concludes that the optimal time horizon for such systems is one year, ensuring sufficient consideration of seasonal effects. However, given the dimensions of this model, it is not feasible to achieve this objective within a reasonable computing timeframe. Overall, existing MILP-based IES models either neglect long-term thermal interactions and losses or rely on highly detailed formulations that become computationally impractical for annual optimization problems. Consequently, a gap remains between physically accurate IES representation and computationally efficient MILP integration.

As already mentioned, energy system optimization can generally be divided into operational optimization and design optimization. While operational optimization focuses on the optimal scheduling of systems with fixed component sizes, design optimization additionally determines component capacities and investment decisions. As a result, the integration of seasonal TES and IES into design optimization represents an even greater challenge, as long optimization horizons and high temporal resolutions substantially increase the computational complexity. To mitigate this, several strategies have been proposed in the extant literature. Gabrielli et al. [28] compare three MILP-based design approaches, ranging from representative uncoupled design days to sequentially linked days and fully hourly resolved annual simulations. While the latter two methods capture seasonal storage behavior more accurately and come notably closer to the optimum, they require significantly higher computation times than conventional design-day approaches. Kotzur et al. [29] extend this concept by introducing intra- and inter-period time layers that account for cross-period SOC changes. Lindholm et al. [30] propose an iterative interval-halving approach with fixed initial and final SOC.

For this reason, the objective of this work is to develop and validate an approach that enables the integration of nonlinear IES behavior into MILP-based optimization in a computationally efficient manner. Rather than modifying the underlying optimization algorithm, the proposed method follows a modeling and preprocessing strategy, in which nonlinear system behavior is evaluated externally and subsequently incorporated into the MILP formulation in a linearized form.

The core contribution is a numerical preprocessing methodology that calculates the geothermal heat transfer between the storage and the surrounding soil and represents it as time-dependent loss parameters. In this way, complex thermal interactions and phase-change effects can be captured while preserving the computational advantages of MILP. The extent of the preliminary analysis process can be modified depending on the specific use case and level of detail required. Within the optimization model, the IES is represented using a SOC-based structure augmented by an enthalpy-based formulation to account for transitions between sensible and latent heat storage.

The methodology is validated using a real-world multi-supply energy system installed in a research building at the University of Bayreuth, which includes a 500 m³ seasonal IES and provides heating, cooling and electricity. Measurement data with hourly temporal resolution are used to compare simulated and measured storage behavior over an entire reference year. The study is conducted as an operational optimization with fixed component sizes in order to focus on the validation of the storage model. Subsequently, the proposed approach is integrated into a design optimization framework to demonstrate its applicability beyond operational scheduling. Finally, the transferability of the proposed approach to other seasonal TES technologies, such as aquifer, cavern or pit thermal energy storage, is discussed.

2. Description of the real-world energy system

The considered supply system is located in the Technology Alliance Upper Franconia (TAO) building, the home of the Center of Energy Technology (ZET) at the University of Bayreuth. Laboratories and workshops account for around 4000 m² of the total building area of 5600 m².

2.1. Energy demands

In this study, high-resolution long-term measurement data from the TAO research building is employed. The demand for heating, cooling and electricity is utilized from 1st January 2023 to 31st December 2023. The annual energy requirement comprises 771 MWh of heating, 413 MWh of cooling and 1481 MWh of electricity. Information regarding the measurement systems employed and a comprehensive emissions analysis can be found in previous publications [31–34].

A visual representation of the annual load profiles of the three grids is provided in Fig. 1. On the heating demand side, a distinct seasonal dependency can be observed. This is attributable to the restriction of the heat demand to heating and air conditioning purposes. The utilization of process heat or domestic hot water is not a necessity in this non-residential building. Conversely, cooling demand is a constant requirement, exhibiting substantially reduced seasonal variability in contrast to the heat demand. In essence, this phenomenon can be attributed to the high proportion of laboratory cooling water, which is required to be supplied in a practically continuous basis. The necessity for cooling is also dependent on the specific research activities and the academic year. As a result, the demand levels remain relatively constant, and no obvious annual temperature dependency can be identified.

2.2. Energy system TAO

A complete overview of the supply system, including the nominal capacities and the integration of the IES, is shown in Fig. 2. The heating demand is mainly accounted within the space heating by radiators and ventilation systems, as there is no domestic hot water provision. The cooling requirement is divided into ventilation and cooling, as well as equipment cooling via the laboratory cooling water grid.

The heat is delivered by a gas boiler (GB) and a combined heat and power unit (CHP), which are connected to the various consumer areas via a single heat distribution grid. The cooling supply consists of an absorption chiller (AC) linked to the CHP unit, an electricity-driven compression chiller (CC) and the option of free cooling (FC) at low ambient temperatures. Due to difficulties encountered in the design of the AC, its operation in the combined system is not technically feasible,

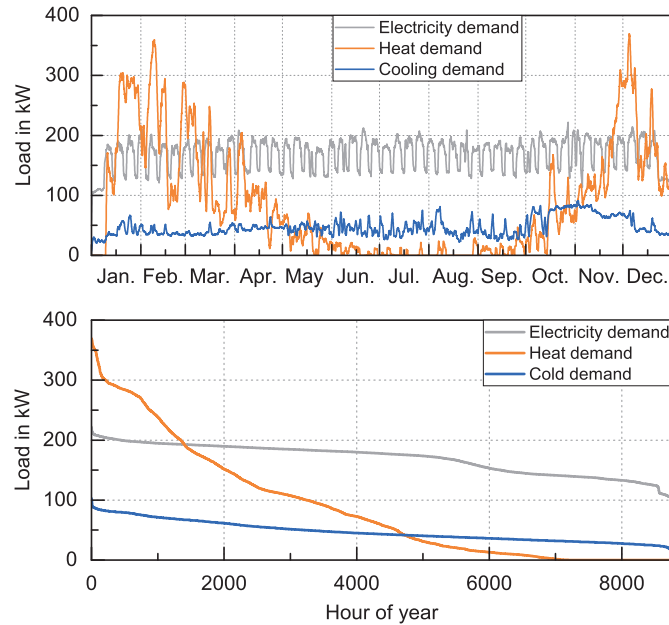


Fig. 1. Load profiles (top) and annual duration lines (below) in an hourly resolution for the TAO buildings supply grids for heat, cold and electricity of the year 2023.

meaning it is neglected in the further analysis. The IES acts as an interface between the heating and cooling supply. The HP provides heat via the common distribution system with GB and CHP, whereby the IES system serves as its energy source. Additionally, the cooling grid can also serve as a source for the HP. However, this functionality is not employed in actual operation strategy. When the IES is discharged, cooling energy is contributed via the combined distribution grid.

2.3. Ice energy storage

The IES is situated in the inner courtyard of the research building. It is filled with 443 m³ tap water, which serves as a storage medium. Both hydraulically separated heat exchangers of the withdrawal and regeneration circuit are arranged on an aluminum frame, as shown in Fig. 3, which also contains the most relevant dimensions. The heat exchangers are made of polyethylene pipes and are filled with water-ethylene glycol as heat transfer fluid. These physical characteristics directly inform the preprocessing step for geothermal loss modeling described in Section 3.4.2.

3. Methodology and MILP model

To enable a subsequent comparison of the MILP simulation with real measurement data, the overall structure of the energy system is considered, and its individual components are represented as sub-models, which are described in Section 3.3. The progression of considering the IES in MILP is displayed in Fig. 4 and offers a comprehensive overview of its structural framework.

The methodology section is structured as follows: First, the optimization problem is defined, which in this case consists of minimizing the annual operating costs. Next, the energy balances for the supply grids are formulated, followed by a description of the individual systems as linear models. Finally, the IES system is reformulated. Here, a representative temperature curve of the IES is specified. In a preliminary step, losses of the IES are calculated based on its thermal coupling with the surrounding soil. These losses are then incorporated into the MILP optimization. Depending on the specific requirements, boundary conditions and application of the model, it may not always be feasible to estimate an annual temperature profile in advance. In such cases, an iterative approach can be applied. The temperature profile obtained from a previous model run is used as input for the preprocessing stage, and the entire procedure described in the following Section 3 is repeated.

The resulting overall model is realized through its implementation as Python code in the Spyder environment [35]. This optimization is solved with Gurobi in version 12 [36] on a workstation equipped with an Intel i7-8700 CPU (3.2 GHz) and 32 GB of memory. The MIP gap is 0.5%.

3.1. Operational cost function

The initial step in MILP is to specify an optimization target. In this study, the economic optimum of the annual energy costs K_O is selected to enable an operation optimization. The analysis encompasses the total costs resulting from gas consumption K_{gas} and electricity consumption K_{el} , as well as the revenue from electricity sales E_{el} :

$$\min K_O = K_{gas} + K_{el} - E_{el} \quad (1)$$

K_{gas} is derived from the product of the specific gas costs k_{gas} and the sum of the gas consumption for each increment t , which is an element of all increments H . This principle is applicable to all subsequent equations:

$$t \in H \quad (2)$$

According to the present system, K_{gas} is influenced by the gas consumption of the CHP $\dot{G}_{CHP}$ and the GB $\dot{G}_{GB}$:

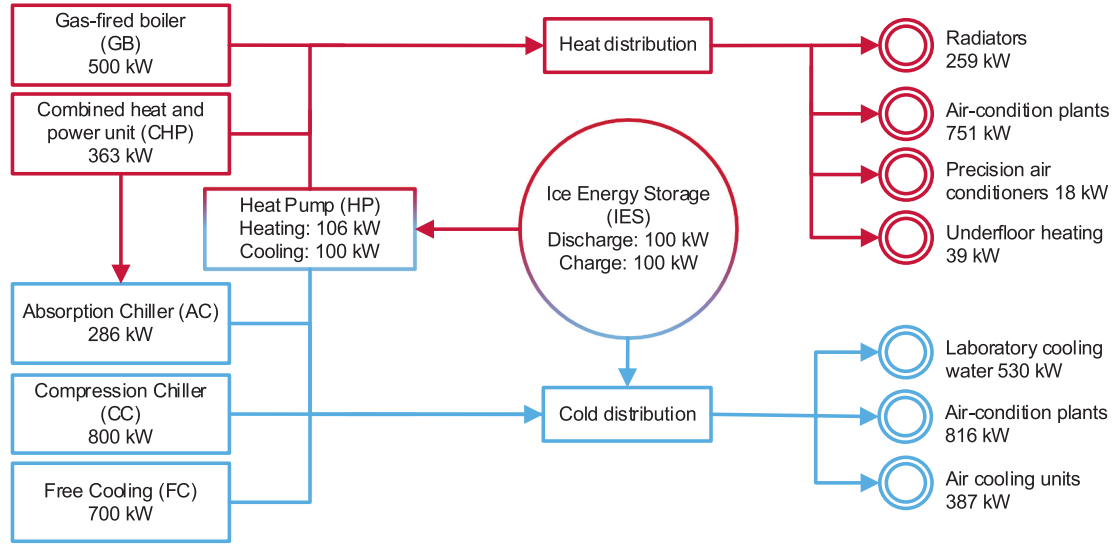


Fig. 2. Scheme of the heating and cooling supply along with the consumer areas of the TAO building at the University of Bayreuth.

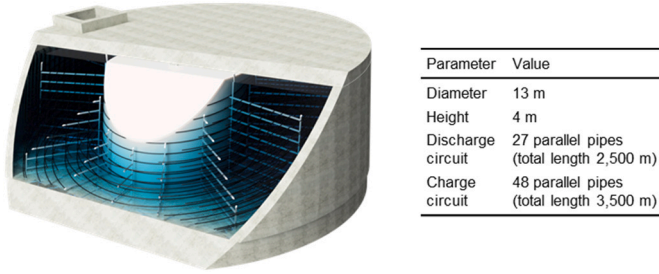


Fig. 3. Sectional CAD view with the key dimensions of the ice energy storage system inside.

$$K_{\text{gas}} = \sum_{t=1}^H k_{\text{gas}} (\dot{G}_{\text{CHP}}(t) + \dot{G}_{\text{GB}}(t)) \quad (3)$$

K_{el} is derived by calculating the sum of the product of specific electricity costs k_{el} and electricity purchased from the public grid $P_{\text{feed,out}}$:

$$K_{\text{el}} = \sum_{t=1}^H k_{\text{el}} P_{\text{feed,out}}(t) \quad (4)$$

A similar approach can be adopted for the revenue generated from electricity fed back into the public grid E_{el} . This is also derived by summing the product of the specific remuneration e_{el} and the electricity sold $P_{\text{feed,in}}$:

$$E_{\text{el}} = \sum_{t=1}^H e_{\text{el}} P_{\text{feed,in}}(t) \quad (5)$$

The static values for specific energy costs utilized in this study are listed in Table 1:

3.2. Superstructure and energy balances

The relationships between the systems are mapped by creating an energy balance for each of the three supply grids. Losses resulting from energy transport are neglected, as measurements are taken directly at the plants.

The internal electricity grid of the case study is supplied by the

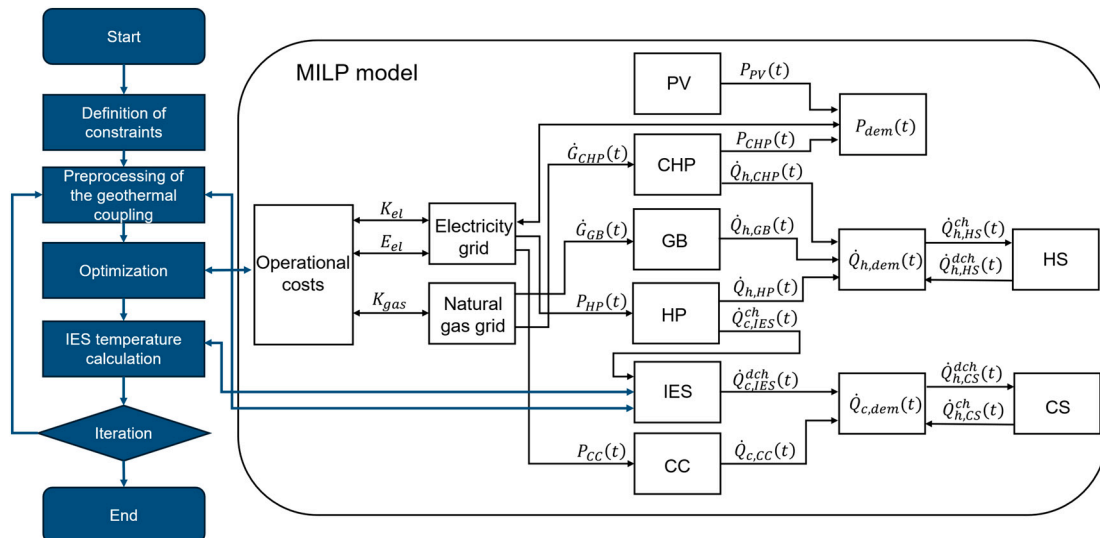


Fig. 4. Structural framework of the MILP model process.

Table 1

Specific energy costs.

Parameter	Unit	Value	Comment
k_{gas}	€/kWh	0.08	Invoice value
k_{el}	€/kWh	0.25	Invoice value
e_{el}	€/kWh	0.16	Invoice value

electricity drawn from the public grid $P_{feed,out}$, the electricity provided by the CHP P_{CHP} and the energy generated by the PV system P_{PV} . The other side of the balance is influenced by the electricity demand of the building P_{dem} , the amount of electricity fed into the public grid $P_{feed,in}$ and the energy consumption of the supply components P_S , which consists out of the temporal demands of the HP P_{HP} , the CC P_{CC} and FC P_{FC} :

$$P_{feed,out}(t) + P_{CHP}(t) + P_{PV}(t) = P_{dem}(t) + P_S(t) + P_{feed,in}(t) \quad (6)$$

$$P_S(t) = P_{HP}(t) + P_{CC}(t) + P_{FC}(t) \quad (7)$$

In the case of the heating grid, the heat demand of the building $\dot{Q}_{h,dem}$ and the charging energy of the HS $\dot{Q}_{h,HS}^{ch}$ are covered by the GB $\dot{Q}_{h,GB}$, the CHP $\dot{Q}_{h,CHP}$, the HP $\dot{Q}_{h,HP}$ and the discharge of the HS $\dot{Q}_{h,HS}^{dch}$:

$$\dot{Q}_{h,GB}(t) + \dot{Q}_{h,CHP}(t) + \dot{Q}_{h,HP}(t) + \dot{Q}_{h,HS}^{dch}(t) = \dot{Q}_{h,dem}(t) + \dot{Q}_{h,HS}^{ch}(t) \quad (8)$$

The cooling grid is supplied via the CC $\dot{Q}_{c,CC}$, the FC $\dot{Q}_{c,FC}$, the discharge of the cold storage $\dot{Q}_{c,CS}^{dch}$ and the discharge of the IES $\dot{Q}_{c,IES}^{dch}$. In this way, the building's cooling requirements $\dot{Q}_{c,dem}$ and the charging energy of the cold storage $\dot{Q}_{c,CS}^{ch}$ are covered:

$$\dot{Q}_{c,CC}(t) + \dot{Q}_{c,FC}(t) + \dot{Q}_{c,CS}^{dch}(t) + \dot{Q}_{c,IES}^{dch}(t) = \dot{Q}_{c,dem}(t) + \dot{Q}_{c,CS}^{ch}(t) \quad (9)$$

3.3. Component models

Subsequent to a detailed delineation of the system's structural framework and interrelationships, the constituent components are designated as submodels. These submodels are described by continuous, integer and binary variables which are expressed in linear equations and inequalities. The parameters utilized can be found in [Table 2](#) in the [Appendix A](#).

3.3.1. Combined heat and power unit

The mathematical representation of the operating behavior and the coupling of the simultaneous provision of heat and electricity is carried out using a binary variable x_{CHP} . This temporal state of the CHP unit is defined by two further binary variables. According to the available evidence, the implementation of a start $x_{start,CHP}$ and stop $x_{stop,CHP}$ state enables the definition of the minimum runtime $t_{min,CHP}$:

$$x_{CHP}(t) = x_{start,CHP}(t) - x_{stop,CHP}(t) + x_{CHP}(t-1) \quad (10)$$

$$\sum_{\tau=1}^{t+t_{min,CHP}} x_{CHP}(\tau) \geq t_{min,CHP} x_{start,CHP}(t) \quad (11)$$

Furthermore, the temporal initiation of the CHP unit is linked to a defined minimum heat requirement $\dot{Q}_{h,dem,CHP}^{start}$:

$$\dot{Q}_{h,dem}(t) \geq \dot{Q}_{h,dem,CHP}^{start} x_{start,CHP}(t) \quad (12)$$

Depending on the operating status, the nominal values for heat $\dot{Q}_{h,CHP}^{nom}$ and electricity P_{CHP}^{nom} are fed into the respective supply grids:

$$\dot{Q}_{h,CHP}(t) = \dot{Q}_{h,CHP}^{nom} x_{CHP}(t) \quad (13)$$

$$P_{CHP}(t) = P_{CHP}^{nom} x_{CHP}(t) \quad (14)$$

Once the energy provision has been defined, the required final energy can be obtained in the form of natural gas $\dot{G}_{CHP}$ by applying the partial efficiencies for heat $\eta_{h,CHP}$ and electricity $\eta_{el,CHP}$:

$$\dot{G}_{CHP}(t) = \frac{\dot{Q}_{h,CHP}(t)}{\eta_{h,CHP}} = \frac{P_{CHP}(t)}{\eta_{el,CHP}} \quad (15)$$

3.3.2. Gas boiler

The heat output provided by the GB is limited by its nominal value $\dot{Q}_{h,GB}^{nom}$. The associated gas consumption is calculated using the efficiency η_{GB} , denoted by the manufacturer's specification:

$$\dot{Q}_{h,GB}(t) \leq \dot{Q}_{h,GB}^{nom} \quad (16)$$

$$\dot{G}_{GB}(t) = \frac{\dot{Q}_{h,GB}(t)}{\eta_{GB}} \quad (17)$$

3.3.3. Heat pump

In order to establish the direct connection between the HP and the IES, the logarithmic mean temperature on the primary side $T_{m,prim,HP}$ is calculated using the time-dependent temperatures of the IES T_{IES} . While these are return temperatures, the flow temperature is determined using the manufacturer-specific temperature difference $\Delta T_{prim,HP}$:

$$T_{m,prim,HP}(t) = \frac{T_{IES}(t) - (T_{IES}(t) + \Delta T_{prim,HP})}{\ln \left(\frac{T_{IES}(t)}{T_{IES}(t) + \Delta T_{prim,HP}} \right)} \quad (18)$$

The logarithmic mean temperature on the secondary side $T_{m,sec,HP}$ is also calculated using the manufacturer-specific data for the flow temperature $T_{out,sec,HP}$ and return $T_{in,sec,HP}$ temperature:

$$T_{m,sec,HP}(t) = \frac{T_{out,sec,HP} - T_{in,sec,HP}}{\ln \frac{T_{out,sec,HP}}{T_{in,sec,HP}}} \quad (19)$$

When the mean temperatures at the evaporator and condenser are known, the Lorenz coefficient of performance $COP_{L,HP}$ can be calculated as the theoretical maximum of the HP. The real coefficient of performance COP_{HP} can then be estimated using the internal exergetic efficiency of the cycle process $\eta_{ex,i,HP}$:

$$COP_{L,HP}(t) = \frac{T_{m,sec,HP}(t)}{T_{m,sec,HP}(t) - T_{m,prim,HP}(t)} \quad (20)$$

$$COP_{HP}(t) = \eta_{ex,i,HP} COP_{L,HP}(t) \quad (21)$$

Finally, the heat provided can be calculated using the electrical power consumption of the heat pump, which is limited by the defined maximum P_{HP}^{nom} :

$$\dot{Q}_{h,HP}(t) = P_{HP}(t) COP_{HP}(t) \quad (22)$$

$$P_{HP}(t) \leq P_{HP}^{nom} \quad (23)$$

The energy balance of the HP facilitates the description of the cooling energy provided to the IES $\dot{Q}_{c,IES}^{ch}$ [37]:

$$\dot{Q}_{c,IES}^{ch}(t) = \dot{Q}_{h,HP}(t) - P_{HP}(t) \quad (24)$$

Subsequently, the losses associated with the provision of cooling from the HP are addressed through the implementation of an efficiency factor for the loading of the IES. This is described in [Section 3.4.1](#).

3.3.4. Compression chiller and free cooling unit

In contrast to the HP, the CC is directly dependent on the ambient temperature T_{amb} via the connection with the FC device. The data for T_{amb} is derived from the measurements taken by the weather station of the University of Bayreuth [38]. In this way the logarithmic mean temperature on the secondary side $T_{m,sec,CC}$ is calculated according to Eq.

(18). This calculation considers T_{amb} and a temperature difference $\Delta T_{sec,CC}$. The logarithmic mean temperature on the primary side $T_{m,prim,CC}$ is determined by utilizing the established flow and return temperature of the refrigeration grid. Subsequently, these results can then be used to estimate the real energy efficiency ratio EER_{CC} of the CC, considering the Lorenz energy efficiency ratio $EER_{L,CC}$ and the internal exergetic efficiency $\eta_{ex,i,CC}$:

$$EER_{L,CC}(t) = \frac{T_{m,prim,CC}(t)}{T_{m,sec,CC}(t) - T_{m,prim,CC}(t)} \quad (25)$$

$$EER_{CC}(t) = \eta_{ex,i,CC} EER_{L,CC}(t) \quad (26)$$

Consequently, the electrical power consumption of the CC is constrained to a nominal maximal value $P_{max,CC}^{nom}$ and a nominal minimal value $P_{min,CC}^{nom}$. These constraints are considered in conjunction with the binary variable $x_{CC}(t)$:

$$\dot{Q}_{c,CC}(t) = P_{CC}(t) EER_{CC}(t) \quad (27)$$

$$P_{CC}(t) \leq x_{CC}(t) P_{max,CC}^{nom} \quad (28)$$

$$P_{CC}(t) \geq x_{CC}(t) P_{min,CC}^{nom} \quad (29)$$

If the ambient temperature falls below a predetermined value $T_{amb,FC}^{start}$, the cooling process is exclusively facilitated by the FC. In this instance, an additional binary variable is introduced to describe the operating status of the FC x_{FC} :

$$x_{CC}(t) + x_{FC}(t) \leq 1 \quad (30)$$

$$x_{FC}(t) T_{amb}(t) \leq T_{amb,FC}^{start} \quad (31)$$

The provision of cooling and the electricity consumption of the FC unit can be determined by specifying nominal capacity values $\dot{Q}_{c,FC}^{nom}$ and P_{FC}^{nom} :

$$\dot{Q}_{c,FC}(t) \leq x_{FC}(t) \dot{Q}_{c,FC}^{nom} \quad (32)$$

$$P_{FC}(t) \leq x_{FC}(t) P_{FC}^{nom} \quad (33)$$

3.3.5. Heating and cooling short-term energy storage

The status of the TESs, which are regarded as perfectly stirred water tanks, is delineated through an energy balance and the explicit Euler method. This implies that the temporal energy load SOC is defined by the previous time step, the charging $\dot{Q}^{ch}$ and discharging $\dot{Q}^{dch}$ loads and their associated efficiencies η^{ch} and η^{dch} . In addition, the relative loss ϕ_{loss} to the storage state is included [29]:

$$SOC_{h,HS}(t) = SOC_{h,HS}(t-1)(1 - \phi_{loss,HS}) + \eta_{HS}^{ch} \dot{Q}_{h,HS}^{ch}(t) - \frac{\dot{Q}_{h,HS}^{dch}(t)}{\eta_{HS}^{dch}} \quad (34)$$

$$SOC_{c,CS}(t) = SOC_{c,CS}(t-1)(1 - \phi_{loss,CS}) + \eta_{CS}^{ch} \dot{Q}_{c,CS}^{ch}(t) - \frac{\dot{Q}_{c,CS}^{dch}(t)}{\eta_{CS}^{dch}} \quad (35)$$

To account for the available storage capacities, the temporal storage status is constrained by a nominal value Q^{nom} :

$$SOC_{h,HS}(t) \leq Q_{h,HS}^{nom} \quad (36)$$

$$SOC_{c,CS}(t) \leq Q_{c,CS}^{nom} \quad (37)$$

The charging and discharging processes of the storage tanks are limited by C-rates, which represent the ratio of the charging C^{ch} and discharging C^{dch} load capacity to the nominal storage capacity:

$$\dot{Q}_{h,HS}^{ch}(t) \leq C_{h,HS}^{ch} Q_{h,HS}^{nom} \quad (38)$$

$$\dot{Q}_{h,HS}^{dch}(t) \leq C_{h,HS}^{dch} Q_{h,HS}^{nom} \quad (39)$$

$$\dot{Q}_{c,CS}^{ch}(t) \leq C_{c,CS}^{ch} Q_{c,CS}^{nom} \quad (40)$$

$$\dot{Q}_{c,CS}^{dch}(t) \leq C_{c,CS}^{dch} Q_{c,CS}^{nom} \quad (41)$$

3.3.6. Photovoltaic

The Python library pvlib is employed to model the performance of the PV module [39]. This library provides a substantial number of established physical models and location-related solar irradiance libraries. To this end, the Sandia Array Performance Model (SAPM) [40] is utilized to determine the power output by assessing operating conditions in conjunction with irradiance data from Photovoltaic Geographical Information System (PVGIS) [41]. In addition to irradiation and cell temperature, the semi-empirical model accounts for angle-dependent effects and spectral influences. This enables precise mapping of the power output at module level. The input parameters for the SAPM model are the peak power P_{PV}^{nom} , the orientation γ_{PV} , the tilt angle α_{PV} , the temperature coefficient μ_{PV} and the efficiency of the inverter $\eta_{inv,PV}$. These parameters are also delineated in Table 2 in the Appendix A.

3.4. Ice energy storage

The next step involves the incorporation of the IES into the overall system as a submodel for seasonal cooling energy storage systems. To accomplish this process, it is first necessary to describe the MILP constraints. Subsequently, the temporal self-loss factor is calculated in a preprocessing step.

3.4.1. MILP model

In the analogous way as for short-term TES, which is described in Section 3.3.5, the behavior of the IES is also mapped in the MILP model with the energy balance and the explicit Euler method [29]. Furthermore, the specific enthalpy h_{IES} is derived through the analysis of the alterations in energy status across the time increments. This ensures the consideration of phase transition within the storage tanks storable water mass $m_{water,IES}$:

$$SOC_{c,IES}(t) = SOC_{c,IES}(t-1)(1 - \phi_{loss,IES,m}) + \eta_{IES}^{ch} \dot{Q}_{c,IES}^{ch}(t) - \frac{\dot{Q}_{c,IES}^{dch}(t)}{\eta_{IES}^{dch}} \quad (42)$$

$$h_{IES}(t) = h_{IES}(t-1) + \frac{SOC_{c,IES}(t-1) - SOC_{c,IES}(t)}{m_{water,IES}} \quad (43)$$

The determination of the temporary storage temperature T_{IES} can be achieved through the utilization of a temperature-enthalpy correlation

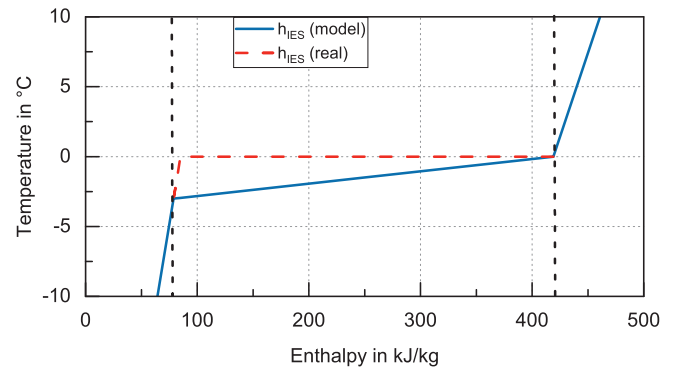


Fig. 5. Numerical temperature-enthalpy correlation h_{IES} of the ice energy storage (IES) model compared to the real course, which are identical at temperatures below -3 °C and above 0 °C.

[26,27]. The ranges are defined by four sample points (see Fig. 5) and the heat capacities for the solid phase c_{ice} , for the phase transition c_{mix} and for the liquid phase c_{liquid} :

$$h_{IES}(T_{IES}(t)) = \begin{cases} h_{IES,ice} + c_{ice}T_{IES}(t), & -10 < T_{IES}(t) < -3 \\ h_{IES,ice} + c_{mix}T_{IES}(t), & -3 \leq T_{IES}(t) \leq 0 \\ h_{IES,liquid} + c_{liquid}T_{IES}(t), & 0 < T_{IES}(t) < 10 \end{cases} \quad (44)$$

The active discharge of the IES is limited by a maximum discharge temperature $T_{max,IES}^{dch}$. The binary variable x_{IES}^{dch} is employed for this purpose:

$$T_{IES}(t-1)x_{IES}^{dch} \leq T_{max,IES}^{dch} \quad (45)$$

Upon attaining $T_{max,IES}^{dch}$, the active discharge of the IES is suspended for a defined period $t_{break,EES}^{dch}$. This situation can be described in a similar way to Section 3.3.1 using the binary variables $x_{start,EES}^{dch}$, $x_{stop,EES}^{dch}$ and $x_{break,EES}^{dch}$:

$$x_{EES}^{dch}(t) = x_{stop,EES}^{dch}(t) - x_{start,EES}^{dch}(t) + x_{EES}^{dch}(t-1) \quad (46)$$

$$\sum_{\tau=1}^{t-t_{break,EES}^{dch}} x_{break,EES}^{dch}(\tau) \geq t_{break,EES}^{dch} x_{stop,EES}^{dch}(t) \quad (47)$$

Beyond the two constraints previously outlined, an additional limitation is considered in the form of a maximum value for the discharge load $\dot{Q}_{c,max,EES}^{dch}$:

$$\dot{Q}_{c,EES}^{dch} \leq x_{EES}^{dch}(t) (1 - x_{break,EES}^{dch}(t)) \dot{Q}_{c,max,EES}^{dch} \quad (48)$$

Furthermore, a start T_{IES}^{start} and a target temperature T_{IES}^{target} are specified. The consistency of these temperatures is imperative to enable a seasonal storage behavior [42]:

$$T_{IES}(0) = T_{IES}^{start} \quad (49)$$

$$T_{IES}(H) \leq T_{IES}^{target} \quad (50)$$

$$T_{IES}^{start} = T_{IES}^{target} \quad (51)$$

3.4.2. Preprocessing of the ground-coupled thermal transfer

The subsequent stage in this process is to establish the connection to the surrounding soil. To ensure that the relationships within the MILP model remain linear, this procedure is executed externally as a preprocessing step before the actual simulation. It is important to note that the approach taken in the preprocessing step can be adapted to the energy system under investigation, depending on the specific use case and the required level of detail. In the interest of focusing on the present methodology that is currently being followed, the heat capacity of the surrounding soil is not considered, as was also done in an even more detailed previous model of the IES [31]. Preliminary evaluations have shown that the thermal storage capacity of the surrounding environment has no significant effect on the storage behavior for this simplified TES case study. Due to the limited thermal conductivity of the concrete shell and the seasonal temperature fluctuations both inside and outside the storage tank, the temperature of the soil immediately surrounding the tank is influenced to a greater extent by the surrounding soil temperature than by the storage tank itself.

In the case of the IES, it is first necessary to define a typical temperature profile of the IES, see Fig. 6. This assumption is based on the premise that this profile will remain comparable over an extended period, as it typically follows a consistent seasonal pattern. Depending on the specific requirements, the desired storage behavior can be included in the analysis.

The initial profile is defined via the mean value of the annual temperature $T_{m,pre,IES}$, the amplitude $\Delta T_{pre,IES}$ and the temporal shift of the cosine function $t_{shift,IES}$:

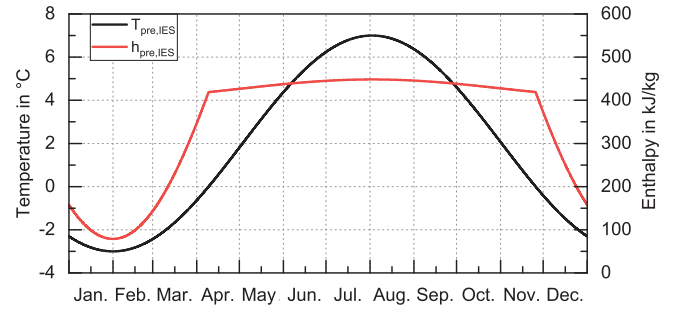


Fig. 6. Assumed annual temperature $T_{pre,IES}$ based on the data reported in [31] and enthalpy curve $h_{pre,IES}$ of the ice energy storage (IES) calculated with the temperature-enthalpy correlation proposed in [26,27].

$$T_{pre,IES}(t) = T_{m,pre,IES} - \Delta T_{pre,IES} \cos\left(2\pi \frac{t - t_{shift,IES}}{H}\right) \quad (52)$$

The definition of a temperature gradient between the storage tank and its surrounding ground necessitates the determination of the ground temperature. This is pronounced due to the high solar influence near the ground surface, resulting in a distinct seasonal temperature curve. The amplitude of this profile decreases with increasing depth z [43]. To this end, the so-called undisturbed ground temperature T_g is determined using the correlation developed by Kusuda and Achenbach [44]. In this context, the storage capacity of the ground is disregarded:

$$T_g(t) = T_{m,amb} - \Delta T_{amb} e^{-z/z_{da}} \cos\left(\frac{2\pi(t - t_{shift,amb})}{t_0} - \frac{z}{z_{da}}\right) + Gz \quad (53)$$

The underlying variables include the average ambient temperature $T_{m,amb}$, the amplitude of the ambient temperature ΔT_{amb} , the temporal shift of the minimum ambient temperature $t_{shift,amb}$, the number of seconds per year t_0 and the geothermal gradient G . The thermal penetration depth z_{da} according to [45] is determined using the parameters specified in Fig. 8 based on the local soil properties:

$$z_{da} = \sqrt{\frac{(t_0 \lambda_g)}{\pi \rho_g c_g}} \quad (54)$$

With the thermal conductivity λ_g , the density ρ_g and the heat capacity of the soil c_g . Thus, the seasonal course of the depth-dependent ground temperature corresponds in simplified form to a cosine function damped by z_{da} , which is shown exemplary for different depths in Fig. 7.

As already mentioned, the total losses $\dot{Q}_{loss}$ are simplified by including only heat conduction. This can be specified by the following equation:

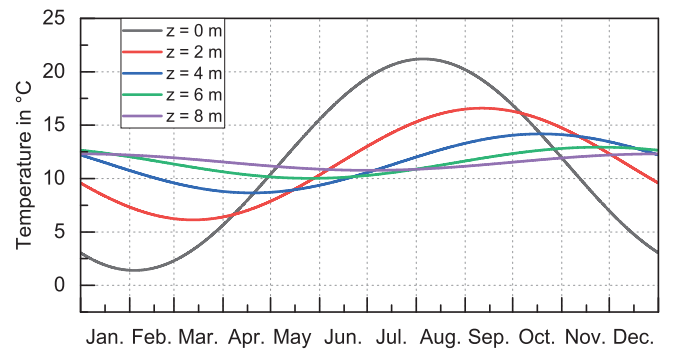


Fig. 7. Annual curve of the undisturbed ground temperature for different depths z .

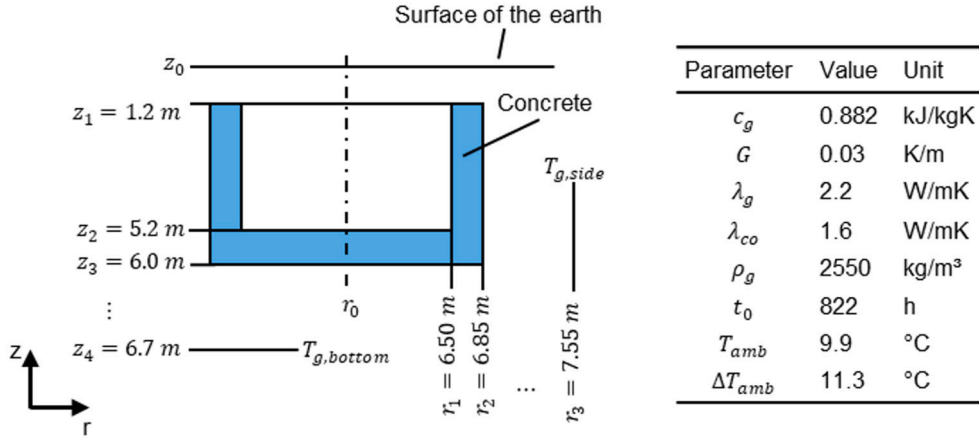


Fig. 8. Schematic illustration of the dimensions of the ice storage in relation to the surrounding soil together with an overview of the employed parameters and properties from [46].

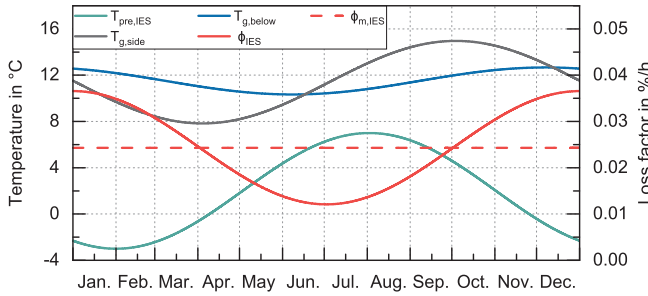


Fig. 9. Annual loss curve ϕ_{IES} and corresponding mean value $\phi_{m,IES}$ compared with the assumed temperature curve $T_{pre,IES}$ based on the data reported in [31] and the undisturbed ground temperatures at the side $T_{g,side}$ in a depth of 3.2 m and below $T_{g,bottom}$ in a depth of 6.7 m of the ice energy storage (IES), calculated according to [44].

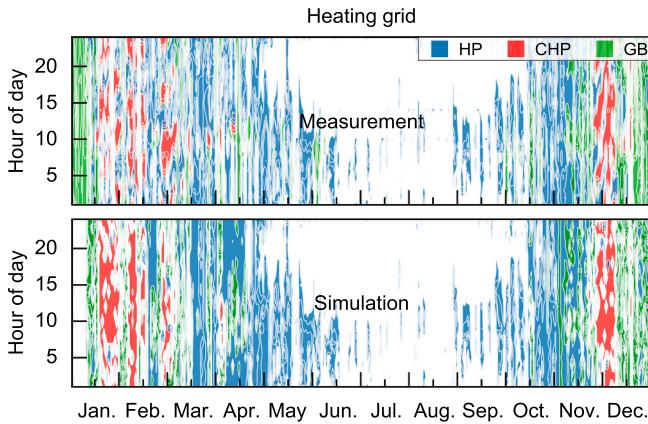


Fig. 10. Heat map illustration of the heating grid's energy supply over time by the components: heat pump (HP), combined heat and power unit (CHP) and gas boiler (GB).

$$\dot{Q}_{loss}(t) = (T_{g,side}(t) - T_{pre,IES}(t))UA_{side} + (T_{g,bottom}(t) - T_{pre,IES}(t))UA_{bottom} \quad (55)$$

In the first part of Eq. (55), the lateral component of heat loss is delineated by the predefined storage temperature $T_{pre,IES}$, the lateral ground temperature $T_{g,side}$ and the lateral heat transfer coefficient UA_{side} . This is defined by the thermal conductivity of concrete λ_{co} , the thermal conductivity of the ground λ_g and the dimensions depicted in Fig. 8:

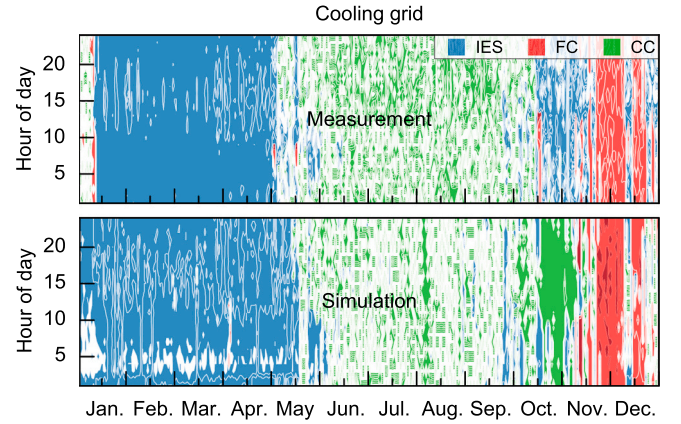


Fig. 11. Heat map illustration of the cooling grid's energy supply over time by the components: ice energy storage (IES), free cooling (FC) and compression chiller (CC).

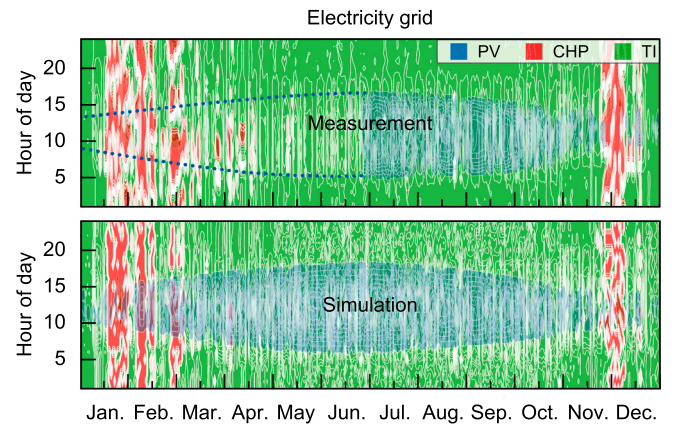


Fig. 12. Heat map illustration of the electricity grid's energy supply over time by the components: photovoltaic (PV), combined heat and power unit (CHP) and transformer input (TI). Measurement gap in PV data until the beginning of July 2023.

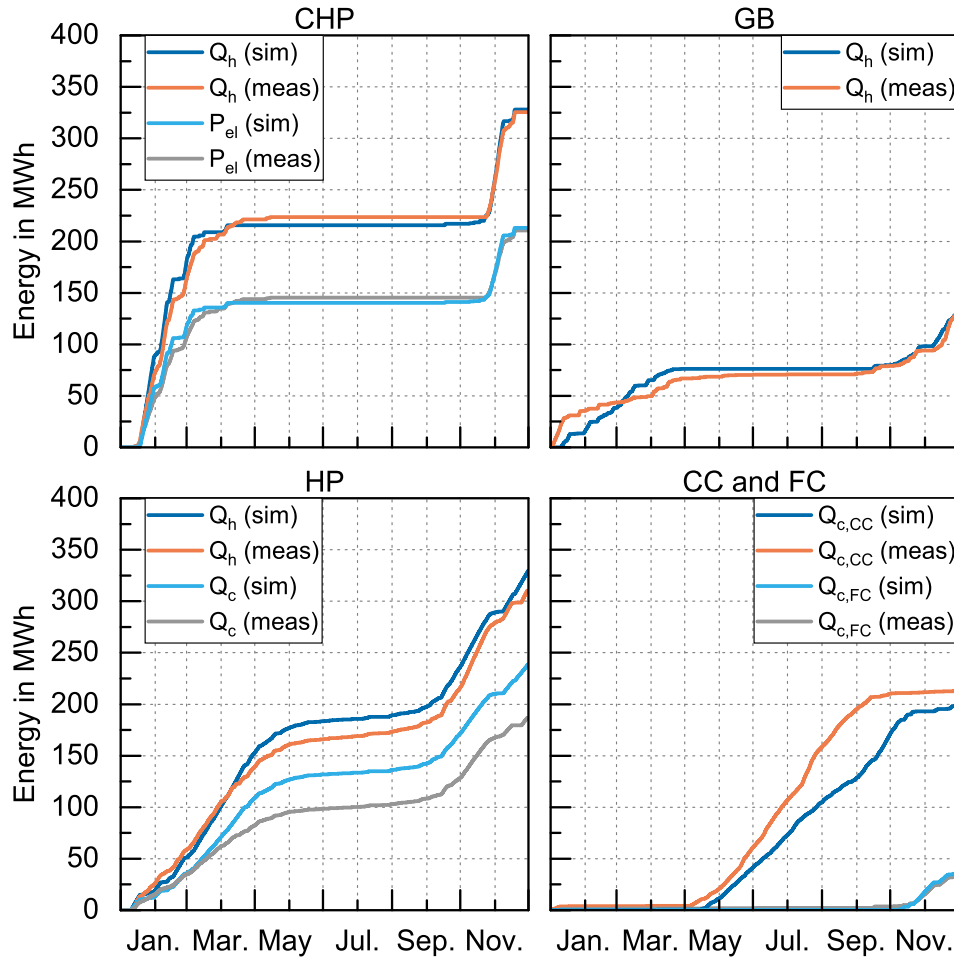


Fig. 13. Annual comparison between measurement (meas) and simulation (sim) of the cumulative provision of heating energy Q_h or cooling energy Q_c by the different components of the coupled energy system: combined heat and power unit (CHP), gas boiler (GB), heat pump (HP), compression chiller (CC) and free cooling (FC).

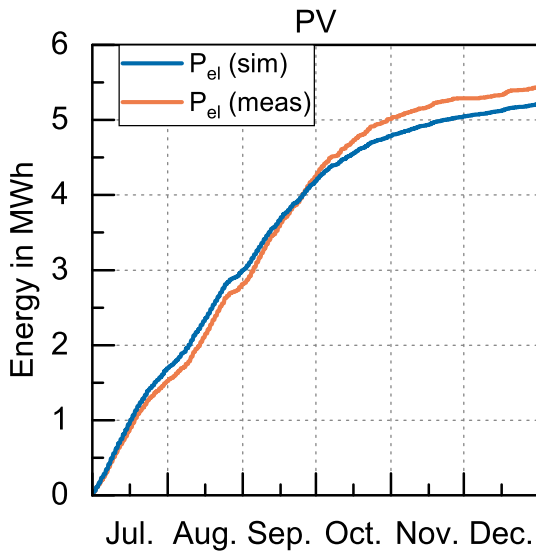


Fig. 14. Comparison between measurement (meas) and simulation (sim) of the cumulative provision of electricity energy P_{el} by the photovoltaic system (PV) between July and December.

$$UA_{side} = \left(\frac{\ln\left(\frac{r_2}{r_1}\right)}{2\pi(z_2 - z_1)\lambda_{co}} + \frac{\ln\left(\frac{r_3}{r_2}\right)}{2\pi(z_2 - z_1)\lambda_g} \right)^{-1} \quad (56)$$

The second part of Eq. (55) is the loss fraction at the bottom of the storage tank. In addition to $T_{pre,IES}$, this depends on the ground temperature at the bottom $T_{g,bottom}$ and the heat transfer coefficient at the bottom UA_{bottom} :

$$UA_{bottom} = \left(\frac{z_3 - z_2}{\pi r_1^2 \lambda_{co}} + \frac{z_4 - z_3}{\pi r_1^2 \lambda_g} \right)^{-1} \quad (57)$$

Heat losses at the top of the storage are neglected, as in addition to a broad layer of soil and concrete, the air inside the not completely filled cylinder acts as insulation resistance.

Once the absolute loss between the IES and the ground has been determined for each increment, it is imperative to conceptualize this storage loss as a function of the temporal storage state. In this context, it is of significant relevance to integrate the size of the loss into the simulation as a relative loss factor. Initially, the mean enthalpy $h_{m,pre,IES}$ is calculated using the predefined temperature or enthalpy curve $h_{pre,IES}$:

$$h_{m,pre,IES} = \frac{\sum_{t=1}^H h_{pre,IES}(t)}{H} \quad (58)$$

The determination of an average energetic storage state $SOC_{c,m,pre,IES}$

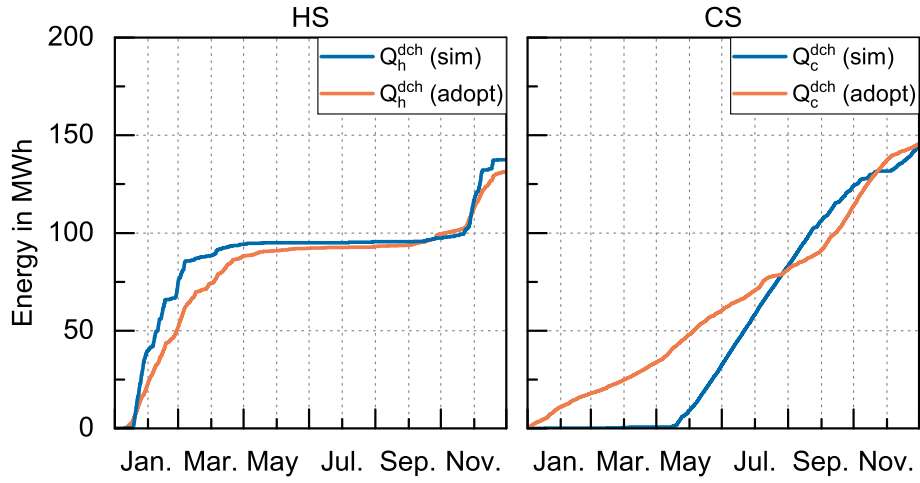


Fig. 15. Annual comparison between adoption (adopt) and simulation (sim) of the cumulative discharge of heating energy Q_h^{dch} or cooling energy Q_c^{dch} by the heating energy storage (HS) and cooling energy storage (CS).

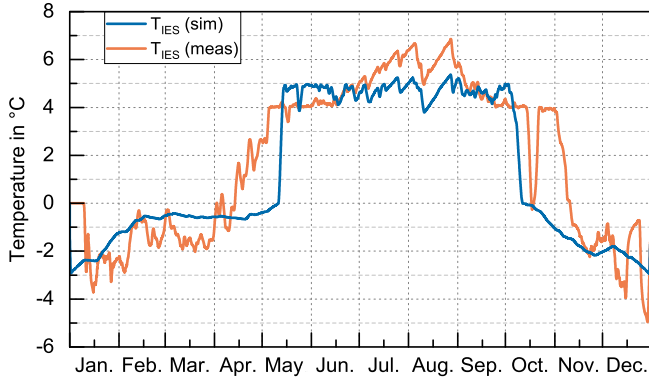


Fig. 16. Annual comparison between measurement (meas) and simulation (sim) of the temperature curve T_{IES} of the ice energy storage (IES).

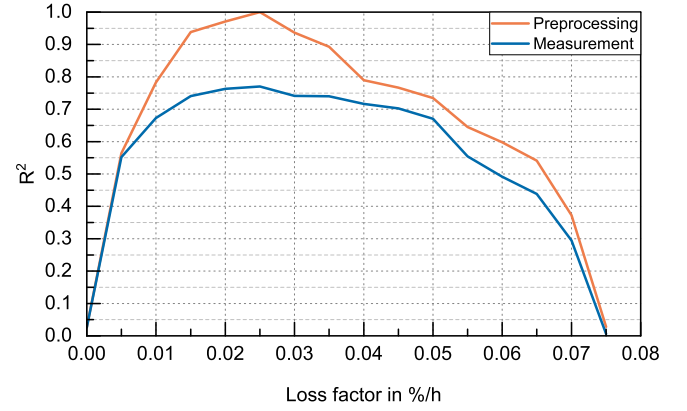


Fig. 18. Representation of changes in the coefficient of determination R^2 for different loss factors in comparison with measurement data and the pre-processed simulation of the annual ice energy storage (IES) temperature profile.

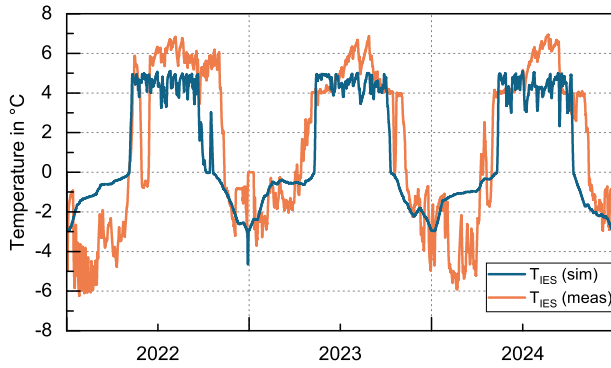


Fig. 17. Comparison between measurement (meas) and simulation (sim) of the temperature curve T_{IES} of the ice energy storage (IES) over a time horizon of three years.

is achieved through the utilization of a reference temperature of the building. This reference temperature is subsequently converted into a reference enthalpy $h_{ref,IES}$ employing the temperature-enthalpy model and $m_{water,IES}$:

$$SOC_{c,m,pre,IES} = (h_{ref,IES} - h_{m,pre,IES})m_{water,IES} \quad (59)$$

In comparison, the time losses for each increment can be quantified by a relative loss factor ϕ_{IES} and the annual mean loss factor $\phi_{IES,m}$, see

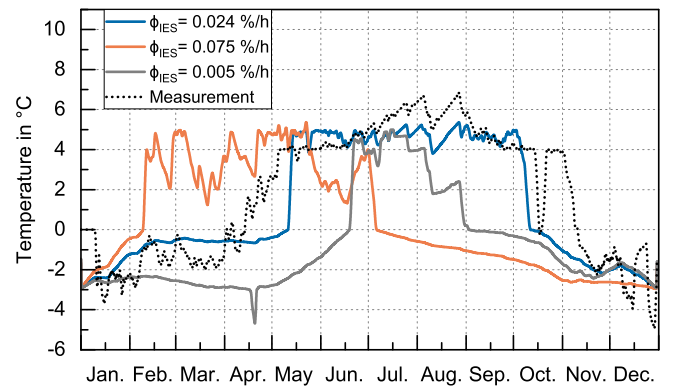


Fig. 19. Comparison of the temperature curve of the ice energy storage (IES) with different loss factors ϕ_{IES} and the measured curve of 2023.

Fig. 9:

$$\phi_{IES}(t) = \frac{\dot{Q}_{loss}(t)}{SOC_{c,m,pre,IES}} \quad (60)$$

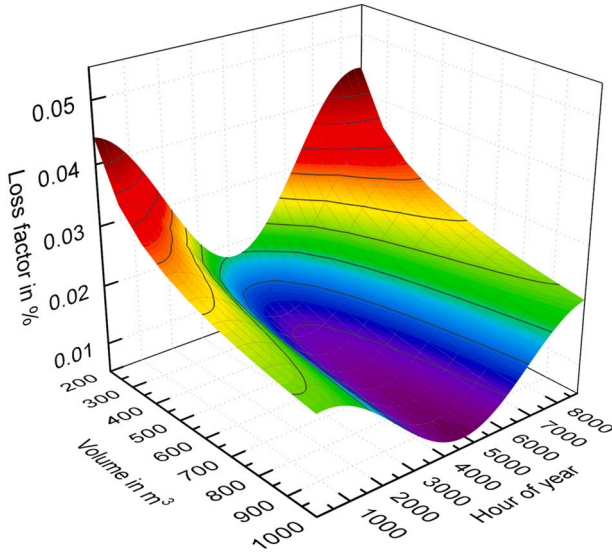


Fig. 20. Illustration of the loss factor as a function of the available volume range for the MILP design optimization.

$$\phi_{m,IES} = \frac{\sum_{t=1}^H \phi_{IES}(t)}{H} \quad (61)$$

Depending on the application, either the complete loss curve or the constant average loss factor can be used for the subsequent MILP model implementation.

4. Results and discussion

In this chapter, the results determined with the MILP model are compared with the measurement data of the real energy system in an hourly resolution. For the purpose of this study, the year 2023 has been selected as the reference year, as it is the time period during which the most comprehensive measurement data is available for all components. Furthermore, the implications of modifying the IES loss factor will be examined, followed by a discussion of the potential integration of geothermal coupling for enhancing design optimizations.

In order to facilitate a comparison between the most time-efficient model and the measurement data, the predefined storage curve from

Fig. 6 will be utilized in the subsequent sections. For the following validation, the premise is established that the seasonal storage behavior of the IES system under consideration can be estimated. In the present configuration, therefore, it can be assumed that this is an optimization case or a prediction case for model predictive control (MPC). In instances where storage behavior cannot be estimated in advance, the iteration step delineated in Section 4.4 can be employed.

4.1. Validation

The solution of the MILP model can be realized in a time frame of approx. 30 min (1829 s) using the present system configuration, see Section 3. To ensure an efficient representation of the temporary interaction between the systems, as well as to enable comparison of the simulation results with the measurement data from the real energy system, heat maps are created for the three internal supply grids. These are further split into two diagrams: measurement data and simulation data. The representation of the temporal operation of the suppliers is achieved through the use of different colors, see Figs. 10 to 12.

Firstly, an examination will be conducted of the chronological sequence and interaction between the supply systems in the heating grid, see Fig. 10. A comparison of the measurement data and the simulation results generally yield a comparable overall picture. It has been observed that the components are particularly active during the winter months. During summer months, the HP (blue) is only

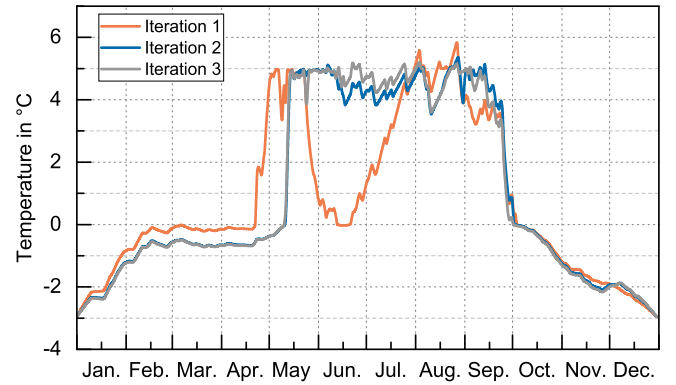


Fig. 22. Comparison of different iteration steps of the ice energy storage temperature when no typical temperature profile is specified in the pre-processing step.

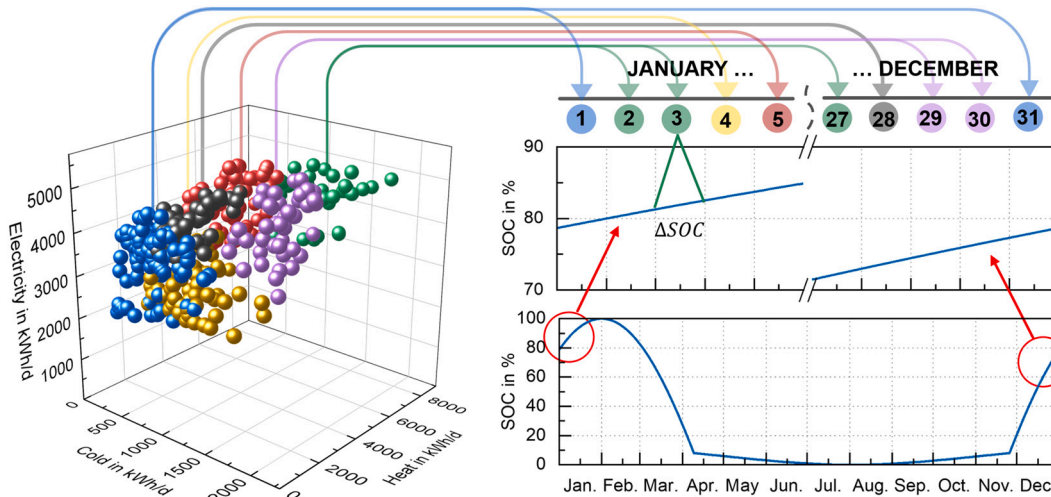


Fig. 21. Representation of the design day clustering with k-medoids (left) and the subsequent calendar assignment, including the seasonal status of charge curve (SOC) of the ice energy storage (IES) (right).

operational for a limited number of hours, thus ensuring the provision of heating energy for short-term periods. The simulated heat map diagram reveals elevated HP operation in specific regions. This observation is also confirmed by the cumulative results of component specific energy supply and will be discussed in the further analysis of this section. Conversely, the CHP unit (red) is only operational during periods of elevated heat demand that extend over a considerable duration. These results indicate that the conditions employed in this study facilitate sufficient representation of the CHP, with this component model operating at comparable times to the real system. The GB (green) is utilized flexibly to accommodate peak loads. While the running times of the GB demonstrate a high degree of consistency throughout the period under review, an anomaly is observed at the beginning of the year. The measurement data demonstrates GB operation at the beginning of January that is not considered in the simulation. This development is attributable to the specified load profile (see Section 2.1), which does not stipulate any load during this period. This discrepancy can thus be attributed to GB operation that is not recorded in the heating demand profile.

In the context of examining the cooling grid, the initial results of the IES-MILP model, which forms the central focus of this work, are discussed, see Fig. 11. In this case as well, a similar overall picture emerges. The detailed analysis of the available measurement data, as illustrated by the upper heat map diagram, indicates that the cooling energy demand can be provided exclusively by regeneration of the IES (blue) until approx. mid of May. In comparison with the reality, the simulation allows the regeneration of the IES to be extended by several days. During the summer months, the CC (green) assumes primary responsibility for supply. As the season of autumn approaches, the IES can already be recharged in part by the HP, which is the reason why regeneration occasionally provides cooling energy again at this point. In contrast to real operation, the CC is also used even more frequently during the start of winter period. This development could be due to the optimization of the discharge processes, whereby the usage of the energy already stored takes place at a later point in time. The functionality of the FC (red) is contingent upon external conditions. Consequently, the operational period is considerably constrained, thereby ensuring a good correlation of this time period between the simulation and the measurement data. A subsequent examination of the simulation of cooling energy provision reveals the IES-MILP model's capacity to adequately represent the seasonal storage process already for temporal analysis.

Following the examination of the two thermal supply grids, an investigation of the internal electrical supply grid will be conducted. In this instance as well, the operating times of the components are presented in the form of two heat maps, see Fig. 12. In addition to the previously discussed operation of the CHP (red), the PV feed-in (blue) can also be observed here. Due to a data gap, only records from approx. July onward are available in this repository. From then on, the PV model provides comparable feed-in times to the real system. The concentration of electricity supply around midday is attributable to the southern orientation of the PV modules. The remaining electricity demand is covered by the public grid (green).

After the temporal validation, the simulation results are also analyzed quantitatively by comparing the cumulative energy amounts over the course of the reference year, see Fig. 13. The temporal energy quantities of the CHP and GB show significant agreement with the measured data. An analysis of the HP reveals also a notable correlation of heat and cold supply, especially in the winter months. A heightened energy supply has been documented during the transition between spring and summer months. This discrepancy may be due to several reasons. First, there is an optimized operating mode that can differ from the real system operation. Second, the simplified HP model used does not account for the temperature dependence of the internal exergetic efficiency. However, the heat map of heating energy supply also demonstrates an increased utilization of the HP, see Fig. 10. This effect is therefore attributed to an optimized operating strategy. Consequently, the amount of cooling energy provided by the CC is slightly lower. The

operational dynamics of the FC can also be seen in the same diagram that illustrates the CC. Through the threshold value of the ambient temperature, an adequate simulation of the operation times can be expected.

In view of the mentioned data leak concerning the measurement of the PV system, the comparison of the cumulative energy curves commences in July, see Fig. 14. The analysis of this demonstrates that the SAPM model offers a satisfactory representation of the provision of PV electricity during the period under consideration. Deviations in total energy volumes over this period can be classified as minor.

As previously outlined, the functions of the submodels exert an influence on the overall system and, by extension, the operation of the IES. Consequently, it is recommended to undertake also an analysis of the short-term energy storage systems. Direct measurements that would be comparable with the simulation results are not available at this point. Nevertheless, an estimate can be obtained by comparing the energy production of the supply plants with the total demand for each time step. The observed discrepancy is attributed to the storage systems. This resultant curve showing the annual energy quantities provided for the heating and the cooling grid, see Fig. 15.

A comparison of the assumed and simulated curve reveals that the behavior of the HS can be adequately represented. An analysis of the CS indicates that its utilization at the beginning of the year exceeds the levels predicted by the simulation. This development can be explained by the optimization algorithm, which helps to avoid the storage of cooling energy originating from the IES. This results in a reduction in double storage losses. The short-term cold storage is therefore only operated when the IES can no longer provide sufficient energy, and the CC is used.

According to the analysis of the individual components of the overall energy system, a detailed investigation of the storage behavior of the IES will now be carried out as the primary result of this study. To describe and compare the annual condition of the IES, the temperatures recorded in the tank are averaged and contrasted with the simulation result, see Fig. 16.

The two temperature curves confirm the results previously analyzed using the heat map of the cooling energy supply. The annual profile shows that the seasonal storage behavior can be represented with the IES-MILP model used. It should be noted that the simulated curve within the transition range between 0 °C and −3 °C demonstrates a slower rate of behavior in comparison to the measured data. This phenomenon can be attributed to the enthalpy model employed (see Section 3.4.1), which distributes the melting enthalpy across this temperature range. The loss factor can be evaluated during phases without loading or unloading cycles. This is evident in the example year under consideration, particularly in July and August. During these months, sections with a constant rise in temperature can be observed in both curves. Consequently, this rise is defined exclusively by the loss to the surrounding ground. Based on the observation of an almost parallel course between measurement and simulation in these periods, the hypothesis is put forward that the calculated loss factor corresponds to the correct order of magnitude. In October, the reloading process is initiated in both simulation and real storage. While this process persists in simulation, in reality, this energy is reused in the cooling grid. This discrepancy is consistent with the findings depicted in Fig. 11 and can be ascribed to the increased running time of the simulated CC during this period.

Furthermore, to perform a defined comparison of the two annual temperature profiles, the coefficient of determination R^2 is determined:

$$R^2 = 1 - \frac{\sum_{t=1}^H (T_{IES}^{meas}(t) - T_{IES}^{sim}(t))^2}{\sum_{t=1}^H (T_{IES}^{meas}(t) - T_{m,IES}^{meas})^2} \quad (62)$$

This results in a value of 0.77 for the year 2023.

In addition, the IES temperature is simulated over a period of several years, see Fig. 17. An examination of the available measured data

reveals an adjustment in the maximum discharge temperature from 4 °C to 6 °C between the years 2022 and 2023. For this reason, the simulation employs an average value of 5 °C, yielding an R^2 value of 0.64 over a three-year period.

As previously mentioned in the introduction to Section 3, the iteration step is not executed for the results that are presented, as the most time-efficient model is to be validated. Due to the analogical progression between the initial profile and the simulated profile indicates that an iteration exerts a negligible influence on the overall result. Nevertheless, in instances where substantial deviations from the assumed profile are observed, the increased time required may prove worthwhile.

4.2. Sensitivity analysis

Following the validation of the storage behavior, a sensitivity analysis of the loss factor is conducted. For this purpose, additional loss factors are evaluated in increments of 0.005%/h around the preprocessed reference value of 0.024%/h. To assess the impact, R^2 is calculated for each value according to Eq. (62), considering both the agreement with measured data and the agreement with the preprocessed simulation, see Fig. 18.

The analysis reveals increased sensitivity for decreasing loss factors when compared to measured data. Conversely, a higher factor demonstrates a moderate decline until 0.05%/h. To illustrate this behavior, a comparison is made between a significantly too small factor, a clearly too large factor and the predefined value, see Fig. 19. The elevated factor of 0.075%/h has the potential to trigger an early phase change, thereby restricting the duration over which the accumulated cold energy stored during the winter months can be utilized. In contrast, a factor of 0.005%/h that is too low has the opposite effect, meaning that the total phase change occurs clearly later. These findings indicate that the loss factor has a substantial influence on the simulated storage behavior. Moreover, the storage dynamics exerts an influence on other supply systems, emphasizing the necessity of accurately determining the loss factor when implementing a SOC storage model.

4.3. Outlook design optimization

This chapter offers a perspective on the potential applications of the IES-MILP model in the context of seasonal design optimization. Given the existence of numerous methodologies documented in the extant literature for integrating seasonal storage design into MILP (see Section 1), the present study will exclusively address the procedure on how the described approach can be prospectively used as an additional method using an assumed storage curve and soil coupling.

The same system configuration as presented in the previous operation optimization is used in this case study to ensure comparability of the results, see Fig. 2 and Table 2 in the Appendix A. However, unlike in the previous work, the component sizes and system capacities are not predefined. Instead, they are treated as optimization variables within the MILP framework. The optimization therefore determines the optimal sizing of the individual system components under the specified boundary conditions.

As delineated in Section 3.4.2, the calculation of the loss curve is contingent upon a multitude of influencing factors. In context of such design scenarios, the dimensions of the storage tank in question are of particular relevance. Consequently, the emphasis in this section is on the tank's volume. For the assumed design of the storage system, a selection range of the internal volume $V_{i,IES}$ is therefore specified first. This is defined by a minimum volume $V_{i,min,IES}$, a maximum volume $V_{i,max,IES}$ and the available increment ΔV_{IES} :

$$V_{in,IES} = \{V_{i,min,IES} + n\Delta V_{IES} \mid n \in \mathbb{Z}, 0 \leq n \leq N\} \quad (63)$$

$$N = \frac{V_{i,max,IES} - V_{i,min,IES}}{\Delta V_{IES}} \quad (64)$$

The determination of the internal dimensions of a cylindrical storage tank is predicated on the ratio $f_{i,IES}$ of its height $l_{i,IES}$ and radius $r_{i,IES}$.

$$f_{i,IES} = \frac{l_{i,IES}}{r_{i,IES}} \quad (65)$$

Assuming that $f_{i,IES}$ remains constant, it is possible to determine the internal dimension for each volumetric iteration v :

$$l_{i,IES}(v) = \sqrt[3]{\frac{v}{\pi} f_{i,IES}^2}, \quad v \in V_{i,IES} \quad (66)$$

$$r_{i,IES}(v) = \sqrt[3]{\frac{v}{\pi f_{i,IES}}}, \quad v \in V_{i,IES} \quad (67)$$

Subsequent to the consideration of the storage structure's wall thicknesses, the possibility exists for the transfer of the internal dimensions to external dimensions. According to Section 3.4.2, the calculation of the loss curve for each v is now possible. The resulting three-dimensional surface is illustrated in Fig. 20. Given the dependence of the loss factor on the dimensions of the storage unit, it is essential to employ the average value of the loss area in this context to prevent the emergence of nonlinear relationships in the MILP optimization. Therefore, the mean loss factor $\phi_{i,IES,m}$ is calculated for this surface:

$$\phi_{i,IES,m} = \frac{1}{NH} \sum_{v \in V_{i,IES}} \sum_{t=1}^H \phi_{i,IES}(v, t) \quad (68)$$

Consequently, this mean factor can be incorporated into a design methodology for MILP. It is important to note that this approach can be extended to other variables, such as $f_{i,IES}$ or the depth of the storage to the surface of the earth, see Figs. 25 and 26 in the Appendix A. In summary, the precision of the loss factor is contingent upon the delineated range of the considered parameters that are available for selection. The remaining variables which are necessary for calculating the loss curve are assumed to be predefined in this case based on the respective conditions and the available manufacturer data.

Once a connection to the ground has been established, a general description of the design optimization process can be provided. Given the substantial computing demands inherent in the annual review at hourly resolution, a series of designated design days are accomplished from the year under consideration. The selection process is executed through the utilization of a clustering approach, employing the k-medoids method. This allows the daily combination of heating, cooling and electricity requirements to be apportioned across a series of typical days, denoted by D , which reflect the three load profiles of the supply grids. For this purpose, the Python library scikit-learn [47] is used:

$$d \in D \quad (69)$$

According to Domínguez-Muñoz et al. [48], each day of the year is assigned to a design day. This results in a specific number of calendar days W_d for each design day d :

$$w \in W_d \quad (70)$$

To account for both the daily frequency of the systems and the seasonal behavior of the IES, a typical annual storage curve $SOC_{pre,IES}$ is assumed, as in Section 3.4.2. This profile is determined by the percentage of stored cold energy from the enthalpy curve in Fig. 6.

Subsequently a daily contribution is implemented to recalculate the fluctuations of SOC for each calendar day. In this regard, the daily difference $\Delta SOC_{pre,IES}$ is calculated with the initial hour u_s and concluding hour u_e :

$$\Delta SOC_{pre,IES}(d, w) = SOC_{pre,IES}(u_e(d, w)) - SOC_{pre,IES}(u_s(d, w)) \quad (71)$$

Fig. 21 illustrates the allocation of design days and the daily implementation of the storage behavior.

Following the allocation of daily status changes, the next step entails the selection of maximum ΔSOC_{max} and minimum status of charge

changes ΔSOC_{min} for each design day group:

$$\Delta SOC_{max}(d) = \max_{k \in K_d} \Delta SOC(d, w) \quad (72)$$

$$\Delta SOC_{min}(d) = \min_{k \in K_d} \Delta SOC(d, w) \quad (73)$$

Consequently, two extreme cases are manifested for each design day, which can be incorporated into the system design optimization.

In first tests, this is applied to the MILP model of the case study, encompassing six uncoupled design days. Taking into account a volumetric increment of 50 m³ and the investment costs of systems described by Wirtz et al. [10], Gabrielli et al. [28] and Vetterli et al. [22], this results in a usable storage volume of 400 m³ for the IES with a computational time of 12 s. Depending on the manufacturer's size gradations, and specific investments costs, the result is comparable to the real net volume of 443 m³. Consequently, further research could be constructive in exploring the potential of this methodology in the context of integrating seasonal storage systems in MILP design optimization.

4.4. Iteration step for unknown storage behavior

If a representative storage temperature profile cannot be specified in advance for preprocessing storage losses, the simulation can be carried out using an iterative approach. This situation typically arises when system properties are unknown or when no characteristic temporal patterns can be identified. Within the model, the objective is achieved by using the temperature profile calculated in each iteration to update the loss curve for the subsequent iteration, see Fig. 4. To examine this procedure, the MILP model is provided with an annual input profile that assumes a constant temperature of 0 °C, neglecting any seasonal variation. The simulation is performed over three iterations. The resulting temperature profiles indicate that a typical seasonal trend already emerges after the second iteration, see Fig. 22. In the final iteration, only minor changes are observed, suggesting that the solution has largely converged. In this case study, the absence of a predefined temperature profile approx. doubles the simulation time, although this effect depends on the characteristics of the storage system. Once the storage behavior has been sufficiently characterized, a representative temperature profile can be defined and used in future analyses. This approach is applicable to both operational optimization and design optimization.

5. Conclusion

The present paper proposes a methodology for the MILP-based modeling of long-term TES within complex multi-energy systems that is computationally efficient. The approach is validated using a real-world trigeneration system of a research building, providing heat, cold, electricity and incorporating a 500 m³ seasonal IES. The primary objective is the integration of a physically consistent yet computationally tractable storage model into a high-resolution MILP framework.

The IES is represented using a SOC-based model that captures both sensible and latent energy storage through an enthalpy–temperature correlation. In contrast to many existing MILP-based approaches, geothermal heat exchange between the uninsulated storage tank and the surrounding soil is considered. To preserve computational efficiency, this nonlinear thermal interaction is evaluated within a preprocessing step. Based on an undisturbed ground temperature assumption and a representative seasonal storage profile, system-specific storage loss characteristics are derived and subsequently incorporated into the MILP model in a linearized form.

The complete annual operation optimization can be solved within approx. 30 min, despite the high level of interconnection and complexity

of the multi-energy system. A comparison between simulated results and measurement data demonstrates good agreement for both temporal operation patterns and cumulative energy flows. The seasonal behavior of the IES is captured with a coefficient of determination of 0.77 for the annual temperature profile and 0.64 over a three-year observation period.

Due to its modular structure, the proposed framework is transferable to other multi-energy system configurations. The storage modeling approach is also applicable to different types of seasonal TES, such as aquifer, cavern or pit thermal storage systems. Initial investigations further indicate that the methodology can be extended to design optimization problems. Future work should therefore focus on applying the approach to system sizing tasks and on further improving the representation of long-term thermal interactions within MILP-based energy system optimization frameworks.

It is important to acknowledge that the approach presented here operates under the assumption of perfect foresight with regard to boundary conditions and demand profiles. Furthermore, the methodology has been developed to achieve a balance between physical accuracy and computational efficiency. More detailed simulation models, such as reported in the literature [31], which explicitly resolve additional physical processes and spatial effects, have the potential to yield more accurate results. Consequently, the proposed method is particularly suited for system-level optimization and planning studies, while high-resolution simulation tools remain indispensable for detailed component-level analyses.

CRedit authorship contribution statement

Chris Burkel: Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Marco Griesbach:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Marco Wirtz:** Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Florian Heberle:** Writing – review & editing, Writing – original draft, Conceptualization. **Andreas Jess:** Writing – review & editing, Writing – original draft, Supervision, Project administration. **Dieter Brüggemann:** Writing – review & editing, Writing – original draft, Supervision, Project administration.

Author statement

We confirm that all authors have reviewed and approved the revised version of the manuscript entitled “Numerical preprocessing of ground-coupled thermal impacts on seasonal ice energy storage systems for mixed-integer linear programming”.

The manuscript has been revised according to the reviewer's comments, and all authors agree with its resubmission to the Journal of Energy Storage.

Declaration of competing interest

The authors declare that there is no conflict of interest.

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Appendix A

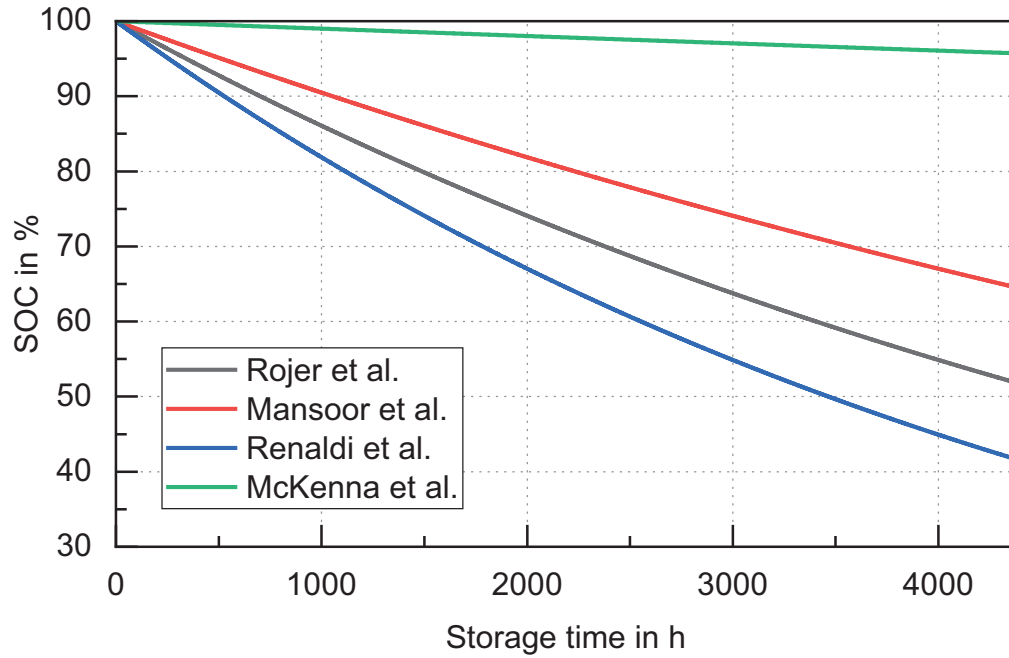


Fig. 23. Comparison of different loss factors for seasonal thermal energy storage (TES) from the extant literature.

Table 2
Model component parameter.

Component	Parameter	Unit	Value	Comment
CHP	P_{CHP}^{nom}	kW	238	Manufacturer data
	$Q_{h,CHP}^{nom}$	kW	366	Manufacturer data
	$\eta_{el,CHP}$	%	35	Manufacturer data
	$\eta_{h,CHP}$	%	54	Manufacturer data
	$t_{min,CHP}$	h	3	System parameter
GB	$Q_{h,GB}^{nom}$	kW	500	Manufacturer data
	η_{GB}	%	90	Manufacturer data
HP	P_{HP}^{nom}	kW	23	Manufacturer data
	$T_{in,sec,HP}$	K	303	System parameter
	$T_{out,sec,HP}$	K	308	System parameter
	$\Delta T_{prim,HP}$	K	-3	Manufacturer data
	$\eta_{ex,i,HP}$	%	40	Assumption
CC	$P_{max,CC}^{nom}$	kW	216	Manufacturer data
	$P_{min,CC}^{nom}$	kW	20	System parameter
	$T_{in,prim,CC}$	K	285	System parameter
	$T_{out,prim,CC}$	K	279	System parameter
	$\Delta T_{sec,CC}$	K	3	Manufacturer data
	$\eta_{ex,i,CC}$	%	50	Assumption
FC	P_{FC}^{nom}	kW	10	Manufacturer data
	$Q_{c,FC}^{nom}$	kW	50	Manufacturer data
HS	$Q_{h,HS}^{nom}$	kWh	300	Calculated
	η_{HS}^{ch}	%	100	[10]
	η_{HS}^{dch}	%	100	[10]
	$\phi_{loss,HS}$	%	0.5	[10]
	C_{HS}^{ch}	%	100	System parameter
	C_{HS}^{dch}	%	100	System parameter
CS	$Q_{c,CS}^{nom}$	kWh	70	Calculated
	η_{CS}^{ch}	%	100	[10]
	η_{CS}^{dch}	%	100	[10]
	$\phi_{loss,CS}$	%	0.5	[10]
	C_{CS}^{ch}	%	100	System parameter
	C_{CS}^{dch}	%	100	System parameter
IES	$Q_{c,max,EES}^{dch}$	kW	100	System parameter
	η_{IES}^{ch}	%	95	Assumption

(continued on next page)

Table 2 (continued)

Component	Parameter	Unit	Value	Comment
PV	η_{IES}^{dch}	%	95	Assumption
	$m_{water,IES}$	kg	443,000	[31]
	T_{IES}^{start}	K	270	Empirical
	T_{IES}^{target}	K	270	Empirical
	$T_{m,pre,IES}$	K	275	Empirical
	$T_{ref,IES}$	K	293	Assumption
	$\Delta T_{pre,IES}$	K	5	Empirical
	$t_{shift,IES}$	h	720	Assumption
	P_{PV}^{nom}	kW	12	Manufacturer data
	γ_{PV}	°	180	System parameter
	α_{PV}	°	30	System parameter
	μ_{PV}	1 K ⁻¹	-0.003	Assumption
	$\eta_{inv,PV}$	%	96	Assumption

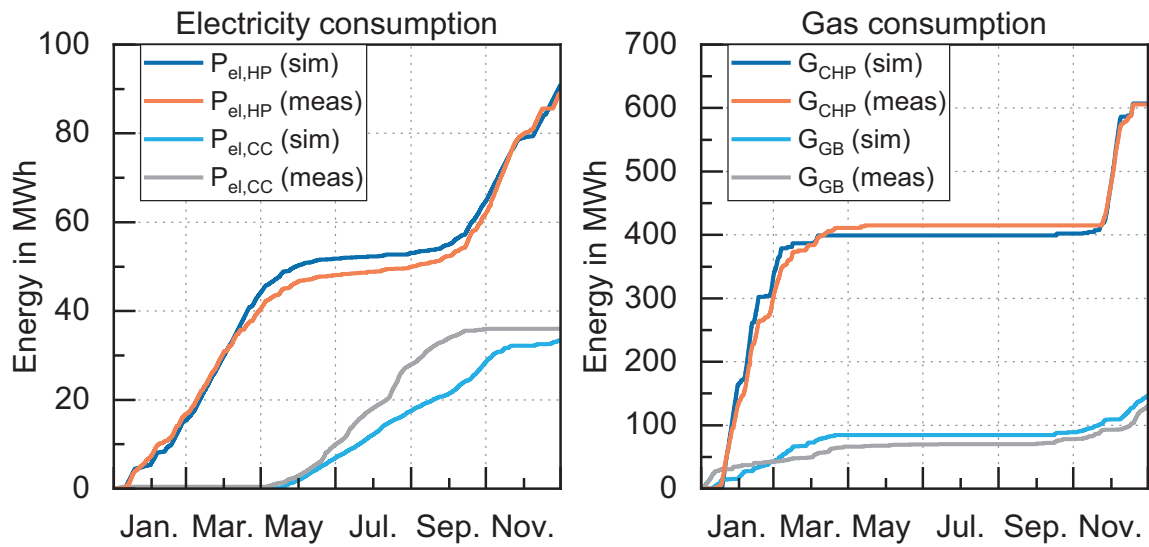


Fig. 24. Annual comparison between measurement (meas) and simulation (sim) of the cumulative consumption of gas G and electrical energy P_{el} by the different components of the coupled energy system: combined heat and power unit (CHP), gas boiler (GB), heat pump (HP), compression chiller (CC).

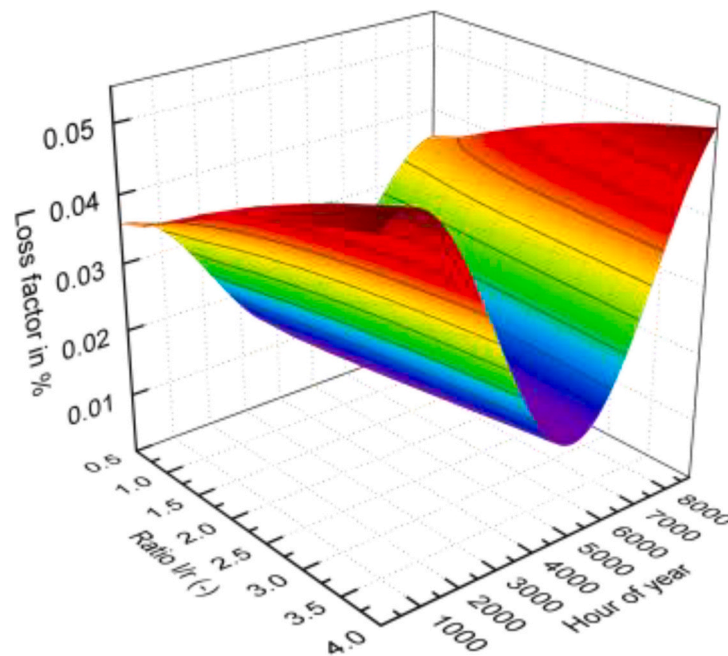


Fig. 25. Illustration of the loss factor as a function of the ratio range of height (l) and radius (r) for the MILP design optimization.

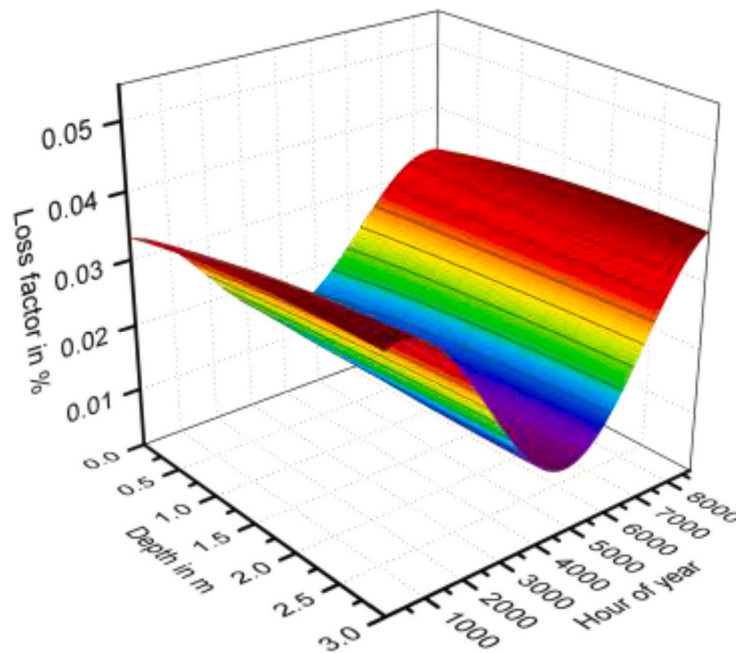


Fig. 26. Illustration of the loss factor as a function of the depth range for the MILP design optimization.

Data availability

Data will be made available on request.

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