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Pathway towards a non-linear integrated optimal control and sizing methodology for clean hybrid, multi-energy vector district heating and cooling systems

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Abstract

The heating and cooling of buildings represents a major share of global energy demand and associated carbon dioxide emissions, motivating the transition towards clean hybrid district systems integrating heat pumps, solar collectors, PV panels, PV-T panels, and energy storage. To minimize both investment and operational costs in these multi-energy vector districts, this paper presents a pathway towards a Integrated Optimal Control and Sizing (IOCS) framework that combines detailed physics-based models in Modelica with non-linear Model Predictive Control implemented via the Toolchain for Automated Control and Optimization (TACO). The methodology is demonstrated through two Belgian district use cases, representing a virtual mixed-use district (which is cooling-dominated) and a real-life heritage district (which is heating-dominated). A comparative analysis evaluates (1) conventional sizing methods, (2) an earlier developed two-step iterative IOCS method, and (3) a direct IOCS approach, which directly optimizes component sizes within a single optimal control problem. Results show that both IOCS methods substantially reduce the total cost of ownership (TCO), with the direct IOCS achieving the lowest TCO in all scenarios for both use cases (up to 69% reduction for the virtual district and 30 % for the heritage district under typical weather conditions, while stress-testing in extreme weather conditions still yields TCO reductions of respectively 55 and 19 %). Key findings include significant downsizing of ground-source heat pumps and borefields, enhanced utilization of building thermal inertia, and hybridization with air-source heat pumps and chillers. The direct IOCS approach also significantly reduces computational effort compared to the two-step method, with optimization times decreased by up to 50%, suggesting practical feasibility for larger-scale. These results underscore the value of incorporating operational flexibility into the design phase, enabling more compact, cost-efficient, and renewable-based energy systems for future districts to make the energy transition more feasible and affordable.

Keywords: Integrated optimal control and sizing; Optimal control, Model predictive control; Modelica ;Clean Hybrid Collective Systems; Multi-Energy Vector District, Total Cost of Ownership

1. Introduction

The heating and cooling of buildings accounts for a significant fraction of global energy use and associated carbon dioxide emissions, underscoring the urgent need to transition towards renewable and residual energy sources. In recent years, a clear shift has been observed from stand-alone, gas-dependent building heating systems toward collective, hybrid, multi-energy vector networks . These systems integrate multiple energy carriers - heat, cold, and electricity - within a shared infrastructure. In optimized configurations, thermal energy is typically provided through a combination of ground-source and air-source heat pumps or chillers, often supported by solar thermal collectors, while electricity is locally generated through photovoltaic installations and supplemented by grid off-take.

By combining multiple renewable technologies and storage systems, hybrid, multi-energy vector districts can

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dynamically select the most efficient, clean or cost-effective energy source at any given time. This leads to improved year-round efficiency, lower operational costs, and reduced environmental impact compared to conventional, decentralized systems [1]. The resulting system flexibility (from storage systems, network and building thermal capacity) also enables demand response and time-of-use tariff optimization, further enhancing both economic and environmental performance. However, realizing the full potential of these collective systems requires intelligent design and control. Strong interdependencies between technologies, storage, and buildings, spanning multiple time scales and energy vectors, make both design and operation inherently complex. Proper technology selection, accurate sizing, and optimal control coordination are therefore essential to achieve optimal performance and financial viability.
Beyond operation, the economic feasibility of these systems is strongly influenced by investment cost. Many renewable and storage technologies are capital-intensive, meaning that oversizing can have significant financial implications. Traditionally, system design and control have been addressed sequentially: technologies are selected and sized first, and a control strategy is developed afterwards. However, since sizing and control are inherently interdependent, this sequential approach often leads to a suboptimal situation. The installed capacities determine how effectively a system can be controlled, while the control strategy influences the thermal and electrical loads that dictate component sizes. This interdependence is particularly evident in shallow geothermal borefield systems, where both annual ground thermal balance and short-term peak loads affect the required borefield size. Advanced controllers such as Model Predictive Control (MPC) can alleviate these issues by exploiting flexibility, for example, by shifting heating or cooling loads in time to reduce peak demands and long-term imbalances, thereby enabling smaller and more cost-effective designs. This motivates the need for an **Integrated Optimal Control and Sizing (IOCS)** methodology, which jointly optimizes both investment (CAPEX) and operational (OPEX) decisions to achieve truly optimal system performance. By doing so, the potential of optimal control strategies to reduce investment costs can already be captured during the design phase, in addition to the operational savings realized during system operation.

Model Predictive Control (MPC) offers a powerful foundation for such an IOCS methodology. MPC is a model-based optimal control strategy that anticipates future disturbances such as weather, occupancy, and energy prices, and determines optimal control actions by solving a constrained optimization problem at each time step[2]. Its ability to incorporate system dynamics, forecasts, and constraints allows it to exploit the flexibility of storage devices, network and building thermal inertia, and energy vector coupling, making it a natural system integrator for hybrid multi-energy vector districts. MPC formulations can be broadly classified as (i) white-box, based on physical models, (ii) black-box, using data-driven methods, and (iii) grey-box, combining both [2]. Among these, white-box approaches are best suited for IOCS since they can be applied even in the absence of operational data. However, their performance depends on the accuracy and detail of the physical model [3]. In particular, including key system non-linearities, such as the temperature-dependent coefficient of performance (COP) of heat pumps, and explicit modeling of building thermal physics are crucial for accurate prediction and control. Moreover, as a large part of the load shifting potential is represented by the buildings' thermal inertia, it is crucial to take this into account [4].

Despite their potential, current IOCS methods for hybrid, multi-energy vector systems still face major limitations. **Most existing approaches don't take into account the actual controller that will be used in operation** and either **linearize critical system dynamics and/or rely on fixed building demand profiles, thereby neglecting the flexibility potential of the buildings.**

Existing IOCS methods in literature can be grouped into three main methodological categories [5].The first and most common category uses mixed-integer linear programming (MILP) formulations to co-optimize system sizing and operation. While computationally efficient, these formulations typically neglect non-linearities and building dynamics. The second category employs non-linear or non-convex formulations to better capture system physics [6], [7], [8], but these studies still rely on predefined building load profiles. The third category consists of multi-level optimization frameworks where sizing and control are addressed in separate but connected layers [9], [10], [11]. Although the latter approaches are flexible, they rarely model building physics or non-linear control interactions. Only one recent study, by Mugnini et al. (2025), combines both non-linearities and building dynamics within a single optimization framework, but it focuses on a single residential building with a simplified air-source heat pump system [12].

Another major gap in the literature lies in the treatment of geothermal borefields. Despite their high capital cost (and thus significant impact of proper sizing) and strong coupling with system operation, **borefields are often modeled in a simplified or static manner**. Most studies either omit explicit borefield modeling, treating it as a fixed cost per unit of ground-source heat pump capacity or consider it only during the operational optimization without feedback to design optimization [11], [13]. More recent works by Fiorentini et al. (2023) and Blanke et al. (2024) introduced simplified or fixed-depth borefield models within IOCS frameworks, but these approaches remain limited in generality and accuracy [8], [14].

To address these shortcomings, this paper presents an Integrated Optimal Control and Sizing (IOCS) framework for hybrid, multi-energy vector district heating and cooling systems that does consider the important non-linear system dynamics and includes explicit detailed building modeling. The proposed framework enables the optimal sizing of key system components, including ground-source heat pumps, geothermal borefields, air-source heat pumps, air-source chillers, solar thermal collectors, photovoltaic (PV) panels, photovoltaic–thermal (PV-T) panels, thermal buffer tanks, and batteries.

The framework builds upon detailed, non-linear, physics-based models developed in Modelica, an object-oriented, equation-based, multi-domain modeling language. It leverages the open-source IDEAS library, which provides validated HVAC component models and a comprehensive package for building envelope modeling [15]. The workflow of the IOCS framework consists of three main steps. First, users develop Modelica models of the district buildings, employing the building envelope models from the IDEAS library. Second, users select the set of components to be included in the optimization and define the corresponding cost functions per unit size. Third, they specify the relevant boundary conditions, such as weather data, energy price profiles, and occupant behavior. The outcome of these steps is a highly detailed Modelica representation of the entire energy system, fully parameterized except for the component sizes to be optimized.

Subsequently, the developed IOCS framework couples this Modelica model with the Toolchain for Automated Control and Optimization (TACO), a Modelica-based toolchain that translates detailed physical models into non-linear programming (NLP) based optimization problems and solves them efficiently [16]. Originally designed for implementing non-linear, physics-based MPC in large buildings and districts, TACO enables the IOCS framework to incorporate the actual optimal control behavior expected during operation directly into the sizing phase. This ensures that component design inherently reflects realistic operational dynamics, particularly when MPC is employed in practice.

Particularly, this paper presents the development trajectory towards this IOCS framework, which evolved through three major stages that finally lead to the IOCS framework for hybrid, multi-energy vector district heating and cooling systems that does consider the important non-linear system dynamics and includes explicit detailed building modeling:

(i) *integration of geothermal borefield* sizing with optimal control (non-linear, physics-based MPC), previously detailed in [17].

(ii) development of a *two-step IOCS* method that combines TACO for NLP-based optimal control with a MILP-based sizing optimization in an iterative procedure, as described in [5]

(iii) extension of this two-step method with *direct size optimization using TACO*, eliminating the need for iterative coupling.

This paper presents the results of stage (iii), which extends the two-step IOCS method into a direct IOCS method that achieves enhanced cost reductions while significantly reducing computational effort. Since this direct method builds explicitly on the two-step method and share the same user input and model setup, the key features, building blocks, and insights of Stage (ii) are briefly revisited to support understanding.

The proposed direct IOCS method is demonstrated using two district-scale case studies in Belgium, highlighting its potential for total cost reduction compared to conventional sequential sizing and control methodologies. In addition, a comparative assessment between the iterative two-step IOCS method (Stage ii) and the direct IOCS approach (Stage iii) is presented, evaluating both cost performance and computational efficiency.

2. Methodology

2.1. Stage 1: integration of geothermal borefield sizing with optimal control.

The first stage of the IOCS framework integrates geothermal borefield sizing with non-linear, physics-based MPC of hybrid heating and cooling systems. Proper borefield sizing is critical, as drilling costs dominate total investment, yet traditional methods rely on fixed demand profiles and ignore the impact of control strategies, often leading to oversizing, especially in hybrid GSHP–ASHP systems.

To address this, two iterative approaches were developed that couple optimal control with borefield sizing: a **semi-integrated** and a **fully-integrated** method [17]. Both use detailed Modelica models and TACO to first optimize operational costs and generate load profiles, which are then used for borefield sizing with conventional tools such as GHEtool [18].

In the semi-integrated method, the borefield is represented by a pre-computed fluid temperature profile, requiring multiple iterations to converge and offering a trade-off between accuracy and computational effort. The fully-integrated method embeds a dynamic borefield model directly in the optimal control problem, allowing control actions to adapt to the ground's thermal response. This eliminates initialization steps and minimizes oversizing, but at a very high computational cost.

Case studies on residential and office buildings showed that semi-integrated methods overestimate borefield depth by 12–24%, while the fully-integrated method achieved near-optimal sizing [17]. Although these approaches successfully link control and sizing, they are not suitable for a full IOCS framework: they require repeated, expensive optimizations and remain biased toward operational cost minimization rather than total cost optimization. In practice, minimizing operational costs (e.g., favoring GSHPs in winter due to higher COPs) can increase borefield size, whereas a controlled shift to ASHPs could slightly raise operating costs but reduce investment costs.

Despite these limitations, the dynamic Modelica borefield model and g-function-based ground modeling proved highly valuable and were therefore adopted in the two-step IOCS method described in Section 2.2.

2.2. Stage 2: Two-step IOCS method

Building on the findings of Stage 1 (described in Section 2.1), this stage introduces a two-step Integrated Optimal Control and Sizing method that couples TACO for non-linear optimal control with a mixed-integer linear programming (MILP) sizing layer (targeting multiple components) solved with Gurobi. This approach retains the high-fidelity, physics-based control formulation in TACO, ensuring an accurate representation of real-life model predictive control behavior[1], while keeping the overall size optimization computationally tractable for large-scale systems.

2.2.1. User input and model setup.

The two-step IOCS method relies on a pre-developed Modelica template model and a corresponding energy-flow-based Gurobi template of a central heating and cooling system. A simplified hydraulic scheme of this central energy system is shown in Figure 1, while the corresponding Modelica model is shown in Figure 2. As an example, Figure 3 provides a detailed view of the solar thermal collector (STC) model, illustrating the level of detail within the Modelica environment, including explicit modeling of valves, pumps, and hydraulic connections. The Gurobi model, in contrast, represents a higher-level, energy-flow-based abstraction. It enforces energy balances for heat (including cold) and electricity, defines the technical limits of each component, and describes the dynamics of thermal and electrical storage systems using simplified relationships.

On the thermal side, the system comprises a ground-source heat pump (GSHP), an air-source heat pump (ASHP), an air-source chiller (ASCHI), solar thermal collectors (STC), and photovoltaic-thermal (PV-T) panels, all connected in parallel to a central thermal storage tank (TTES). A heat exchanger (HEX) allows for

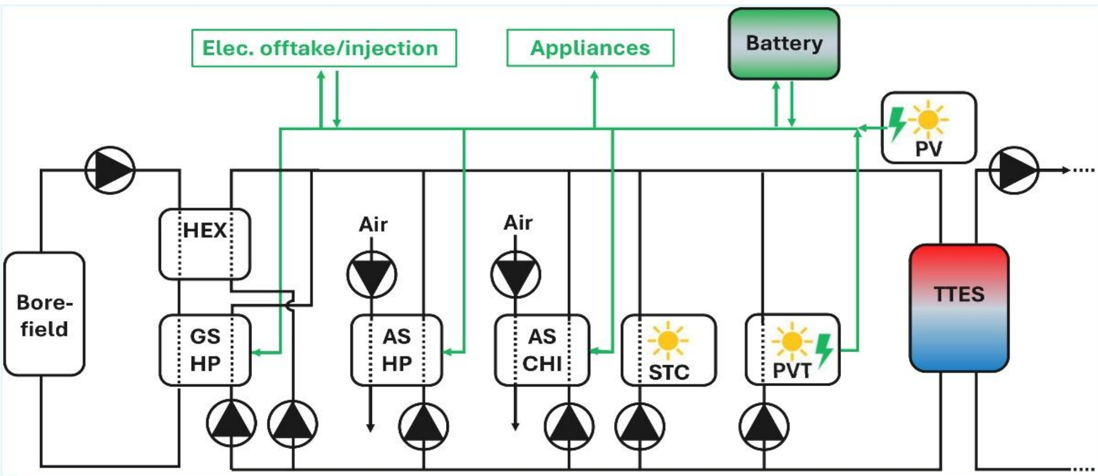

Figure 1: Simplified hydraulic scheme of the central energy system that is used as template in the two-step IOCS method [5].

passive cooling or borefield regeneration. On the electrical side, the system connects to the electrical power grid for electricity import and export, includes detailed models for a battery and photovoltaic (PV) panels, and can incorporate user-defined appliances profiles. For more detailed information on the modeling of the individual components in both Modelica and Gurobi, the reader is referred to [5]. Finally, users are responsible for creating the building models (in Modelica) and connecting them to the central energy system template. This provides flexibility to represent any district configuration while maintaining a consistent structure for the central energy system.
The overall IOCS method is implemented in Python, which coordinates the coupling between TACO (for optimal control) and Gurobi (for size optimization). Within this Python framework, users can:

- Select which components from the central energy system template are included in the optimization
- Define boundary conditions (weather data, occupancy schedules, internal gains, etc.)
- Specify economic parameters such as investment cost functions, interest rates, and observation time for the calculation of the total cost of ownership (TCO).

2.2.2. Concept and information flow.

The two-step IOCS loop consists of three main parts executed iteratively:

1) **Control optimization**: TACO solves a one-year, non-linear optimal control problem for fixed component sizes, minimizing operational costs and thermal discomfort. This yields optimized hourly profiles for heat and cold demand, borefield loads, and electricity use, which are passed to the sizing step.
2) **Sizing optimization:** A MILP problem is solved in Gurobi to minimize total annualized costs (CAPEX + OPEX) based on the optimized operational profiles. A key innovation is the integration of a depth-dependent, g-function-based borefield model that captures borefield temperature evolution over its full lifetime, enabling explicit optimization of the investment-operation cost trade-off. The borefield model was validated against GHEtool, showing sub-meter depth differences and temperature deviations below 0.02°C.
3) **Convergence check:** Total cost of ownership and thermal discomfort are evaluated. If cost changes fall below a threshold and comfort constraints are satisfied, the loop terminates; otherwise, updated component sizes are fed back into the control optimization..

2.2.3. Application

The two-step IOCS method was successfully applied to two Belgian district use cases (see Section 3.1). The analysis was performed under both typical and extreme weather conditions to assess robustness. The

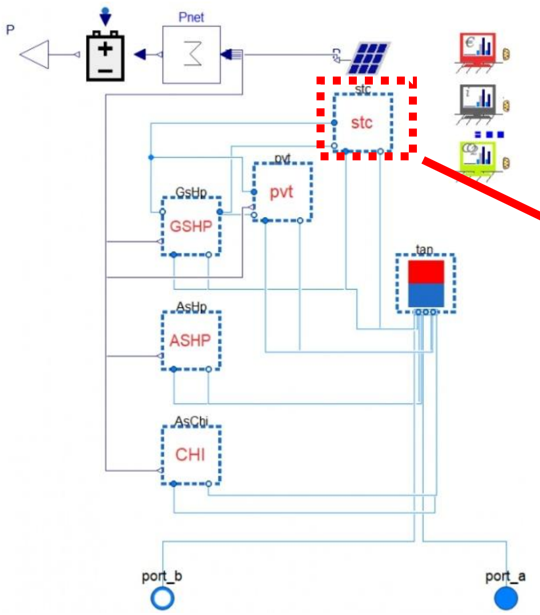

Figure 2: Modelica model of the central energy system.

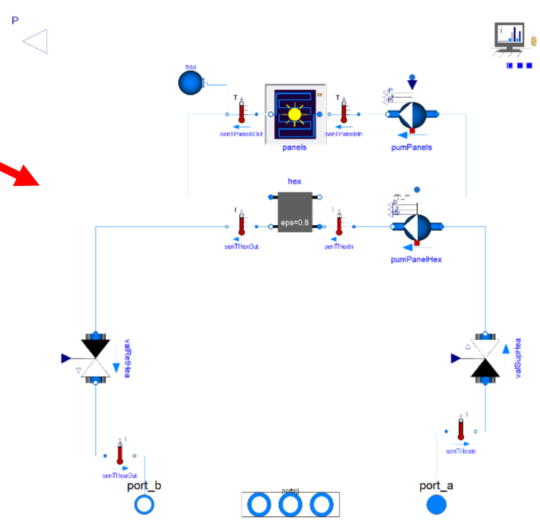

Figure 3: Modelica model of the solar thermal collectors.

results demonstrated significant reductions in total cost of ownership (TCO) compared to an *optimally* *controlled system* with component sizes determined through 'traditional' sizing methods (see Section 3.2). In the first use case, TCO savings ranged from 65% to 51%, while in the second case they ranged from 30% to 18%, depending on the weather scenario. These savings indicate that, relative to systems that are not only traditionally sized, but also traditionally controlled *with rule-based control strategies* the potential cost reduction will be even greater.

The main limitation of the two-step IOCS method, however, lies in its computational intensity. Convergence required between 12 and 16 hours for the first use case and between 33 and 44 hours for the second use case. This high computational effort primarily stems from the repeated solution of large-scale optimal control problems, which are inherently demanding. Reducing computation time is challenging, as the detailed physics-based modeling needed to ensure physical fidelity inevitably increases complexity. In the second use case (a residential district of 15 buildings), for instance, the optimal control problem comprised 881 state variables and 31 optimization variables per time interval. With 8760 hourly intervals across the optimization horizon, this resulted in an extremely high-dimensional problem, fully explaining the substantial computational burden.

2.2.4. Positioning towards Stage 3.

Stage 2 successfully established an IOCS method that integrates the actual MPC behavior of the operational system, implemented through TACO, already during the design phase. The main remaining challenge, however, is the need to alternate between non-linear control optimization and MILP-based sizing in an iterative process, which results in substantial computational effort. In addition, because the sizing optimization still relies on simplified energy-flow models, there remains room to improve overall accuracy. Stage 3 therefore advances this approach by directly optimizing component sizes within the non-linear TACO framework, eliminating the iterative coupling and achieving a tighter and more consistent integration between system design and control.

2.3. Stage 3: Direct IOCS with TACO

TACO is a Modelica-based toolchain that heavily relies on the IDEAS library and is specifically developed for solving optimal control problems within the context of model predictive control (MPC). Consequently, it assumes that all parameter values in the Modelica model are fixed and not subject to optimization. This assumption holds for pure control applications, where component sizes and physical parameters are predefined. Accordingly, all parameters, including those related to component sizing, are declared as regular Modelica parameters, which cannot be directly optimized using TACO.

However, TACO does permit the optimization of parameters declared as `parameter input`, provided that no regular parameters depend on them. In the IDEAS library, most component parameters are implemented as regular parameters, and many of these depend on size-related parameters. This structural dependency prevents direct optimization of component sizes. To overcome this limitation and enable size optimization within TACO, the authors systematically modified the relevant IDEAS component models so that all regular parameters depending on size parameters were redefined as parameter inputs. Given the complex interdependencies among parameters across the various component models, this adaptation was non-trivial and required careful reformulation to maintain model consistency and correctness. Nevertheless, this modification was successfully implemented for all components included in the central energy system template illustrated in Figure 1.

A further challenge arose with the optimization of the borefield size. In the two-step IOCS method, the dependency of the g-functions on borefield depth was represented using a piecewise-constant approximation, introducing integer variables into the optimization problem. Since TACO employs a gradient-based solver to efficiently handle optimal control problems, all model equations must be continuous and at least twice differentiable. Consequently, the piecewise-constant borefield model could not be used directly in TACO, necessitating the development of a smooth, differentiable formulation of the borefield model within the IOCS framework. To achieve this, rational, quadratic, and cubic functions were calibrated to approximate the dependency of g-functions on borefield depth, yielding continuous and differentiable expressions suitable for TACO. The main drawback of this approach is that only the borehole depth can be optimized, while the borefield configuration must be predefined before solving the optimization problem.

The combination of these two developments, namely the reformulation of IDEAS models to include parameter inputs and the construction of differentiable g-function approximations, enabled a complete reformulation of the central energy system template (Figure 2). In this new formulation, component size parameters are embedded directly within a one-year optimal control problem solved by TACO. This eliminates the need for the iterative coupling between non-linear control optimization and MILP-based sizing that characterized the two-step IOCS method, as the optimization of both operational and investment decisions is now handled within a single, unified framework.

As in the two-step method, users are still required to develop detailed building models in Modelica. However, the overall workflow is now significantly streamlined. The Python coordination framework used to manage the coupling between Gurobi and TACO is no longer necessary, since all optimization tasks are executed directly within TACO. Users only need to specify the building models, boundary conditions (such as local weather data, occupancy schedules, and energy price profiles), and the relevant economic parameters. This makes the method highly flexible because all location- and use-case-specific information enters the optimization exclusively through these boundary conditions, without requiring any changes to the underlying optimization structure. Moreover, the method can be easily applied to different buildings/districts, as it would only require a change of the building model without any change to the central energy system template. As a result, the method can be directly applied to different buildings, districts, climates, and market conditions by simply adapting the input data or building model.

To evaluate the performance and computational efficiency of this direct IOCS approach, it is applied to the same two Belgian district use cases previously used with the two-step IOCS method. This enables a direct and transparent comparison between the two approaches in terms of cost savings, accuracy, and computational effort. The two use cases are presented in detail in Section 3, while Section 4 discusses the comparative results and associated findings.

It is worth noting that the direct IOCS method results in very high-dimensional optimal control problems due to the detailed physics-based modeling. For the first use case, the problem comprises 881 state variables, 31 control optimization variables per time step, and 9 size optimization variables; for the second use case, these numbers increase to 3557 state variables, 57 control optimization variables, and 9 size optimization variables. Combined with 8760 hourly time steps, this illustrates both the computational challenge addressed by the direct IOCS formulation and the level of modeling detail achieved in the presented results.

3. Use cases

3.1. Description

The first use case represents a virtual mixed-use district located in Belgium, consisting of three identical low-energy office buildings (each with a conditioned floor area of 200 m²) and three identical low-energy residential buildings (each with a conditioned floor area of 135 m²). This district was originally developed for research on the impact of building renovation levels on the performance of model predictive control in low-temperature district heating and cooling systems [19]. Each office building is divided into two thermal zones, north and south, while each residential building consists of a day and a night zone. The indoor temperature in the office buildings is constrained between 21 °C and 23 °C during office hours (weekdays, 08:00–18:00). In the residential buildings, the day zone temperature must remain between 21 °C and 24 °C, and the night zone between 18 °C and 26 °C, both applying outside of office hours. For a detailed description of the building parameters and construction characteristics, the reader is referred to earlier work [19].

Heat/cold to the buildings is supplied by a two-pipe district heating and cooling network. Each building substation contains a heat exchanger connected to underfloor heating and cooling systems in both zones. The flow on the secondary side is controlled using a circulation pump and two modulating valves, while the primary flow through the heat exchanger is regulated by a third valve.

The second use case, illustrated in Figure 4, represents a real hybrid district energy system located in Bruges (Belgium). It serves 15 small residential heritage buildings that provide assisted living facilities. Each building

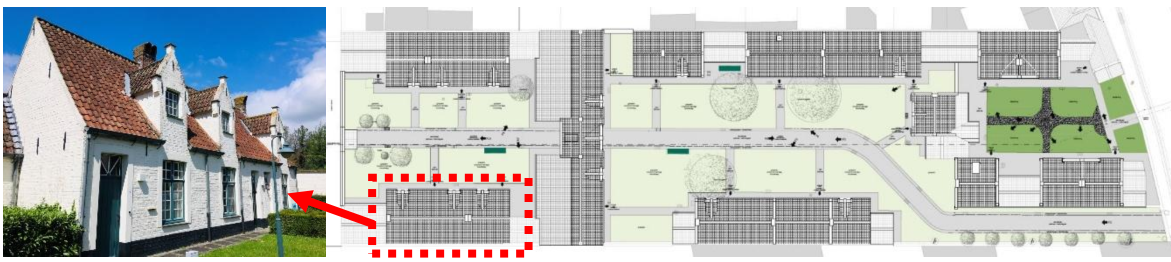

Figure 4: Site plan and example building of the second use case [20].

contains a small bathroom, bedroom, and living area with an integrated kitchen, resulting in a total conditioned floor area of approximately 1000 m². The buildings were recently renovated, and detailed Modelica models were developed to support the design of the collective energy system [20]. The complete model includes 61 thermal zones, of which 15 are actively controlled. Indoor air temperatures in these controlled zones must remain between 21 °C and 26 °C at all times. Use case 2 also has a two-pipe district heating and cooling network. However, in contrast to use case 1, where a substation with a heat exchanger is used, water is circulated directly through the floor heating and cooling systems of each building without a substation heat exchanger. Each building includes a single modulating valve to control the flow. Domestic hot water is supplied by individual electric heaters and is excluded from the model here.

3.2. Benchmark configuration and sizing

To provide a fair performance comparison, both systems were initially sized using traditional engineering approaches. For use case 1 (cooling-dominated), a simplified benchmark configuration was defined with only a GSHP and borefield in the central energy system (thereby assuming passive cooling only). The GSHP capacity was set to 30 kW based on a one-year building simulation under extreme Belgian weather conditions, which indicated total district peak heating and cooling loads of 30 kW and 42 kW, respectively. The borefield was sized using GHEtool, resulting in 18 boreholes (6x3 grid) with a depth of 170 m. For use case 2 (heating dominated), the initial component sizes were based on the actual engineering design used during the renovation, representing advanced[1] Belgian practice. The system includes two 14 kW air-source heat pumps, two 20 kW ground-source heat pumps, a borefield with 8 boreholes (125 m deep), a 0.5 m³ thermal storage tank, 100 m² of PV panels, and 20 m² of PV-T panels. In the model, the ground- and air-source heat pumps are aggregated into single units with equivalent capacities of 40 kW and 28 kW, respectively.

4. Results and discussion

Table 1 shows the economic parameters[2] used for both IOCS methods, while Table 2 summarizes the optimized system configurations and performance indicators for both use cases under typical (TMY[3]) and extreme (XMY[4]) weather conditions. The electricity prices applied are representative of Belgian market conditions. Weather conditions are considered by assuming a fixed yearly profile that is repeated over the system lifetime. Forecast uncertainties are therefore not explicitly considered.
Results are compared with the reference (current-practice) sizing approach and the two-step IOCS method. Note that in the reference results, the system is still optimally controlled, but component sizes are determined using conventional engineering-based sizing methods rather than optimization.

Table 1: Overview of the economic and investment parameters used.

General economic parameters		Technology	Lifetime	Rel. Inv. Cost	Yearly maint. cost
$p_{elec,\ offtake}$	200 €/MWh	GSHP	20 y	250 €/kW	3%
$p_{elec,\ injection}$	50 €/MWh	Borefield	40 y	40 €/m	1%
Interest rate	5 %	ASHP	20 y	900 €/kW	3%
Observation time	50 y	ASCHI	20 y	900 €/kW	3%
		PV	20 y	200 €/m²	2%
		PVT	20 y	500 €/m²	2%
		STC	20 y	400 €/m²	2%
		Battery	10 y	500 €/kWh	1%

For the virtual mixed-use district (use case 1), both IOCS methods achieve substantial reductions in TCO compared to the reference configuration. Under TMY conditions, TCO decreases by 67 % with the two-step

[1] Combining GSHPs and ASHPS is not yet very common in Belgian engineering practice.
[2] The economic parameters used are based on personal communication with the Engineering company Sweco Belgium during the design of the second use case. The company transferred investment cost assumptions and electricity price ranges that are representative for Belgian district-scale projects . These values are consistent with publicly available Belgian market data and are therefore considered realistic reference assumptions rather than company-specific inputs.
[3] Typical meteorological year in Uccle, Belgium, as defined in the IDEAS library [15].
[4] Extreme meteorological year in Brussels, Belgium according to [21].

IOCS and by 69 % with the direct IOCS. Under XMY conditions, the reductions are 51 % and 55 %, respectively. These savings mainly arise from significantly downsizing the ground-source heat pump and borefield. The GSHP capacity decreases from 30 kW in the reference to 12.8 kW (two-step) and 10 kW (direct IOCS) under TMY, while the borefield length drops from 3060 m (18 boreholes of 170 m in a 6×3 configuration) to 460 m (4 boreholes of 115 m, 2×2) and 308 m (4 boreholes of 77 m, 2×2) respectively. Under XMY conditions, the borefield length is reduced from 3060 m (18 boreholes) to 630 m (6 boreholes of 105 m, 3×2) and 540 m (6 boreholes of 90 m, 3×2). The direct IOCS method introduces small auxiliary air-source heat pumps (up to 2.3 kW) and air-source chillers (up to 15 kW) to create a hybrid[5] configuration that relieves borefield load, thereby clearly showcasing the added value of hybridizing HVAC systems. PV deployment also increases substantially, from zero in the reference to 29–44 m² in the optimized systems, helping to reduce operational energy costs. CAPEX is reduced by up to 76 % in the TMY and 63 % in the XMY, while OPEX decreases by 40–54 %. Despite the aggressive downsizing, thermal comfort remains within acceptable limits.

In the real assisted-living residential district (use case 2), which already starts from a hybrid energy system, the relative improvements are smaller but still noteworthy. TCO reductions of 30 % are achieved by both IOCS methods under TMY conditions, and 17–19 % under XMY conditions, compared to the reference. The optimization shifts capacity between the air- and ground-source systems, with the GSHP decreasing from 40 kW to 2.6–4.6 kW under TMY conditions, while the ASHP remains around 20 kW. Under XMY conditions, GSHP capacity rises slightly to 9.8–11.6 kW, while ASHP capacity increases to 24 kW. Borefield size is significantly reduced, from 125 m (8 boreholes, total length of 1000 m) in the reference case to 40–50 m (2 boreholes, total length of 80-100 m) under TMY conditions and 78–110 m (4-3 boreholes, total length of 330-312 m) under XMY conditions. PV capacities remain largely unchanged at 100 m² across both methods and both weather scenarios, while no PV-T panels (nor STC) are installed in the optimized system.

Table 2:Overview of the results of the IOCS methods for both use cases.

Use case 1							
Technology	unit		**TMY**			**XMY**	
		Ref.	2-step	Direct	Ref.	2-step	Direct
ASHP	kW	0.0	0.0	2.3	0.0	0.0	1.2
GSHP	kW	30.0	12.8	10.0	30.0	20.3	16.6
Borefield length	m	3060	460	308	3060	630	540
Borefield depth	m	170	115	77	170	105	90
Borefield config.	-	6 x 3	2 x 2	2 x 2	6 x 3	3 x 2	3 x 2
ASCHI	kW	0.0	6.8	9.2	0.0	8.9	15.3
TTES	m^3	0.5	0.5	0.1	0.5	0.4	0.1
PV	m^2	0.0	20.7	29.2	0.0	23.8	43.9
STC	m^2	0.0	0.0	0.0	0.0	0.0	0.0
PVT	m^2	0.0	0.0	0.0	0.0	0.0	0.0
Battery	kWh	0.0	0.0	0.0	0.0	0.0	0.0
Discomfort	Kh	187	388	309	358	1119	346
CAPEX	k€	133.4	32.9	31.9	133.4	44.2	49.7
OPEX	k€	20.4	19.2	15.8	27.3	36.4	12.6
Maint. Cost	k€	24.9	7.7	6.8	24.9	10.5	21.2
TCO	k€	**178.8**	**59.9**	**54.6**	**185.7**	**91.0**	**83.6**
	Δ%TCO		**-67 %**	**-69 %**		**-51 %**	**-55 %**
Use case 2							
Technology	unit		**TMY**			**XMY**	
		Ref.	2-step	Direct	Ref.	2-step	Direct
ASHP	kW	28.0	20.7	20.5	28.0	25.5	23.5
GSHP	kW	40.0	2.6	4.6	40.0	9.8	11.6
Borefield length	m	1000	80	100	100	330	312
Borefield depth	m	125	40	50	125	110	78
Borefield config.		8 x 1	2 x 1	2 x 1	8 x 1	3 x 1	2 x 2
ASCHI	kW	0.0	0.0	0.0	0.0	0.0	0.0
TTES	m^3	0.5	1.0	0.1	0.5	1.8	0.1

[5] Note that hybrid refers here to the combination of multiple renewable technologies instead of adding a fossil fuel-based boiler.

PV	m^2	100.0	99.7	100.0	100.0	95.5	100.0
STC	m^2	0.0	0.0	0.0	0.0	0.0	0.0
PVT	m^2	20.0	0.0	0.0	20.0	0.0	0.0
Battery	kWh	0.0	0.0	0.0	0.0	0.0	0.0
Discomfort	Kh	169	227	240	218	302	326
CAPEX	k€	130.5	58.6	58.7	130.5	77.0	73.2
OPEX	k€	70.6	89.4	17.7	86.1	109.3	109.1
Maint. Cost	k€	35.4	17.5	88.7	35.4	22.2	21.4
TCO	k€	**236.4**	**165.5**	**165.1**	**251.9**	**208.5**	**203.8**
	Δ%TCO		**-30 %**	**-30 %**		**-17 %**	**-19 %**

Across both use cases, the direct IOCS consistently achieves the lowest total cost of ownership (TCO) by promoting hybrid system configurations and substantially reducing reliance on the borefield. Compared to the two-step IOCS, the cost improvements are modest but consistent. The main distinction between the two methods lies in the direct IOCS's ability to explicitly exploit the buildings' inherent thermal storage capacity within the optimization process. By anticipating future weather conditions and internal gains, the direct IOCS leverages building capacity as an active thermal buffer. This effect is clearly reflected in the significant downsizing of the thermal buffer tank, confirming that the inherent thermal inertia of buildings can effectively provide the flexibility required to mitigate peak loads and support more compact, cost-efficient system designs. This behavior is illustrated in Figure 5, which shows, for use case 2 in the XMY scenario, the condenser power of the ASHP, the outdoor air temperature, and the indoor temperature of one of the dwellings during three winter days. During the day, when outdoor temperatures (and thus ASHP COP) are higher, the ASHP actively charges the building mass by increasing the indoor temperature. This preheating strategy allows the system to anticipate colder night time periods with lower COPs, thereby maintaining thermal comfort while reducing the need for oversized components. Across both use cases and weather scenarios, batteries are never used, indicating that under the conditions considered here the use of building thermal capacity for offering flexibility in electrified collective heating/cooling solutions is more cost-effective than installing batteries. Note that the maximum allowable thermal discomfort is set to 1200 Kh per year for the first use case and 1500 Kh per year for the second, corresponding to a limit of 100 Kh per thermally controlled zone per year. Furthermore, the thermal discomfort values reported in Table 2 represent yearly totals, whereas the other performance indicators refer to the entire observation period.

A comparative analysis also highlights substantial reductions in computational effort. For use case 1, the two-step IOCS requires 12h 44min (TMY) and 16h 23min (XMY), whereas the direct IOCS completes in 8h 59min (TMY) and 6h 36min (XMY). For the larger use case 2, the two-step IOCS requires 33h 18min (TMY) and 43h 45min (XMY), while the direct IOCS finishes in 17h 52min (TMY) and 13h 5min (XMY). These results demonstrate that the direct IOCS method not only achieves lower TCO and more compact system designs, but also significantly improves computational efficiency, particularly for larger districts.

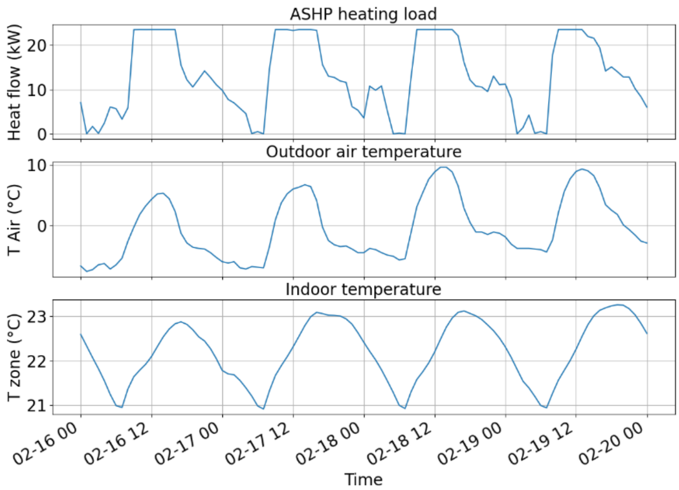

Figure 5: Evolution of ASHP heating power, outdoor air temperature and indoor temperature of one of the dwellings in use case 2 under XMY weather conditions.

5. Conclusion

This paper developed and evaluated a non-linear Integrated Optimal Control and Sizing (IOCS) framework for clean hybrid, multi-energy vector district heating and cooling systems. Building on earlier work, the study extends a two-step IOCS method into a direct formulation in which component sizing and operational control are optimized simultaneously within a single physics-based optimal control problem. The methodology is demonstrated on two Belgian district-scale case studies under both typical and extreme weather conditions and is benchmarked against conventional sizing practices and the earlier two-step IOCS method.

The proposed IOCS framework demonstrates that joint optimization of component sizing and operational control can substantially reduce costs and improve system efficiency in clean hybrid, multi-energy vector districts. Across both use cases, the direct IOCS method consistently achieves the lowest total cost of ownership by fully leveraging building thermal inertia, enabling effective load shifting, and promoting hybrid system configurations that reduce reliance on ground-source heat pumps and borefields. This approach allows for smaller, more cost-efficient installations without compromising occupant thermal comfort. Compared to the two-step IOCS, the direct method provides modest but consistent additional cost savings and significantly improves computational efficiency, reducing optimization times by up to 50%, which enhances scalability for larger and more complex districts. Moreover, the framework highlights the importance of explicitly incorporating flexibility offered by building thermal capacity during design, showing that preheating or precooling strategies can reduce peak loads and (thermal) storage requirements. Overall, these results underline the value of integrating advanced control strategies into the design phase, offering a practical pathway to economically viable, renewable-based, and flexible district energy systems that are robust under varying weather conditions and adaptable to future demand scenarios.

Beyond the presented case use, the method is broadly applicable to other district-scale energy systems. The IOCS method is inherently flexible because location- and use-case-specific aspects are introduced primarily through the building models, boundary conditions (such as weather data, occupancy patterns, and energy price profiles), and the selected set of technologies and cost assumptions. As a result, the same optimization structure can be applied to different climates, building typologies, and market conditions without modifying the underlying model formulation.

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References

[1] A. Soleimani, P. Davidsson, R. Malekian, and R. Spalazzese, ‘Modeling hybrid energy systems integrating heat pumps and district heating: A systematic review’, *Energy Build*, vol. 329, p. 115253, Feb. 2025, doi: 10.1016/J.ENBUILD.2024.115253.

[2] J. Drgoňa *et al.*, ‘All you need to know about model predictive control for buildings’, *Annu Rev Control*, vol. 50, pp. 190–232, Jan. 2020, doi: 10.1016/J.ARCONTROL.2020.09.001.

[3] J. Jansen, F. Jorissen, and L. Helsen, ‘Optimal control of a fourth generation district heating network using an integrated non-linear model predictive controller’, *Appl Therm Eng*, vol. 223, p. 120030, Mar. 2023, doi: 10.1016/J.APPLTHERMALENG.2023.120030.

[4] Lucas Verleyen and Lieve Helsen, ‘The role and CO2 emission reduction cost of battery energy storage in fully integrated, optimally controlled micro energy communities’, *Energy Build*, 2025.

[5] Louis Hermans, Anna Dell’Isola, and Lieve Helsen, ‘Non-Linear Integrated Optimal Control and Sizing Methodology for Multi-Energy Heating and Cooling Systems Including Borehole Thermal Energy Storage’, Submitted to *Geothermal Energy*, 2026.

[6] M. A. Hassan, S. Serra, S. Sochard, H. Viot, F. Marias, and J. M. Reneaume, ‘Holistic non-linear optimization of the layout, sizing, and operation of a district heating plant’, *Energy Convers Manag*, vol. 301, p. 118079, Feb. 2024, doi: 10.1016/J.ENCONMAN.2024.118079.

[7] R. Delubac, M. Sadr, S. Sochard, S. Serra, and J. M. Reneaume, ‘Optimized Operation and Sizing of Solar District Heating Networks with Small Daily Storage’, *Energies (Basel)*, vol. 16, no. 3, Feb.

2023, doi: 10.3390/en16031335.
[8] M. Fiorentini, P. Heer, and L. Baldini, 'Design optimization of a district heating and cooling system with a borehole seasonal thermal energy storage', *Energy*, vol. 262, p. 125464, Jan. 2023, doi: 10.1016/J.ENERGY.2022.125464.
[9] B. van der Heijde, A. Vandermeulen, R. Salenbien, and L. Helsen, 'Integrated optimal design and control of fourth generation district heating networks with thermal energy storage', *Energies (Basel)*, vol. 12, no. 14, 2019, doi: 10.3390/en12142766.
[10] M. A. Hassan and M. T. Araji, 'Hierarchical optimization of district heating plants by integrating evolutionary and non-linear programming algorithms', *Appl Energy*, vol. 373, p. 123935, Nov. 2024, doi: 10.1016/J.APENERGY.2024.123935.
[11] S. Miglani, K. Orehounig, and J. Carmeliet, 'Integrating a thermal model of ground source heat pumps and solar regeneration within building energy system optimization', *Appl Energy*, vol. 218, pp. 78–94, May 2018, doi: 10.1016/J.APENERGY.2018.02.173.
[12] A. Mugnini, F. Caresana, B. Marchetti, F. Polonara, and A. Arteconi, 'Integrated design of heat pump systems: A multi-objective optimized design methodology considering the mutual influence of design and control', *Appl Therm Eng*, vol. 271, p. 126323, Jul. 2025, doi: 10.1016/J.APPLTHERMALENG.2025.126323.
[13] M. Sharifi, I. C. Figueroa, R. Mahmoud, E. Himpe, L. Helsen, and J. Laverge, 'Early-stage optimal design of hybrid GEOTABS buildings in terms of costs and CO2 emissions', *Energy Convers Manag*, vol. 257, p. 115392, Apr. 2022, doi: 10.1016/J.ENCONMAN.2022.115392.
[14] T. Blanke *et al.*, 'Model for dimensioning borehole heat exchanger applied to mixed-integer-linear-problem (MILP) energy system optimization', *Geothermal Energy*, vol. 12, no. 1, Dec. 2024, doi: 10.1186/s40517-024-00301-w.
[15] F. Jorissen, G. Reynders, R. Baetens, D. Picard, D. Saelens, and L. Helsen, 'Implementation and Verification of the IDEAS Building Energy Simulation Library', *J Build Perform Simul*, vol. 11, no. 6, pp. 669–688, 2018, doi: 10.1080/19401493.2018.1428361.
[16] F. Jorissen, W. Boydens, and L. Helsen, 'TACO, an automated toolchain for model predictive control of building systems: implementation and verification', *J Build Perform Simul*, vol. 12, no. 2, pp. 180–192, 2019, doi: 10.1080/19401493.2018.1498537.
[17] L. Hermans, L. Meertens, and L. Helsen, 'Integrated Optimal Control and Borefield Sizing for (Small) Hybrid Heating and Cooling Systems', in *Proceedings of Building Simulation 2025: 19th Conference of IBPSA*, Brisbane, Australia: IBPSA, 2025. doi: https://doi.org/10.26868/25222708.2025.1442.
[18] W. Peere and T. Blanke, 'GHEtool: An open-source tool for borefield sizing in Python', *J Open Source Softw*, vol. 7, no. 76, p. 4406, Aug. 2022, doi: 10.21105/joss.04406.
[19] A. Dell'Isola, K. Walther, and L. Helsen, 'Building Renovation Level Requirements for a 5th Generation District Heating and Cooling Network', in *Proceedings of Building Simulation 2025: 19th Conference of IBPSA*, Brisbane, Australia: IBPSA, 2025.
[20] K. Walther, L. Hermans, L. Meertens, and L. Helsen, 'Simplifying decision-making in model-based co-design of building energy systems through automatically generated optimal controls', in *Proceedings of Building Simulation 2025: 19th Conference of IBPSA*, Brisbane, Australia: IBPSA, 2025.
[21] S. Doutreloup *et al.*, 'Historical and future weather data for dynamic building simulations in Belgium using the regional climate model MAR: typical and extreme meteorological year and heatwaves', *Earth Syst Sci Data*, vol. 14, no. 7, pp. 3039–3051, 2022, doi: 10.5194/essd-14-3039-2022.