

A model-based continuous commissioning method for an efficient integration of ground source heat pumps in the building ecosystem

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ABSTRACT

This paper introduces a model-based continuous commissioning (MBCCx) methodology specifically designed for the identification of control-related performance gaps within heating, ventilation and air conditioning (HVAC) systems equipped with ground-source heat pumps (GSHPs). While conventional continuous commissioning (CCx) is effective in detecting energy performance gaps, MBCCx goes further by using a system model as a reference to pinpoint operational inefficiencies and control faults arising from subsystem integration. The core of the proposed methodology lies in a calibrated physics-based model that represents the system performance as intended during the design phase. A key advantage is its applicability early in a building's operational phase, when data is limited, unlike data-driven methods that rely on extensive historical datasets. This enables the identification of energy-saving opportunities before the system reaches a stable operational state. To address the limitations of prior studies that often focus solely on individual GSHP component performance, this work pioneers the application of MBCCx to whole buildings equipped with GSHPs. The proposed approach employs a detailed 3D building model and component-level HVAC modeling to predict parameters such as room temperatures, heat pump power, and ground heat exchanger temperatures under normal conditions. Significant deviations between monitored values and model predictions serve as indicators of underperforming components or control sequence anomalies. The anomaly detection accuracy is then improved by merging HVAC system and GSHP performance indicators. The methodology is demonstrated through a case study of a recently retrofitted elementary school in Québec, Canada, equipped with five standing column wells as ground heat exchangers.

1. Introduction

The building sector, which is responsible for 30 % of total global final energy consumption [1], could play a key role to mitigate climate change. International Energy Agency's goals include retrofitting 50 % of existing buildings to zero-carbon levels by 2040 and meeting 50 % of the heating demand with heat pumps (HP) by 2045 [1]. However, beyond installing efficient equipment, it is crucial to maintain and optimize performance over time.

1.1. Commissioning and model-based commissioning

The systematic process of verifying and documenting that a building and its HVAC system meet certain performance levels following their

construction or renovation is denominated "Commissioning" (Cx). A recent survey by Crowe et al. [2], which includes 1500 North American buildings, showed that a targeted commissioning work operated by a private firm on an existing building has a median energy saving of 14 %; in some cases, it can achieve over 50 % of demand reduction. Over the years, Cx has become part of building certifications (e.g., LEED [3]) and it has been integrated into some of the world's better-known standards such as the ASHRAE 202 [4] in North America and the international (ISO) and European (CEN) standards drafted by the ISO Technical Committees ISO/TC 205 [5] and ISO/TC 163 [6].

In 2011, the world's largest survey (at the time) on building commissioning, carried out by Mills et al. [2], enumerated a variety of measures classified within three categories: (a) "design, installation, repair and replacement" of any equipment or element of the building; (b) the "operations & controls" of the systems and (c) the "maintenance" of the

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Nomenclature

AHU	Air handling unit
BMS	Building management system
Cx	Commissioning
CCx	Continuous commissioning
COP	Coefficient of performance
CVRMSE	Coefficient of variance of the root mean squared error
ECO	Energy conserving opportunities
EER	Energy efficiency ratio
FDD	Fault detection and diagnosis
GHE	Ground heat exchanger
GOF	Goodness of fit
GSHP	Ground source heat pump
HP	Heat pump
HVAC	Heating, ventilation and air conditioning
MBC	Model based control
MBCCx	Model based continuous commissioning
MPC	Model predictive control
NMBE	Normalized mean bias error
SCW	Standing column well
VFD	Variable frequency drive

building. Its 2020 update [3] stated that 95 % of the measures are related to operations & controls; these are also the measures with the most energy-saving potential. Similarly, Borgstein et al. [4] presented a detailed report about energy audits of 33 office buildings in Brazil and demonstrated that over 75 % of the time the issues were related to operation and maintenance rather than design and construction. The authors also showed how these issues can be solved through Cx or operational changes. Cheng and Lee [5] also found, in their review of research papers between 1977 and 2017, that most of the potential to increase return on investment (ROI) of building energy management system (BEMS) relies on scheduling control features developed for the HVAC and refrigeration systems.

Consequently, most of the literature and industry efforts have focused on “Continuous Commissioning” (CCx) (or ongoing commissioning), as defined in the review by Verhelst et al. [6] as “*a continuous performance evaluation in order to maintain, improve and optimise the performance of building systems during building operation and occupancy.*”

In several projects, in-situ monitoring techniques have been applied to make the Cx and CCx processes more efficient and easily implementable. Sensory feedback, along with diagnostic tools, help the technicians identify and quantify energy-conserving opportunities (ECO) as well as other non-energy issues, such as indoor air quality. According to the abovementioned survey by Crowe et al. [3], this Monitoring-Based Cx (MBCx) achieves statistically more energy savings than the other Cx methods.

The MBCx approach later evolved into Model-Based Continuous Commissioning (MBCCx),¹ which uses reference models as a benchmark to compare the measurement data. The reference models can be built up either from the measurements themselves (data-driven models) or using any other relevant source such as expert knowledge (heuristic) or design data (white-box models).

Verhelst et al. [6] authored an extensive review about MBCCx and identified three sub-domains:

- Economically attractive energy conserving opportunities implementations (ECOI). ECOI includes performance estimations (PE), benchmarking (BM) and energy conserving opportunities (ECOs). The three techniques compare the current building with respect to: (i) the historical performance of the building under investigation (PE); (ii) an exemplar building with a similar layout (BM); (iii) and an alternative building configuration or adapted HVAC installation (ECOs).
- Fault detection and diagnosis (FDD). FDD focuses on component-level models that can detect, identify, locate – and sometimes even predict – operational or sensing faults in the entire HVAC system.
- Model-based control (MBC). MBC includes all type of models made to directly control the HVAC system from simple setups (e.g., an open-loop controller that resets a supply temperature based on a building steady-state model) to more complex solutions such as model predictive control (MPC), which predicts the system’s states to make control decisions.

With the advent of building automation systems (BAS), MBCCx can also be used to automatically detect underperforming or anomalous behavior in the system. This type of MBCCx operates automatic FDD using the building’s fault-free historical energy performance as a reference. These automated MBCCx techniques can be identified as a mixture of ECOI and FDD. Several studies explain how these methods can be implemented in a BAS [7–9] or also in a Building Information Modeling (BIM) framework [10,11].

In order to use MBCCx for the automatic detection of anomalies, it is crucial to decide which metrics and time intervals are used to give an alarm signal to the building energy managers. Harmer and Henze [12] presented a white-box MBCCx application in which they found that, for their case study, a weekly interval with a 6 % difference for electricity and a 15 % difference for heating minimized alarm fatigue. They also found that to prevent false alarms at lower loads, it is necessary to either use a scaling ratio that weighs down small energy periods or to use a minimum absolute threshold of energy usage to be able to give the alarm. Piscitelli et al. [13] used an Artificial Neural Network (ANN) model to identify anomalous electricity profiles of a university building. They obtained a 93.7 % alarm precision when considering as “anomalous” the days in which, at least for 6 h, the electricity usage exceeded 3 times the standard deviation calculated between the ANN and the fault-free experimental data.

1.2. Commissioning of ground-source heat pump systems

Another evolution in HVAC systems in the last decades has been the worldwide increase in the implementation of ground-source heat pumps (GSHPs) [14], which typically consume from 3 to 5 times less energy compared to electric or fossil fuel boilers [15]. Moreover, GSHPs have a higher and more stable performance than air-source HPs thanks to the thermal inertia of the ground. This enhanced performance and stability is typically more appreciated in cold climates (e.g., northern Europe, northern USA, Canada, cold regions of China etc.) where GSHPs have become more widely adopted [14,16] since the additional installation costs can be justified by a significant performance edge over air-source alternatives.

GSHPs require adding a whole new section to the HVAC systems, including several pumps, pipes, sensors and more controllers. Consequently, managing the HVAC operation becomes more complex and the system is more prone to control and performance issues arising from the integration of all the different parts of the HVAC system. This topic is well discussed in a recent report on the monitoring work of 6 GSHPs installations in Germany (Bockelmann and Fisch [17]), according to which a regulation phase is essential to achieve optimal integration among the geothermal system, the building structure, additional thermal conditioning systems, and the end-users. According to the authors’ experience, a successful integration hinges upon implementing

¹ In a similar context MBCCx can be referred as well to “Monitoring-Based Continuous Commissioning” similarly to MBCx. However, for the sake of clarity, in this paper MBCCx is used only for those that highlights the use of a reference model.

holistically coordinated control strategies that must be double-checked and monitored during operation until the regular operation is achieved. An important remark from their work is also that the detection of system and operating faults is more challenging for GSHPs because the high thermal inertia can hide operational errors that, in the long term, can create a ground energy imbalance, thus affecting the performance of the GSHPs.

Several studies in the literature address the performance monitoring of GSHPs. Spitler and Gehlin [18] reported the monitoring results of a GSHP system of a student center in Stockholm (Sweden) equipped with five 40 kW water-to-water HPs and 20 closed-loop boreholes drilled in hard rock. It was found that performance gaps were mainly due to simple operational issues, e.g., a 24-h Legionella protection provided by an electric resistance heater, or an uninterrupted operation of circulation pumps and high flow rates in the borehole circuit. The authors also reported that they identified several issues with current methods to calculate the Seasonal Performance Factor (SPF) in commercial buildings, mentioning they should be extended to larger boundaries and consider the rest of the building (e.g., ventilation fans, pumps). García-Céspedes et al. [19] proposed a new method to calculate the partial load factor (PLF) for double parallel stage GSHPs accounting for efficiency degradation over time. They developed and validated their model based on monitoring data of a GSHP system located in a three-floors office building in Catalonia (Spain). In the case study examined, the linear fit indicated a yearly performance decrease of COP and EER by 1.6 % and 4.0 %, respectively. These results motivated a physical maintenance procedure, which revealed that one of the 3-way valves showed deficient performance (incomplete closing) and was causing an unwanted connection between the evaporator and the condenser water circuits. It was also found that the water filter on the evaporator side had a significant amount of dirt, which reduced the flow rate.

Some studies used GSHPs monitoring data to build numerical models or to train data-driven models. Barla [20] presented a comprehensive monitoring and modelling study on the geothermal system used by a groundwater heat pump for the air conditioning of a large skyscraper in Turin (Italy). After having performed real-time monitoring and pumping tests of the wells, a detailed Finite Element 3D model of the entire geothermal system was built, making it possible to successfully interpret the pumping tests and predict the effects of aquifer's behavior in the long term. Park et al. [21] trained a multiple linear regression (MLR) and an artificial neural network (ANN) model over in-situ monitoring data of a large-scale GSHP system installed in a hospital in Southeastern Korea, and they managed to predict the hourly heating performance with satisfactory accuracy by the MLR (3.6 %) and ANN (1.8 %) models. Also Yan et al. [22] demonstrated the capability of data-driven models to precisely predict long-term behavior of GSHPs using in-situ monitoring data. They first used a Data Mining (DM) technique to understand which parameter to use as inputs and outputs for a Back-Propagation Neural Network (DPNN) model. They also found that a minimum of 71 days in winter and 30 in summer of short-term monitoring data were required to train the model with a deviation below 3 %.

1.3. Paper novelty and objectives

The literature review has shown several examples of performance monitoring and training of data-driven models applied to GSHP systems. These studies tend to focus on the GSHP alone without considering its integration into the building, the only exception being the above-mentioned study by Bockelmann and Fisch [17] which emphasizes the need for closer monitoring of the integration between the GSHP, the building, and the rest of the HVAC system. Given these considerations, MBCCx seems promising for GSHP systems. A robust reference model could more effectively manage the increased HVAC complexity and the overall integration between the subsystems.

Despite this potential, to the authors' knowledge, no studies address MBCCx for buildings equipped with a GSHP. The present paper proposes

a novel white-box MBCCx methodology for HVAC systems using GSHPs. The proposed method adopts a 'whole-building' approach, focusing on the interaction between the building and its HVAC subsystems to identify underlying suboptimal performance caused by inadequate integration between the components. Such inefficiencies may occur even when individual components function as intended, but the control sequences fail to ensure their efficient coordination. These performance gaps can be automatically identified by continuously comparing the system's operation with the model. To ensure an accurate anomaly detection, it is essential to determine a performance metric that accounts for different subsystems simultaneously. This work proposes to merge the goodness-of-fit metric for the GSHP power consumption with a similar metric for the ground heat exchanger (GHE).

Since the white-box model is physics-based, it can provide a benchmark of how the system should perform rather than reproduce exactly how it actually performs, which would be the case with a data-driven model. This benefit is especially important during the first months of the operation of a building when there is not enough data to train ANNs models properly, but there is already a pressing need to operate CCx to ensure the system is performing as expected. Additionally, white-box models allow the exploration of different control strategies that could improve the overall energy efficiency. The possibility of exploring hypothetical scenarios means that the MBCCx method can be used both for FDD and for the assessment of ECOI measures.

As a demonstration of the proposed methodology, a case study is presented where the HVAC system and the building are all simulated in TRNSYS 18 [23] and the thermal response of the boreholes is co-simulated in MATLAB [24]. The TRNSYS model considers both design data and field experimental data; the MATLAB ground model uses a non-stationary convolution method developed by Beaudry et al. [25,26] which combines the ground loads with several transfer functions representing the thermal response of the ground in different flow rate conditions. This method can be used for conventional closed-loop GHEs or for standing column wells (SCWs), discussed in the next section. The building model includes a detailed infiltration model developed by NIST [27] and a ground coupling simulation for the ground temperatures. The HVAC system includes an air handling unit (AHU) with ventilation regulation, a hydronic heating network that delivers thermal energy through PID controlled radiators, an air heat recovery device, and a water-to-water HP. Thanks to the modular nature of TRNSYS, the HVAC system configuration can also be easily adapted to any real-world application.

1.4. The role of MBCCx for early adopters of technology: The case of standing column wells (SCWs)

When significant investments are made to improve performance and promote energy efficiency, building managers have an interest in ensuring that the technology performs as expected. However, adopting a technology that lacks widespread use carries considerable risk due to limited expertise. This is the case with SCWs, a promising type of GHE, as practitioners are often more familiar with closed-loop GHEs. In this context, MBCCx serves as a valuable resource, offering reliable performance insights, especially when other references are scarce.

Despite being a technology that achieves significant energy savings in the building sector, GSHPs struggle to gain widespread adoption mainly due to the high drilling costs of conventional closed-loop GHEs [28]. In an attempt to reduce costs, different GHE setups have been investigated over the years. One such setup is the open-loop GHE, which uses directly groundwater as a heat source/sink for the HP [29]. This leads to two benefits: an increase in heat exchange through the transfer of mass (advection) and a source/sink temperature closer to the undisturbed ground temperature. As a result, fewer or shallower boreholes are required, reducing the total investment costs. However, open-loop systems require a very productive aquifer to operate properly. Therefore, their implementation is limited to suitable sites having a good

hydrogeological potential.

Another type of GHE is the standing column well (SCW) which is defined as a 75–450 m deep open borehole drilled mostly in bedrock with a typical diameter of 150 mm [30]. Like open loop systems, SCWs also use groundwater, but they reintroduce most of the water flow into the same wells. Consequently, they do not require particularly productive aquifers. They can still benefit from advection by discharging part of the groundwater into another well, called the “injection well” (typically placed at least 10 m apart from the others). This operation, called “bleed”, creates a depression cone around the well that triggers water-flow in the surrounding fracture network, promoting advective heat transfer. The enhanced advection brings the groundwater in the SCW to a temperature closer to the undisturbed ground temperature (meaning warmer in heating mode and colder in cooling mode).

Section 2 presents the proposed methodology with recommended general guidelines for creating a model intended for CCx. Section 3 illustrates the application of this method to a case study demonstration featuring five 135-m deep SCWs and an injection well. The latter will include the simulation results and some exemplary results of the MBCCx process.

2. Proposed novel methodology

Focusing on having a benchmark of ideal operation, this MBCCx method aims to create a comprehensive, “whole-building” representation that can accurately reproduce the performance and operation *intended by design*. Therefore, when data is available, it is crucial to avoid creating a model that inadvertently “picks up” existing *operational* issues in the mechanical system. A MBCCx model should reflect how the building systems *are meant* to work, while integrating real-world conditions, such as actual infiltration rates, occupancy profiles and weather patterns.

A “whole-building” MBCCx approach requires a model that incorporates all the subsystems along with the building itself. As a result, using a modular modeling software tool capable of representing the interactions of multiple blocks with each other is recommended. Examples of such software include TRNSYS [23] and the open-source Modelica [31].

The main proposed steps are the following:

1. **Modeling the building itself**
 - a. Zoning, building envelope and internal gains
 - b. Models for air infiltration rates and ground coupling
2. **HVAC modeling**
 - a. Modeling and calibration of the HP
 - b. Integration between the HP and the building model through a heating distribution system
 - c. Development and integration of a GHE thermal response model
3. **Data monitoring, model calibration and validation**
 - a. Data monitoring of the real building and data processing
 - b. Model calibration and model validation against experimental data
4. **MBCCx**
 - a. Automatic identification of anomalous days
 - b. Diagnosis of control sequence problems through a detailed parameter comparison
 - c. Identification of better control sequences that can lead to energy savings

2.1. Modeling the building itself

The very first thing to decide when modeling a building is how to divide it into different thermal zones, also called “thermal blocks” by the ASHRAE standard 90.1 [32]. This standard (Table G3.1–7&8) and the literature [33] agree on similar zoning guidelines. ASHRAE zoning criteria align well with CCx’s needs; Table G3.1–7 considers HVAC

Zones as defined by the HVAC terminals that supply space conditioning. This zoning approach facilitates matching the simulation with air zone measurements.

When it comes to defining the thermal properties of the building envelope, special attention should be given to the thermal mass capacity since it has a major influence on the response of the building to different control sequences. While the thermal properties of the external building envelope and the interior walls are usually well-defined, most modeling guidelines often neglect the remaining internal thermal mass (e.g. furniture, equipment). A simpler way to account for the internal thermal mass is to multiply the air thermal capacity by a factor, often between 5 and 10. A more precise method relies instead on the definition of interior planar thermal mass objects [34] that can be implemented in building energy simulation software [35].

Internal heat gains have a significant impact on the building’s thermal balance. Compliance models often rely on standards and fixed schedules, but for CCx, actual building schedules should be preferred, and the occupancy of each zone should be estimated based on real-world data. To ensure the highest accuracy, previous data on the total electricity consumption should be used to infer lights and equipment gains by deducting HVAC electric power from the total billed power. If measured data is unavailable, lighting electric gains can still be estimated applying per-area based values from standards. However, to achieve the most accurate results, input data (particularly hours of operation) should be based on either detailed monitoring data of existing spaces or a thorough analysis of the exact requirements of future spaces [36]. The estimation of equipment electric load profiles matched well with experimental data when calculated using information on user behavior obtained through interviews, technical data obtained through walk-in visits, and measurements on the consumption of electric loads [37].

Compliance models typically recommend standard fixed air infiltration rates (ASHRAE 90.1 G3.2.1.7). However, since air infiltration significantly impacts heating loads and is highly variable, it is crucial to implement a more realistic infiltration rate for CCx. While detailed bulk airflow models can be used, simpler regression models based on temperature differences and wind speed may also provide sufficient accuracy. It is recommended to consult the literature for a model that is appropriate for the specific building type and climate zone. For instance, Ng et al. [27] fitted the EnergyPlus infiltration empirical equation for 5 different types of commercial buildings and 8 different U.S. climate zones. It is worth noting that the presence of mechanical ventilation significantly alters the fitted parameters when turned on or off.

The boundary temperature of the ground surrounding the building also has a significant impact on building heat losses. Compliance models and standards typically suggest using an annual or monthly average ground temperature (ASHRAE 90.1 Table G3.1–14). However, this simplified method significantly reduces the accuracy of the model. It is recommended to evaluate such temperature using physics-based algorithms known as “ground-coupling” [38]. These models differentiate the ground for different building zones and are typically based on a finite-difference approach. To keep a high accuracy the meshes are denser near the external walls, where the temperature changes quickly.

2.2. HVAC modeling

2.2.1. Equipment

HVAC technical diagrams are typically very complex and include a variety of components that do not need to be represented in an energy model. Thus, the overall HVAC system diagram can be simplified, but the core loops through which the energy flows should be maintained as they are in the actual setup. For instance, keeping the same number of heat exchangers and pumps as the actual HVAC system is a good practice. It is also recommended that HVAC components (e.g., pumps, buffer tanks, heat exchangers, manifolds) be sized according to their actual design specifications.

For buildings with mechanical ventilation, air flow rates should be set based on the design specifications for each zone. The modeler should pay particular attention to the sizing of the Air Handling Unit (AHU) fan, as this produces significant heat gains that will be added to the building. *In-situ* measurements of the fans' power requirements are recommended. For new buildings, heat gains can be estimated based on the maximum rated power of their electric motors.

A first step towards GSHP modeling is obtaining the heat pump's performance map. Often, manufacturers will not provide the entire map but rather a few operational points. If this is the case, it is still possible to use the few available performance points to fit a model. A popular and simple model to fit is the DOE-2 (Department of Energy, U.S.) empirical chiller model [39]. Once the performance map is obtained, it is suggested to first model the HP alone together with its load and source loop so that the HP model can be tested and calibrated to give the expected results when varying source and load inlet temperatures. As a first approach, the source loop can be connected to a simplified GHE, and its full model can be added later.

Once the HP model is ready it can be connected to the building model. In order to do so, a heating distribution system must be put in place as well as thermostats that regulate the heat flow towards the building. The modeler should take particular attention on the control sequences.

2.2.2. HVAC controls

Since one of the CCx main objectives is to identify control sequence issues (particularly, supervisory control problems), the HVAC control in the model does not reproduce the exact code implemented in the building management system (BMS). Instead, it must reproduce the *intended functionality* that the HVAC designer transmitted to the control contractor through a general control sequences document. By following this approach, the model will be capable of spotting anomalies in how the current controls are set up, rather than simply reproducing these issues.

However, when specific control sequences cannot be replicated within a model, incorporating recorded data directly is acceptable. An example of such an occurrence is when fluid flow rates depend on the position of pressure-controlled valves and system's pressure is not modeled.

Proper calibration of some local controllers, such as the room thermostats and the HP controller, which are the main determinants of the entire model's thermal dynamics, is crucial to achieving the intended performance. This calibration is particularly important because the model, regardless of its level of accuracy, will inevitably differ from reality, requiring a different control calibration.

It is worth mentioning that while compliance energy models typically use a 1-hour timestep, for CCx, it is strongly recommended to use a 1 to 15-minute timestep that should match the measurement sampling rate of the sensors installed in the building. Using a high time resolution allows the model to reproduce the rapid dynamic responses of the HVAC system so that they can be effectively compared with the measurements, thus enabling the identification of inefficiencies throughout the system.

2.2.3. Ground response modeling

The main role of the ground response model is to calculate the GHE's outlet temperature based on inlet temperature, mass flow rate, and undisturbed ground temperature. The fastest techniques known in the literature to predict the behavior of GHEs with varying power loads rely on the principle of superposition. These methods have been mainly developed over time for the more mass-spread closed-loop GHEs. They use both temporal and spatial superposition simultaneously through the convolution of transfer functions with an incremental power load vector. A more detailed and comprehensive review of this domain can be found in a book chapter by Spitler and Bernier [40].

However, all these superposition methods rely on the linearity and stationarity of the model response, and every transfer function is

generated for a specific fixed ground flow rate. The assumption of fixed flow rates prevents the study of the impact of dynamic control strategies that adapt the pumping power to optimize the operation of GSHP systems. These superposition methods are, therefore, not suitable for MBCCx applications.

A method to overcome this limitation was recently investigated by Beaudry et al. [25,26], which developed for the first time a non-stationary convolution method for the simulation of GHEs. This is achieved by allowing different transfer functions to be included within the convolution matrices, each representing different values of ground flow rates. The work was validated experimentally through multi-flowrate thermal response tests (MF-TRT).

Although the same method can be applied to SCWs, the process for obtaining the transfer functions is different [25]. Unlike closed-loop GHEs, SCWs, in favorable geological conditions, primarily transfer heat through advection [41,42]. Consequently, analytical solutions developed for closed-loop systems (e.g. finite line source), which account solely for conductive heat transfer, are not applicable for SCWs. Currently the only way to generate transfer functions for SCWs is either through complex 3D finite-element numerical models or by analyzing thermal response tests (TRT) data with a deconvolution algorithm [43].

Several studies demonstrated that using variable speed drives to pump the heat carrier fluid flowrate in GHEs brings significant annual energy savings by decreasing the frequency at partial loads [44–46]. Consequently, it is strongly recommended that MBCCx be pursued using a non-stationary convolution method for the simulation of GHEs.

2.3. Data monitoring, model validation and calibration

The first part of the Cx process relies on data collection, monitoring, and processing. Ideally, every piece of HVAC equipment should have sensors measuring fluid temperatures, flow rates, current intensities, frequency modulation, power factors and any other relevant parameter. The BMS should capture and store sensor data in a database with a high frequency (1–15 min). Once the data is properly cleaned and processed, it can be directly compared with the model simulation results for validation. It is advised to utilize a simulation timestep equal to the measurement timestep or to ensure that the latter is divisible by the former. This allows for the downsampling of the simulation results without compromising their accuracy. Furthermore, for the validation and calibration procedure, it is important to select a period that does not have any evident fault and in which the building is operating within the expected indoor temperature setpoints.

The most important parameters that need to be in line with experimental data are the HP's thermal output, and the inlet and outlet temperatures of the GHE. These parameters represent the core of the energy flows from the source to the load. They should numerically be validated in compliance with the ASHRAE Guideline 14 (Section 4.3.2.4) [47] which states that hourly simulated data should have a coefficient of variance of the root mean square error (CVRMSE) under 30 % and a normalized mean bias error (NMBE) below 10 %. Validating the data with hourly rather than sub-hourly timestamps simplifies the process by "smoothing out" the cyclic on/off patterns of deadband controllers. These cycles are difficult to capture perfectly and can create significant errors, making the validation process significantly harder.

In summary, for the model to perform well during validation, it needs to be properly calibrated. This means focusing on aspects that are not typically part of the standard FDD process, such as control setpoints and model estimates of internal gains, air infiltration rates and building thermal mass.

2.4. Model-based continuous commissioning

2.4.1. Fault detection and diagnosis (FDD)

Once the model is calibrated and validated, it can be used to automatically identify which are the anomalous days and to verify where the

divergency originates by comparing the most critical parameters with the model results.

The “Goodness-of-fit” (GOF) metric [12,48] will be used as follows to evaluate the daily performance of the main heat pump (HP) and of the ground heat exchanger (GHE):

$$GOF_{HP} = \left[\frac{(w_{CVRMSE}^2 \cdot CVRMSE_{HP,output}^2 + w_{NMBE}^2 \cdot NMBE_{HP,output}^2)}{w_{CVRMSE}^2 + w_{NMBE}^2} \right]^{1/2} \quad (1)$$

$$GOF_{GHE} = \left[\frac{(w_{CVRMSE}^2 \cdot CVRMSE_{GHE}^2 + w_{NMBE}^2 \cdot NMBE_{GHE}^2)}{w_{CVRMSE}^2 + w_{NMBE}^2} \right]^{1/2} \quad (2)$$

where w_{CVRMSE} and w_{NMBE} are the weights associated to the CVRSMSE and the NMBE. Previous studies [12,48] assigned a 1:3 weight for ($w_{CVRMSE} : w_{NMBE}$) because building energy managers tend to prefer the models to reproduce the mean energy use more accurately than the hour-by-hour variation. However, in this work a 1:2 weight strikes a better balance between reflecting overall energy use and capturing the HVAC system’s short-term fluctuations. $CVRMSE_{GHE}$ and $NMBE_{GHE}$ are calculated with the same logic but with unitary weights:

$$CVRMSE_{GHE} = [CVRMSE_{T,inlet}^2 + CVRMSE_{T,outlet}^2]^{1/2} \quad (3)$$

$$NMBE_{GHE} = [NMBE_{T,inlet}^2 + NMBE_{T,outlet}^2]^{1/2} \quad (4)$$

Once GOF_{HP} and GOF_{GHE} are calculated, they can be combined within one parameter:

$$GOF_{GSHP} = \frac{GOF_{HP} + GOF_{GHE}}{2} \quad (5)$$

where the two GOFs are normalized (with min–max scaling) into GOF'_{HP} and GOF'_{GHE} . Combining these two performance metrics has revealed to be more effective in minimizing the false negatives (anomalous days detected as normal) and false positives (normal days detected as anomalous) compared to the GOF_{HP} or the GOF_{GHE} alone. As shown later in the results, the most optimal threshold for the new GOF_{GSHP} metric was found to be 0.2, meaning that days with a GOF_{GSHP} above 0.2 can be detected as anomalous.

Once anomalous days are detected, model results can be compared side-by-side with the anomalous experimental data. It will be possible to see where and how the real system is diverging from the expected behavior. Different system components can be compared to localize where the differences originate. The model will also show how the system should have performed as *intended by design*. This approach allows quantifying the impact of faults or control issues that have been identified.

2.4.2. Identification of energy conserving opportunities (ECO)

While the abovementioned approach ensures that the model reflects the intended operation of the HVAC system, it does not guarantee optimal performance. The system may be underperforming even if matches the intended design. Suboptimal control strategies or implementation can lead to wasting a significant amount of energy. For instance, in GSHP systems, the electricity consumption of the pumps is often at the root of a significant decrease in the system’s seasonal COP (SCOP) compared to the standalone seasonal performance of the heat pump. However, the model can be used to identify and test different control strategies that can increase the overall system’s efficiency. Additionally, these strategies can be evaluated under different weather scenarios to ensure their long-term effectiveness.

3. Case study demonstration

The case study building is a primary school located in Mirabel, Québec, Canada. The HVAC system of the school was renovated in 2022 with a 70-ton GSHP system featuring five 135-meter-deep SCWs and an injection well. The renovation included the substitution of most convectors and ventilation ducts, and the addition of a new air heat recovery unit. The heating is distributed through the building via peripheral convectors (126 kW of capacity) and a ventilation system with an AHU (41 kW of capacity). Two building zones, namely the gym and the administration zone, are equipped respectively with one 28.6 kW water-to-air HP and two 8 kW water-to-air HPs, in addition to ventilation and convectors. However, the HPs serving the administration zone were not operational throughout 2023 due to an undersized pump. The new system started its operation in January 2023 and has since been monitored with a CCx program. The results for the entire year have been published by Beaudry et al. [49]. It was demonstrated that SCWs allowed a 73 % reduction in total drilling length and a 50 % decrease in overall construction costs compared to closed-loop GHEs. This work will instead focus on the very first 40 days of operation (18th January – 28th February) after the control sequences have been adjusted. The emphasis on the coldest period of the year is due to the system being sized primarily for heating loads, which constitute the majority of the building’s overall energy demand. The MBCCx process has been aimed at finding control issues related to the heat distribution (convectors, ventilation, etc.) and the heat generation (heat pump and ground heat exchanger). Further details are available in other publications that have examined the same case study [42,50].

3.1. Building modeling

The building was first modeled in 3D in Sketchup 2019 [51] using the TRNSYS 3D plugin (Fig. 1). This model incorporated 23 thermal zones which have been determined following ASHRAE guidelines (see section 2.1). Construction details were obtained from as-built plans and the thermal properties and densities of the layers were taken from Quebec’s building certification standard [52] and from the ASHRAE Handbook 2017 [53]. Additional thermal mass was initially added by multiplying the air thermal capacity by 10. Thermal mass was later increased during calibration by adding wooden objects into the thermal zones (see section 3.5 for more details).

Schedules for occupancy heat gains are based on the timetables of the school building; they are linearly interpolated hour by hour to have more realistic thermal dynamics in the building. The total number of people in the building has been estimated to be around 400 (360 students + 40 employees) and the occupancy density has been redistributed in each room according to realistic assumptions based on the use type of each zone. The amount of occupancy gain per person is taken from the ASHRAE 90.1 standard [32]. Equipment and lighting gains are instead regulated with calibrated profiles derived from the total measured electricity use (see section 3.5).

Air infiltration can greatly affect building demand in cold weather conditions. For this reason, a detailed infiltration model recently developed by Ng. et al. (NIST) for U.S. commercial buildings [54] has

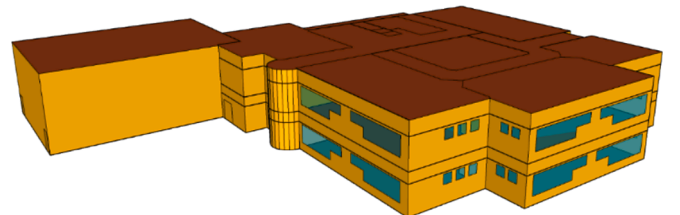


Fig. 1. 3D model of the Cle-des-champs primary school in Mirabel, Québec, Canada.

been used. This model considers both the impacts of wind velocity and of stack effect.

The building model incorporates a “ground coupling” model to provide a realistic ground temperature as a boundary condition. In TRNSYS, the ground temperature can be simulated using a 3-D ground coupling model based on a finite difference approach which uses Kasuda’s correlation [55]. The ground can be divided into several zones to estimate the near-ground temperature (2–3 m below the ground floor) for different parts of the building. However, since this algorithm slows down the TRNSYS simulation significantly, precompiled boundary temperatures can be used in successive runs to reduce computing time.

3.2. HVAC modeling

The model’s HVAC system diagram (Fig. 2) kept the same heat exchangers and the same number of loops of the real system. However, the following simplifications have been made:

- The gym’s water-to-air heat pump has been lumped into the main water-to-water heat pump.
- The 5 submersible pumps of the SCWs are merged with the SCW circulating pump.
- The overall layout of valves has been simplified and their behavior has been modeled through manifolds and variable speed pumps.

This model features two heating distribution systems: (i) by ventilation and (ii) by hydronic heating. Both of these systems are controlled through a manifold. A 30 % (v/v) propylene glycol solution is utilized on the source side to enable temperatures below 0 °C. Additionally, it is employed on the load side to prevent freezing of the AHU coils in the event of a fault, which could result in the fresh air significantly cooling the fluid. An electric boiler is included as an auxiliary system, to be employed only when the water-to-water heat pump is unable to meet the heating power requirements.

The heat pump performance map was created through a polynomial regression based on nine operating points supplied by the manufacturer. The regression employs an adaptation of the DOE-2 (Department of Energy, U.S.) empirical chiller model [39] tailored for the heating mode. It considers alterations in the inlet evaporator temperatures (source temperature) and the outlet condenser temperature (the heat pump heating setpoint). Nonetheless, it does not account for fluctuations in the condenser or evaporator flow rates. This limitation is not significant

since these flow rates are maintained constant in the actual setup.

Once the HVAC diagram is determined, it can be modeled through a physical-based (white-box) modeling framework. For this work, TRNSYS [23] was chosen for its versatility, accuracy, and modularity. The modeled HVAC system is divided into four loops: the ground loop, the Heat Pump (HP) source loop, the HP load loop, and the building loops. One of the building loops is assigned to the Air Handling Unit (AHU), and the other is assigned to the hydronic convector heating system. Both the AHU and convectors interact with the building model by exchanging inputs and outputs.

3.2.1. Ground loop

The SCW thermal response model is connected to the plate heat exchanger, which protects the HP evaporator from groundwater impurities. Ground flow rates are controlled with a multi-level pumping system that replicates the real control sequences. Freeze protection is also implemented using a deadband control to activate the electric boiler and disable the heat pump when the groundwater inlet temperature drops to 2 °C (setpoint 3 °C, deadband 2 °C). The ground pump includes 5 submersible and 1 circulating pump, with power use estimated via a cubic regression based on total flow rate.

3.2.2. HP source loop

On the HP source side, flow rate is fixed for durability, though a VFD enables alternative control strategies. A buffer tank is included for system stability.

3.2.3. HP load loop

On the HP load side, the hot water collector is divided into supply and return lines, simulating a real heat pump deadband controller. Flow rate remains fixed but adjustable via a VFD. The flow splits into three streams upon reaching the supply collector: to the AHU, convectors, and the return line. An auxiliary electric boiler in parallel to the heat pump can operate independently if the heat pump shuts off due to freezing or faults.

3.2.4. Building loops

The building has two heating systems: a ventilation system that heats air through an AHU and a hydronic system using perimeteric convectors (red loop). Fresh air enters the AHU after pre-heating via a heat recovery unit. AHU fans, sized to 20 kW, operate on a fixed schedule, with supply temperature linearly adjusted from 24 °C at –15 °C external to 20 °C at

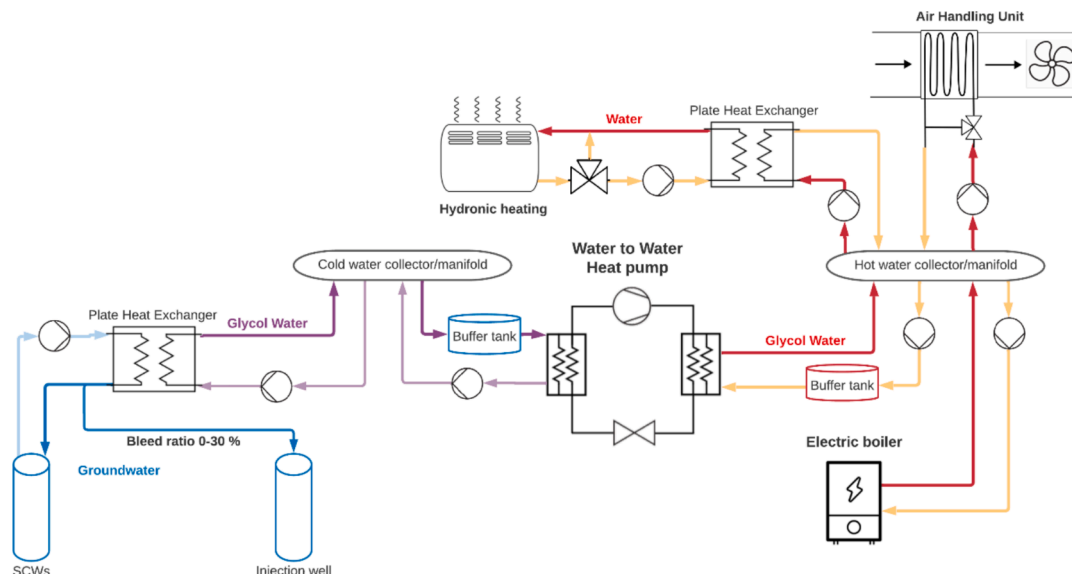


Fig. 2. Simplified diagram of the case study HVAC system.

15 °C. A heat exchanger separates the propylene glycol solution from the convector water. In the “Convectors” TRNSYS macro block, each building zone has a PID thermostat that controls water flow through each convector, while unused flow is directed to the heat exchanger. The AHU and convectors serve different building zones, with air temperature feedback to each zone’s controller.

3.3. Ground response modeling

The TRNSYS HVAC system integrates a ground response model through a connection with the MATLAB engine. This is possible thanks to an interface layer that enables communication between the TRNSYS Fortran routine and the MATLAB engine. Alternatively, a Python connection could yield similar results [56].

The newly developed non-stationary convolution method mentioned in section 2.2.2 is used in its spectral form [26] to simulate five SCWs and the injection well. A set of 42 g-functions has been generated from a 3D extension of the numerical model developed by Jacques and Pasquier [50] for this case study GHE. The 3D extension uses median hydraulic and thermal properties drawn from the joint distributions for the three geological units and five hydrostratigraphic units. The 42 g-functions represent a combination of 6 groundwater pumping flow rates (100, 200, 300, 400, 500, 600 L/min) and 7 bleed ratios (0 %, 5 %, 10 %, 15 %, 20 %, 25 %, 30 %). However, only the combinations with a bleed rate not exceeding 90 L/min will be considered, since in-situ experimental tests have shown that exceeding this threshold can result in overflow of the injection well.

3.4. Data collection and processing

To apply continuous commissioning on the case study building, data was collected through a vast array of typical HVAC sensors that stored data on a cloud platform. Sensors have been monitoring with a 5-minute frequency the building’s air temperature and humidity, as well as the thermal and electrical parameters of every piece of HVAC equipment. Energy balance calculations were used to check the validity of measurements and when necessary to correct the values of poorly calibrated sensors. More details can be found in Baudry et al. [49].

The overall results, summarized in Fig. 3, illustrate the electric power usage of the HVAC system by component for the week of January 23–29, 2023, with the AHU showing a high energy demand due to its 20 kW fan.

3.5. Model calibration

Model calibration focused mostly on the building thermal mass and the internal heat gains, specifically regarding the electric consumption of lights and equipment. The calibration was carried out manually for a fault-free period in which the indoor temperatures behaved as expected (January 18–29, 2023). Before calibrating the internal gains, the building thermal mass was calibrated to ensure that the building thermal loads were adequately accurate. This was done by adding layers of wood to the thermal zones of the building until the MAE of the mean indoor

temperature of 4 key zones was going below 0.25 °C. Fig. 4 provides a comparison between model and real indoor temperature ranges for four of the school’s classrooms equipped with perimeter convectors. During the night the apparent capacity in the building seems to be larger but a further increase in the model thermal capacity compromises the accuracy in other parts of the day. The resulting MAE of 0.22 °C was deemed to be acceptable for the present application.

The initial estimate for internal gains only considered standard specifications and realistic scheduling, which included 5 W/m² (NECB) for the equipment and 8.7 W/m² (NECB) for the lighting. To increase accuracy, electricity consumption measurements were used to estimate the heat gains. Lighting heat gains were maintained according to the standards; conversely, equipment gains were modified to ensure that the sum of the electrical loads of lighting and of the equipment matches the total “Non-HVAC” metered electrical power. In Fig. 5, the monitored HVAC power consumption in the building has been compared to the electric power billed by the electricity provider. The lighting power usage can be subtracted from the “Non-HVAC” power to obtain the equipment heat gains, represented in Fig. 5 for the week of January 23–29, 2023.

However, not all electricity consumption is converted into heat gains. For example, some loads can originate outside the building, or some gains can be ejected by the ventilation system. For calibration purposes, Herbing et al. [57] used a parameter called “*fElec2Heat*”, which expresses the ratio of electricity converted to sensible heat gain on a scale from 0 to 1. In this work, it was found that fixing *fElec2Heat* at around 0.5 was improving model validation performance parameters (next section).

During the calibration it also became clear that occupancy gains were underestimated, therefore occupancy schedules were adjusted accordingly for daytime classes as well as evening classes, which had not been included in the publicly available timetables.

3.6. Model validation

As discussed in Section 2.3, the model validation is conducted in accordance with ASHRAE Guideline 14, which considers a model valid if the CVMSE is below 30 % and the NMBE is under 5 % for key parameters representing the energy flows of the system. The simulations are performed with time steps of 5 min, mirroring the sampling rate of the experimental data. However, the validation is made on an hourly basis. This way, the cyclic patterns of on/off deadband controllers can be avoided while also being able to comply with the ASHRAE Guideline 14. The three key parameters considered for validation are the HP’s thermal output power and the inlet and outlet groundwater temperatures as they represent the core of the energy flows from the source to the load. Fig. 6 compares these three parameters versus experimental data for the fault-free period. The corresponding CVMSE and NMBE values are presented in Table 1.

The CVMSE and the NMBE meet ASHRAE Guideline 14 standards for all three core system parameters; therefore, the model can be considered validated.

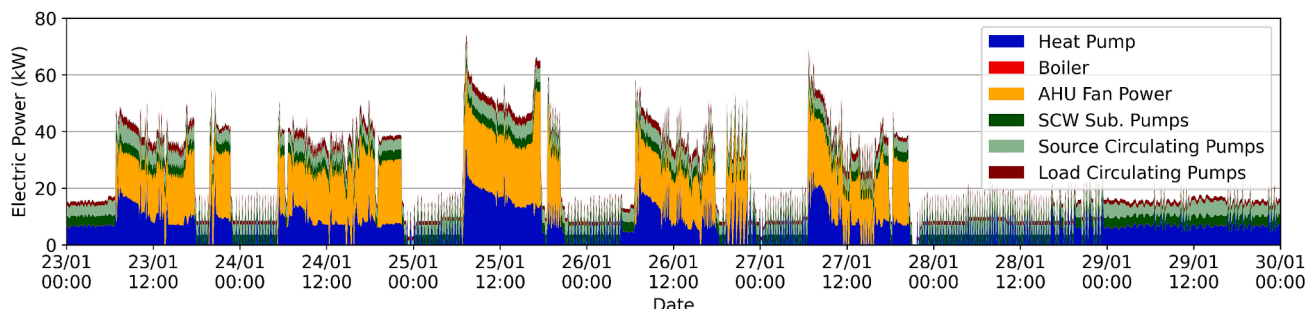


Fig. 3. Stacked plot of the HVAC-related electric power usage by component.

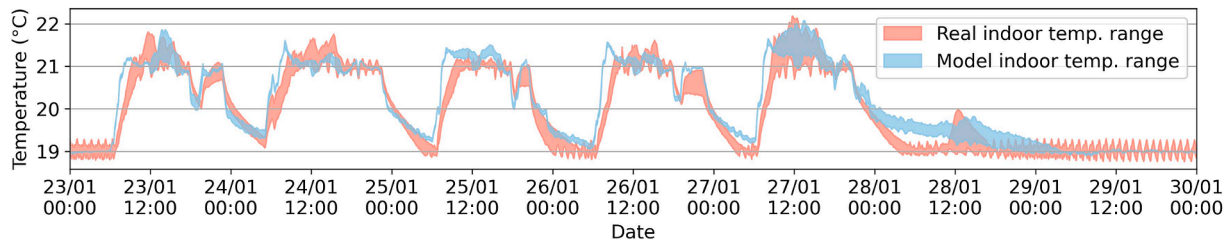


Fig. 4. Model and real indoor temperature ranges of four classrooms.

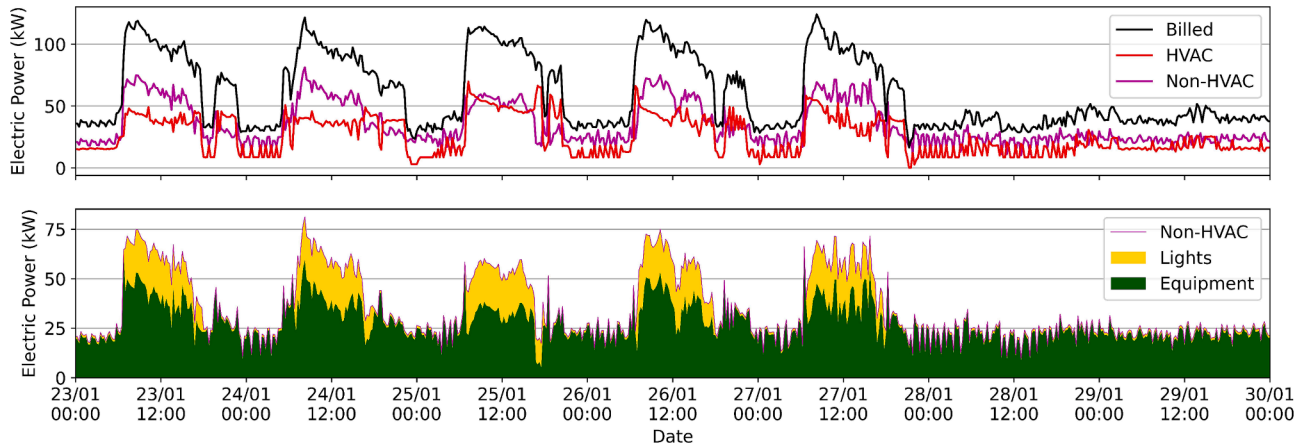


Fig. 5. (top) Non-HVAC electric power is obtained subtracting HVAC-related power from the total power billed by the provider bottom) Stacked graph: the equipment gains are obtained by subtracting light gains from non-HVAC electric power.

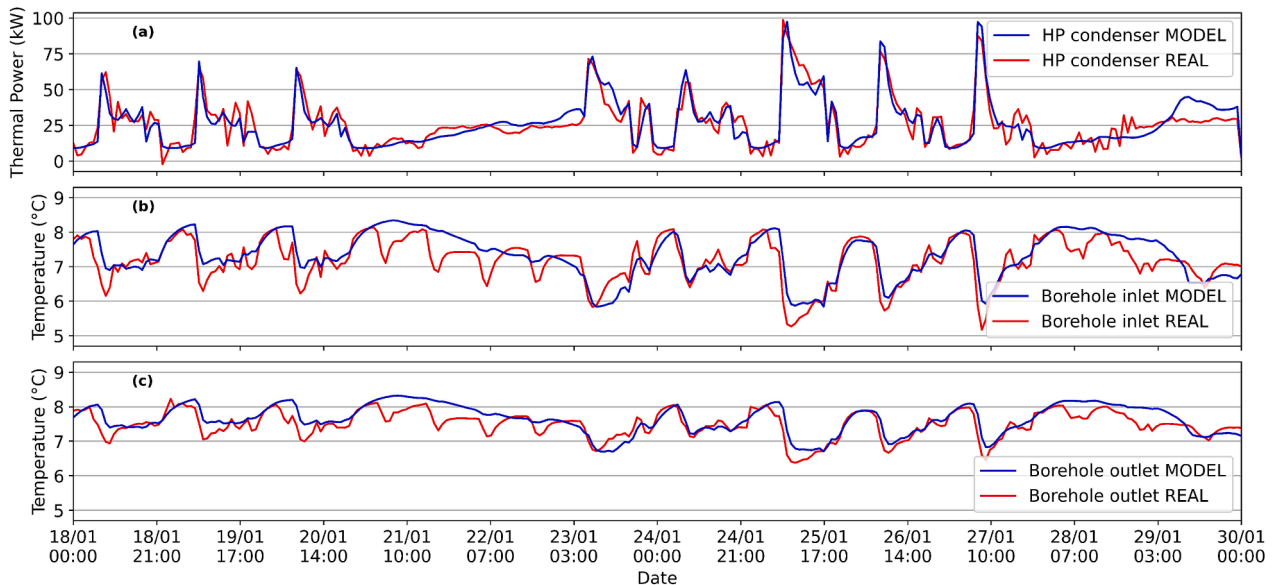


Fig. 6. Validation of the model against experimental data for the calibration period (18 Jan – 29 Jan. 2023) for three core system parameters: (a) Thermal output of the GHSP (b) Borehole inlet temperature (c) Borehole outlet temperature and external temperature.

Table 1

Validation performance of the model for the three core validation parameters over the fault-free calibration period.

	HP's thermal output	GHE's inlet	GHE's outlet
CVRMSE	27.3 %	5.3 %	3.2 %
NMBE	−1.3 %	0.8 %	0.2 %

3.7. Fault detection and diagnosis (FDD)

Once the model is validated, it is possible to leverage it to automatically identify control anomalies as discussed in Section 2.4.1. The GOF_{GSHP} metric has been evaluated for the analyzed commissioning period 18 January – 28 February 2023. Fig. 7 compares the daily GOF_{GSHP} to the daily GOF_{HP} and GOF_{GHE} .

The thresholds to define anomalous days for the three GOF metrics

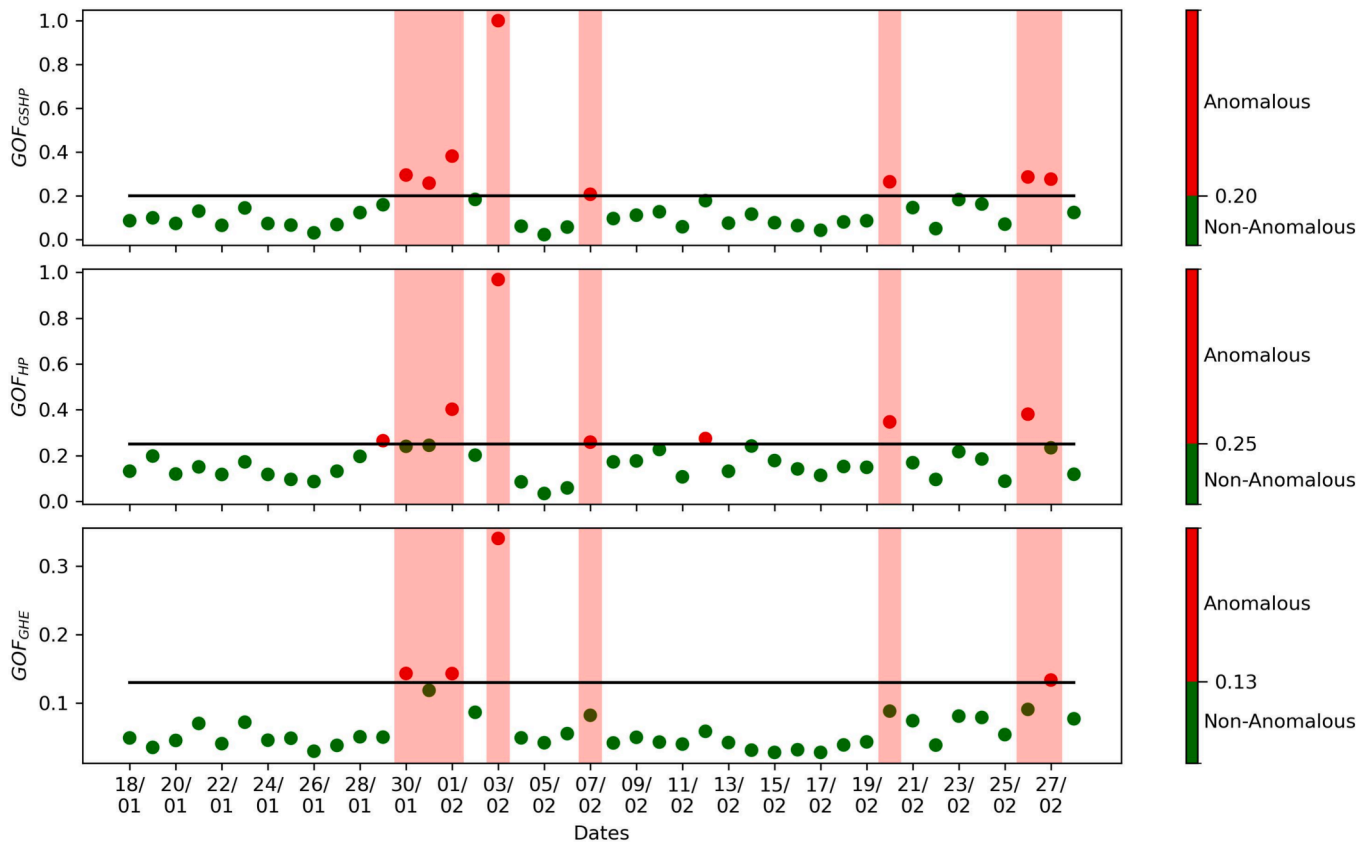


Fig. 7. Goodness-of-fit daily variation with the proposed GOF_{GSHp} metric (top row) against GOF_{HP} based only on the thermal output of the heat pump (second row) and GOF_{GHE} based only on the temperatures in the GHE (bottom row). The periods in red highlight the days that presented an anomalous behavior in the real system. Colorbars on the right refer to the detection threshold used by the MBCCx method to detect anomalies. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

have been chosen to minimize the number of false negatives (FN) (e.g. green dots inside red areas) and false positives (FP) (e.g. red dots outside of red areas). The red zones highlight the days in which the system presented anomalous behaviors. It can be seen that the GOF_{GSHp} metric has zero FN and zero FP, while GOF_{HP} has 3 FN and 2 FP, and the GOF_{GHE} has 3 FN. The GOF_{GSHp} metric manages to get the best of the other two parameters, and when one of the two would have a wrong outcome, the other numerically compensates that error.

Now that the anomalous days have been identified, they can be analyzed to diagnose the faults. The three different types of control issues that have been determined are, in descending order of severity:

- 1) Wrong HP's evaporator protection temperature (1,3 and 7 February)
- 2) Hydronic convectors not giving enough power to keep the indoor temperature setpoint (30 January, 20 February, 26–27 February)
- 3) Anomalies in the supply air temperature through ventilation (31 January)

The first issue can be identified by looking at Fig. 8 where the model is compared to the experimental data for the period 1–7 of February on a 5 min timestep basis. Anomalous days are highlighted in red.

The first notable observation is that the real heat pump exhibited cycling behavior even during regular days, predominantly at low loads, such as weekday nights. This behaviour was not incorporated into the model due to the difficulty in replicating the exact cycling pattern, which would result in a high CVMSE and consequently a high GOF, making it challenging to distinguish regular days from anomalous ones. Although it is considered normal behavior for a heat generator to cycle when the demand is very low, it is still clear that the cycling frequency in the real HVAC system is high. It should be decreased significantly to

reduce wear and tear of the components. However, the days highlighted in red present anomalous heat pump cycling, which means the HVAC system fails to adequately heat the building during those particularly cold days. This issue is evident when comparing the indoor temperatures (d) of the anomalous days with those on February 2. The cause of this anomaly can be identified in (c), where it is possible to see that the inlet temperature at the HP's evaporator will not go below 3 °C, while the model can go below that threshold. This means that the HP's evaporator protection temperature, which is meant to avoid the freezing of the fluid, was set too high compared to the freezing point of 30 %vol propylene glycol solution (about −13 °C). It is suspected that this parameter was changed from −7 °C to 3 °C because of an unapproved change in the control sequence around January 16th–17th.

The second and third control issues can be visualized in Fig. 9. In (g–i) it can be seen how three weekdays (30/01, 20/02 and 27/02) have unusually cold indoor temperatures in the morning and a weekend day (26/02) has some zones largely below setpoint. The convectors (j–l) were not delivering enough thermal power to the zones to keep them at the desired setpoint temperature. It is believed that there was either a fault or an erroneous control implementation in the convectors' controllers. Regarding January 31st (m), the ventilation power delivery was anomalous. The drops in power were caused by sudden decreases in the ventilation supply temperature, which should depend only on the external temperature. For these two issues it was not possible to identify the specific causes in the control sequence as the source code of the HVAC controls was not accessible. Nevertheless, the MBCCx process was able to identify and localize the control anomalies. This information can be then used by the operators to deliver a proper investigation and maintenance.

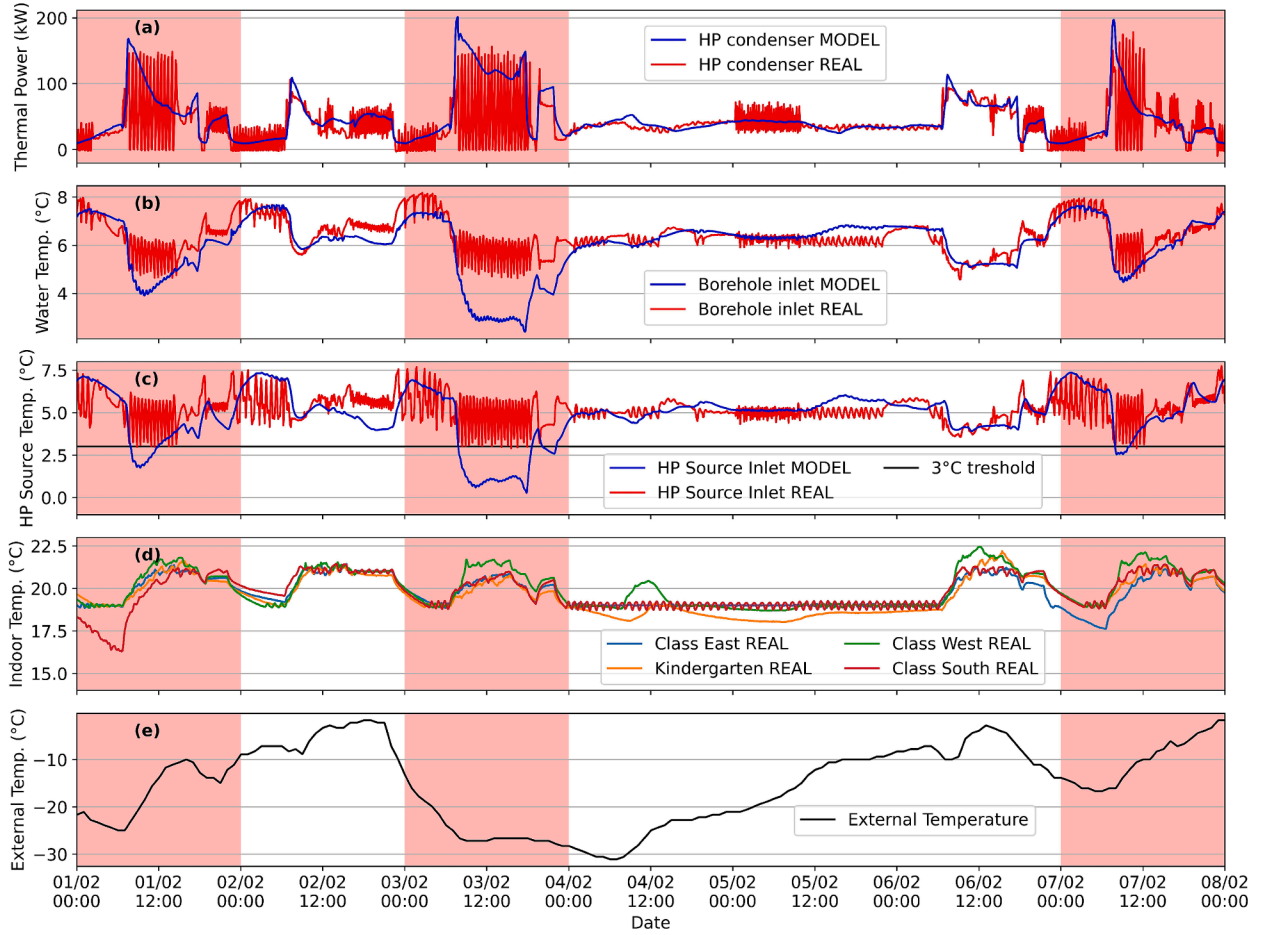


Fig. 8. Simulation results and experimental data for the period 1 Feb – 7 Feb. 2023. (a) Thermal output power of the GHSP (b) Borehole inlet temperature (c) HP source inlet temperature (d) indoor air temperature in 4 school's classrooms (e) external temperature. Highlighted in red are the anomalous days. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.8. Identification of energy conserving opportunities (ECO)

The SCW system was initially designed to operate through variable flow rates using variable-speed submersible pumps. During the installation, however, the VFD control of the pumps was not properly set up to work at the desired range, and each of the 5 pumps could only operate near the maximum capacity of 126 L/min. Therefore, the SCWs could only be either turned off, or operated near 630 L/min. Fig. 10 shows that the total pumping flow rate was oscillating close to 630 L/min for the whole period, and consequently, the model was set to a constant 630 L/min SCW flow rate.

This high pumping rate, however, is meant to be used only during high-demand periods since it requires about 5.7 kW of electric power to run the 5 submersible pumps and the circulating pump. Operating a high pumping rate during periods of high demand is necessary to maintain groundwater at a safe temperature above the freezing point. However, pumping power can be saved without particular concerns when the heating demand is lower. The MBCCx method allows us to see how much energy could be saved by varying the flow rate with different control strategies.

A previous work on this case study [58] explored ideal predictive strategies for a 5-level pumping and bleed control system aimed at reducing energy consumption while avoiding groundwater freezing. Using multiple iterations of the model, it was shown that a “heuristic predictive strategy” could save up to 30 % of total energy and 75 % of pumping energy even during the coldest winter of the last decade (Winter 2015).

This ideal strategy assumes perfect predictions of weather and occupancy, but it can serve as a basis for developing simpler rule-based control strategies suitable for real implementations. To derive these rules, the obtained ideal optimal pumping profiles were analyzed in correlation with the outdoor temperature and occupancy patterns. Results can be seen in Fig. 11. This rule-based approach kept the SCW inlet temperature above 2 °C even on the coldest event of the last decade, while cutting down energy use. For the commissioning period, simulations indicated that this control strategy could have potentially saved roughly 78 % of the pumping energy, reducing the electrical consumption from 5.827 MWh (constant maximum flow) to 1.278 MWh. The electric power consumption of the pumps was estimated with the affinity law as for the following equation:

$$P_{el} = \left(\frac{f}{f_{max}}\right)^3 \cdot P_{el,max}(kW) \quad (6)$$

where f and f_{max} are the measured and nominal frequencies (in Hz) of the equipment, and $P_{el,max}$ is its power rating of the pumps (in this case 5.7 kW).

These potential energy savings estimations are made possible by the accurate whole-building model that was developed for the MBCCx, which enables testing and optimization of control strategies that would otherwise be unattainable.

4. Discussion and conclusions

This paper has proposed an MBCCx method for HVAC systems

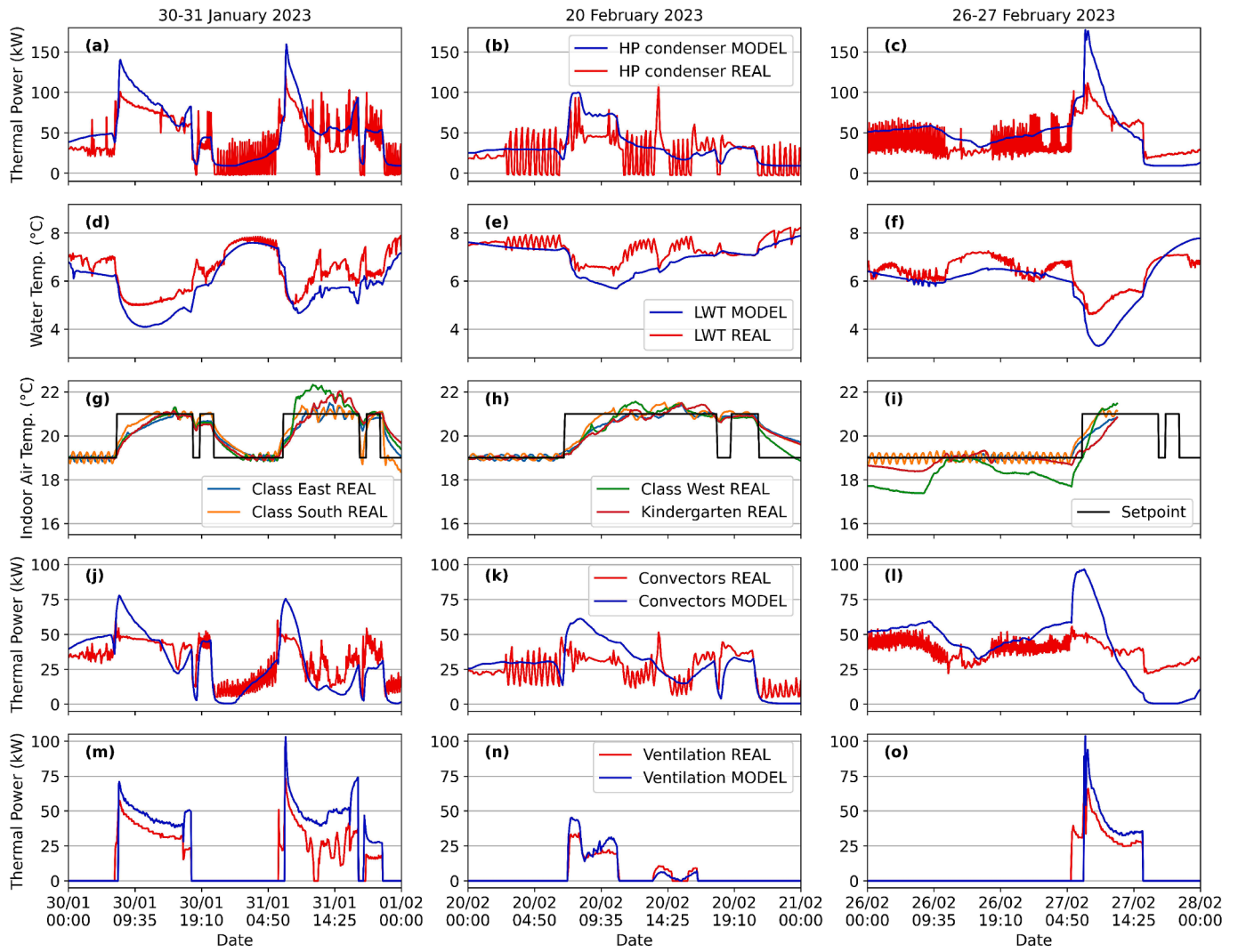


Fig. 9. Simulation results against experimental data during three anomalous periods. (a-c) Thermal output power of the GHSP (d-f) borehole inlet temperature (g-i) indoor air temperature in 4 classrooms (j-l) convectors thermal power (m-o) ventilation thermal power. (i) has missing data on the second part of the 27 of February.

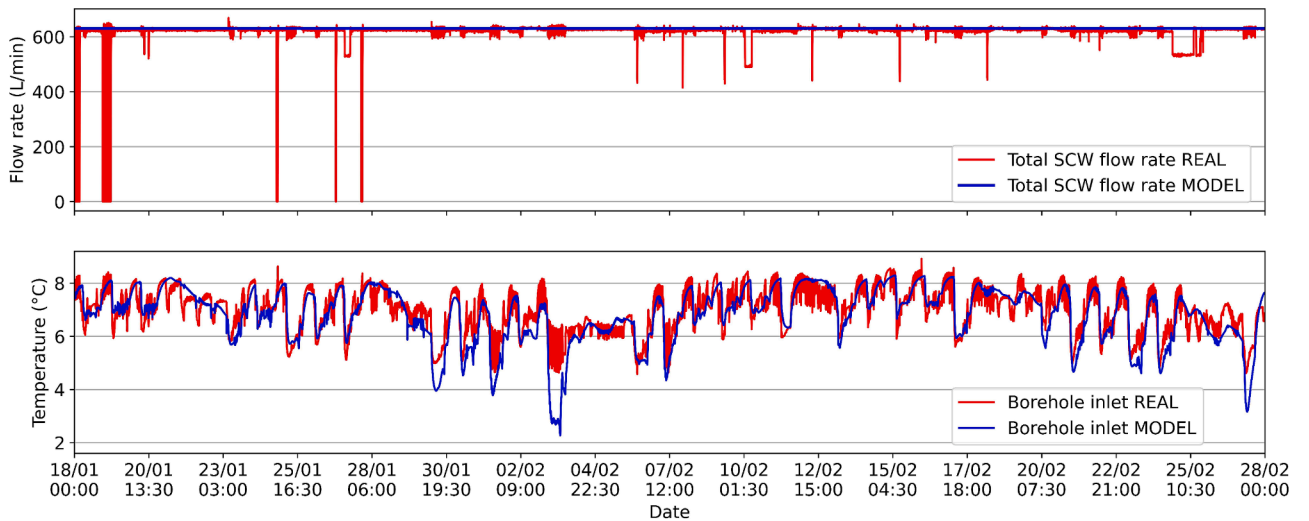


Fig. 10. (top) Total groundwater pumping flow rate in the SCWs during the analyzed commissioning period (bottom) Borehole's inlet groundwater temperature.

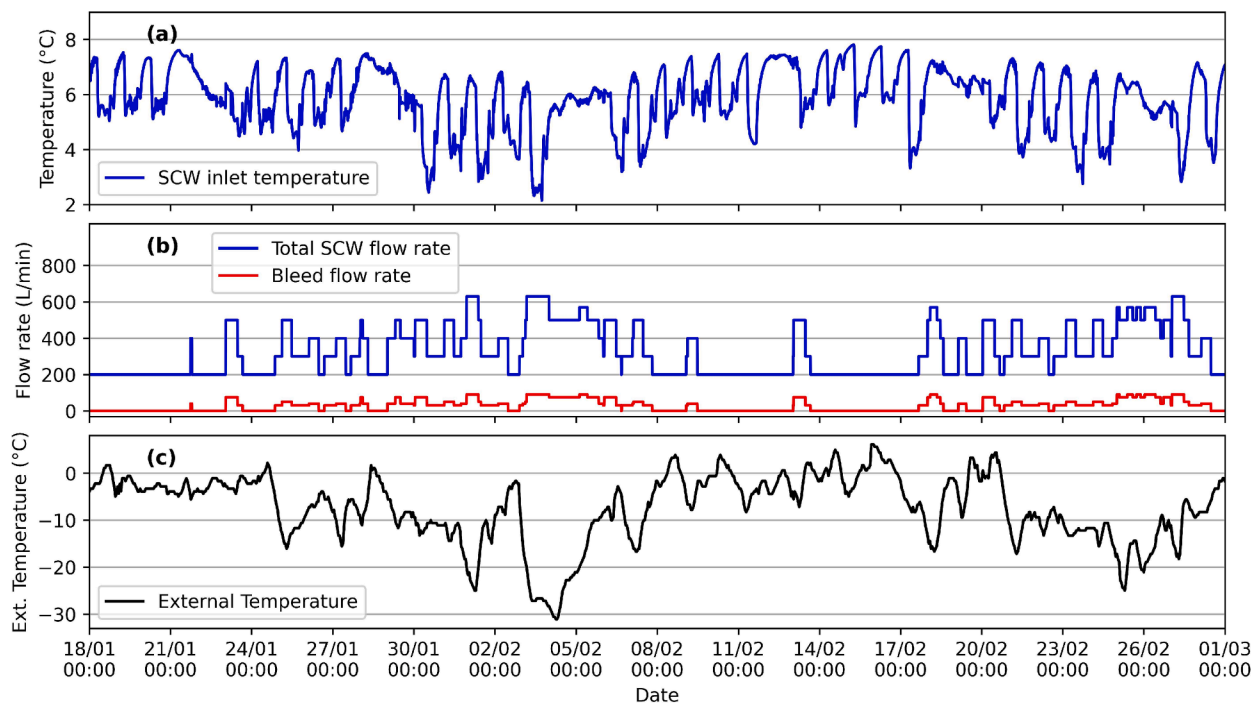


Fig. 11. Simulation results for the analyzed commissioning period when using a rule-based control strategy for the SCW pumping which tries to anticipate high demand events.

equipped with GSHPs. Given the size and complexity of these systems, this commissioning method employs a whole-building modeling approach to identify and diagnose control sequence anomalies across the entire system. A “whole building” approach can consider all the interconnections between the subsystems, and it is suitable to identify suboptimal behaviors resulting from inadequate integration between disparate components. The proposed approach differs from the methods used in the existing literature, which has typically confined commissioning work on the GSHP alone without fully accounting for the potential for underperformance due to control sequence issues that may arise in other system components.

To achieve such objectives, the proposed method uses an accurate physics-based model encompassing all the subsystems (building, HVAC, GHE), which should be modeled and controlled as *intended by design*. This approach prioritizes how the system was intended to perform as decided during the design phase, while avoiding the replication of any mistakes in the implementation of the control sequences. This paper provides technical guidelines to pursue such a modeling approach, and it highlights the differences between this method and the standard procedures. This method often demands stricter requirements and detailed modeling because accurately capturing the real dynamics of the building is crucial for a reliable outcome.

A key benefit to highlight is that this method can be used in the very first months of operation, *when the commissioning work is needed the most*, because, unlike data-driven solutions, large historical datasets are not needed. Once the model is calibrated and validated, it is possible to automatically identify anomalous days by using a goodness-of-fit metric that considers both the output of the GSHP and the fluid temperatures in the GHE. By comparing actual measurements with the model’s predictions, these anomalies can be diagnosed. Moreover, such an accurate model allows exploring different control sequences and the identification of potential energy-conserving opportunities. However, this method has limitations in the expertise required to build and calibrate the model, and in the amount of time required to do it accurately.

To showcase the proposed method, a case study demonstration is presented in the second part of the paper. The HVAC system of a primary school in Québec, Canada, was entirely replaced with a ground source

heat pump (GSHP) system equipped with five 135-meter-deep SCWs. Once the system had been accurately modeled and calibrated, it was possible to analyze the first 42 days of operation following the implementation of the control sequences. The proposed FDD method was capable of correctly identifying all anomalies, with no erroneous detections. In contrast, when examining the heat pump or GHE individually, the GOF metric encountered several false positives and false negatives. It was then possible to diagnose the anomalous days by comparing key model parameters to the measurements.

Three distinct types of control issues were identified and localized within the system: erroneous heat pump control and incorrect heat delivery control of convectors and ventilation units. Finally, it has been demonstrated that the model’s flexibility enables the evaluation of more efficient control sequences; this is possible due to its ability to run multiple scenarios under different conditions. For example, pumping of the SCW groundwater was maintained at the maximum flow rate (630 L/min). By evaluating a theoretically ideal pumping control through multiple iterations of the model, it was possible to derive some simple control rules that could be applied in the BMS to approach the ideal performance. It has been shown that this simple rule-based control strategy could have resulted in a theoretical 78 % reduction in pumping energy during the analyzed commissioning period.

These encouraging results indicate that this MBCCx methodology may prove valuable in enhancing the efficiency of the commissioning phase for complex systems, such as GHSP systems. Future efforts should prioritize the broader implementation of the methodology to solidify its value across various contexts. This includes conducting further case studies in different building types and geographical locations to validate its robustness and identify potential adaptations. Finally, expanding the methodology’s analytical capabilities by incorporating additional FDD criteria for a wider spectrum of HVAC subsystems would provide a more holistic approach to MBCCx.

CRedit authorship contribution statement

Giulio Tonellato: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation,

Formal analysis, Data curation, Conceptualization. **Michaël Kummert:** Writing – review & editing, Supervision, Project administration, Formal analysis, Conceptualization. **José Candanedo:** Writing – review & editing, Supervision. **Gabrielle Beaudry:** Writing – review & editing, Methodology. **Philippe Pasquier:** Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Giulio Tonellato reports financial support was provided by Natural Sciences and Engineering Research Council of Canada. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

The authors do not have permission to share data.

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