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Stochastic approach to ground heat exchanger sizing accounting for weather and ground property variability

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Abstract

Sizing ground heat exchangers (GHE) is typically based on building loads and ground properties, with conventional methods relying on a typical meteorological year and fixed ground and borehole parameters. This study explores how uncertainty in four weather variables and four parameters of the GHE affects the estimation of borehole length. Using 11 scenarios with 5000 coupled building and GHE simulations each, it is shown that borehole length uncertainty can reach 40 m for a borehole length averaging a depth of 165 m. When all eight parameters vary simultaneously, the standard deviation in borehole length is 11.4 m, with 11.2 m attributable to weather variables and only 1.9 m to the parameters of the GHE. The most influential variable is the exterior dry bulb temperature, which presents a borehole length standard deviation of 11.1 m. These findings highlight that accounting for weather uncertainty is critical when selecting borehole lengths to reliably meet thermal loads, thereby ensuring more robust GHE designs.

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Keywords: Monte Carlo; BES; GHE; Optimisation; Sizing

1. Introduction

To design a ground heat exchanger (GHE), both the building characteristics and the thermal properties of the ground are required. The former are used to determine the thermal loads to be covered by the ground source heat pump (GSHP), and the latter are for sizing the GHE [1]. Building thermal loads are typically estimated based on two main components: (1) the properties of building materials, and (2) the climatic conditions of the region where it is located [2]. As a result, accurate estimation of the required GHE length is inherently complex, and the uncertainty of the input variables can lead to GSHP systems that are either undersized or oversized.

The design process of a GSHP system begins with determining the heating and cooling loads required to maintain room temperatures near predefined set points. These thermal loads are generally estimated by building energy simulations (BES), which depend on both building characteristics and local weather conditions. To capture these influences, BES tools such as EnergyPlus [3] rely on a wide range of input parameters, including detailed weather data. Such data are usually provided through typical meteorological year (TMY) datasets, which represent the average climatic conditions of a given region [4–6]. In Canada, TMY datasets are available as Canadian Weather for Energy Calculation (CWEC) files, which are obtained from the Canadian Weather Energy and Engineering Datasets (CWEED) [7]. CWEC files provide hourly weather data for a typical year at specific locations across the country, based on 20 years of historical CWEED measurements. CWEC and other TMY datasets are commonly used but have limitations in representing the full range of weather variability in the BES outputs. For example, Wang et al. [8] compared BES using CWEC files with those using individual annual records from the CWEED dataset, and reported significant differences in peak energy demand. Their findings highlight that CWEC datasets may fail to capture extreme conditions

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present in actual weather records. To address this limitation, studies such as Chun Yin Siu and Zaiyi Liao [9] have recommended performing BES with multiple years of weather data rather than relying on a single TMY.

Using a given building thermal load dataset, GHE simulations are performed to verify if the spacing, depth, and configuration of the boreholes lead to fluid temperatures exceeding the GSHP temperature limits. Analytical models, such as the infinite and finite line source models [10,11] are widely used because of their simplicity and computational efficiency. However, for complex geological or hydrogeological conditions, detailed numerical models are preferred for accurately representing the underground heat transfer processes. These simulations rely on input parameters describing ground properties and borehole characteristics. Similarly to the estimation of building thermal loads, uncertainties in the ground properties or GHE construction can significantly affect the sizing of the ground loop. To address this, stochastic or probabilistic approaches can be employed, enabling systematic variation of input parameters and evaluation of their influence on the required borehole length.

The conventional approach to sizing a GHE begins by estimating the ground thermal loads from the building's heating and cooling demands and the geothermal heat pump performance. Based on these ground thermal loads, the number and configuration of boreholes are defined. The borehole length is then iteratively adjusted to ensure that the ground thermal loads are met, typically up to a specified fraction of the peak load [12], while keeping the GHE circulating fluid within operating temperature limits [13]. Although few studies, such as Huang et al. [14], have proposed combined simulations that couple BES and GHE sizing, none have used one within a stochastic framework.

This study aims to quantify the impact of uncertainty in weather variables and the thermal and geometric inputs of the GHE, used in BES and GHE simulations, respectively, within a combined approach to GHE sizing. The methodology integrates EnergyPlus for BES [3], the finite line source (FLS) model of Claesson and Javed [15] for GHE simulation, and the alternative sizing equation with hourly loads for borehole length estimation [16,17]. To evaluate the influence of uncertainty, four weather variables and four parameters associated with the GHE are randomly sampled within a Monte Carlo framework.

2. Methodology

This section outlines the approach used for quantifying uncertainty in GHE sizing. It first presents the building model used in BES. After, it illustrates the weather data employed and explains how uncertainties for four variables are addressed. Then, we describe the GHE simulation and sizing processes, including how uncertainty is integrated for four parameters used in the GHE simulation. Finally, we explain how all these steps are integrated within a stochastic framework to evaluate the overall uncertainty in GHE sizing.

2.1. Building model

This study employs a U.S. Department of Energy reference building model [18], designed in compliance with the ASHRAE 90.1–2004 standard [19]. The model represents a single-story office with five thermal zones and an attic, totaling 511 m^2 of floor area. Such reference buildings are specifically developed to provide well-defined and consistent inputs for BES. In this work, the model is used without modification, and no uncertainty is introduced in its construction properties during the simulations.

2.2. Weather data and uncertainty consideration

Weather data are critical when performing BES, as thermal loads are influenced not only by yearly weather variability [8,9], but also by long-term climatic trends [20]. In this study, the TMY dataset inputted in the EnergyPlus program are the CWEC file for Quebec City's airport, located in eastern Canada. To measure the impact of uncertainty on weather data, four meteorological variables available in the CWEC file are treated as uncertain variables rather than known (deterministic) variables: (1) dry bulb temperature, (2) atmospheric pressure, (3) wind speed, and (4) global horizontal radiation (GHR). These four variables were selected based on their known impact on sensible load calculation in BES [21–23]. Figure 1 shows how the parameters vary. It illustrates both the hourly profiles from the CWEC dataset, and the 20-year variability derived from the CWEEDs.

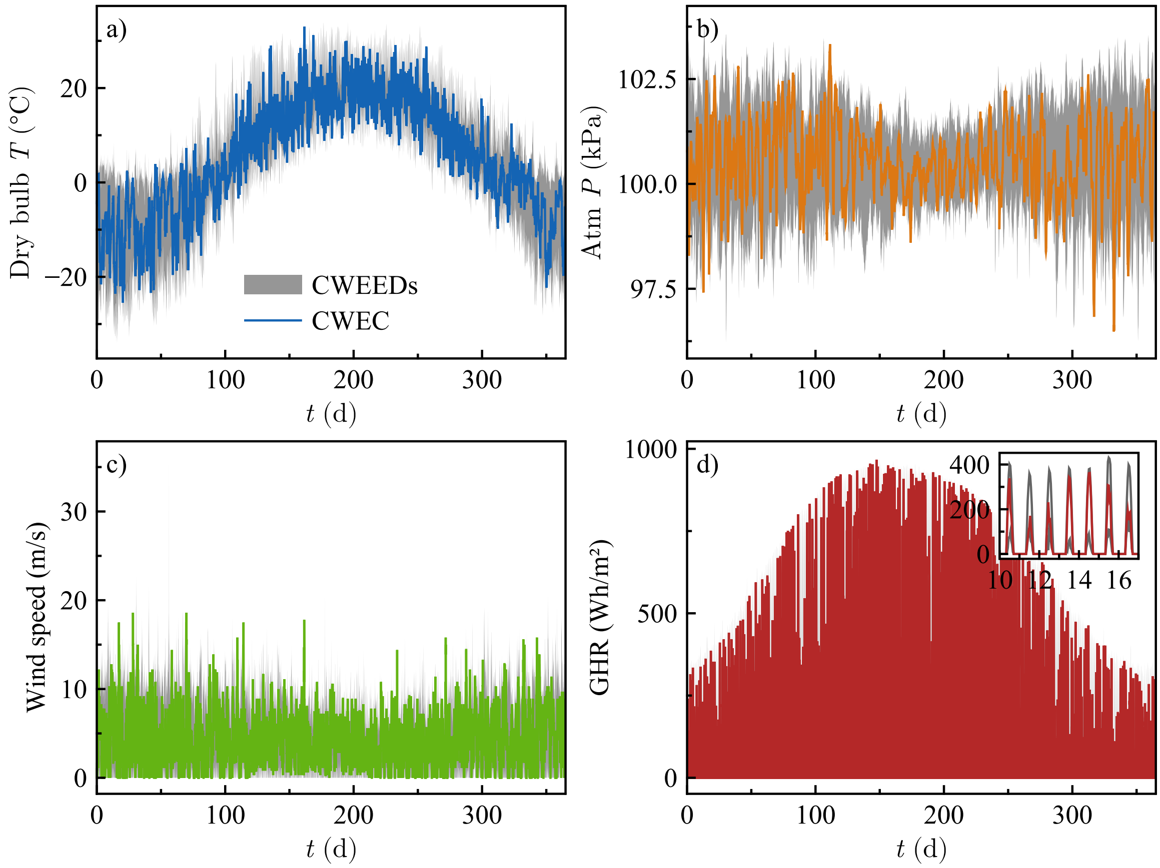

Figure 1. Typical meteorological year (TMY) data from CWEC (colored lines), as well as their 20-year variability range from the CWEED dataset (minimum to maximum, in grey bands) for Quebec City's airport, in eastern Canada. The figure shows a) the dry bulb temperature, b) the atmospheric pressure, c) the wind speed, and d) the global horizontal radiation (GHR).

Instead of adopting a deterministic approach, where parameters are determined from a single dataset which typically results in an overly smooth representation, a stochastic framework is adopted by leveraging a geostatistical framework. Geostatistical simulations are used to generate multiple, statistically plausible yet randomly different realizations of temporal variables [24]. In other words, the simulations can reproduce the statistics of the observed time series and also generate alternative datasets that exhibit the same temporal behavior. This approach enables uncertainties in temporal data to be quantified by illustrating the range of possible outcomes rather than relying on a single smoothed estimate or a simplistic deterministic model.

Uncertainty in dry bulb temperature, atmospheric pressure, and wind speed is addressed using multivariate, non-conditional geostatistical simulations applied to each hourly value over a 20-year period [25]. Prior to simulating the time series, each variable is preprocessed to remove non-stationary patterns. First, a moving average with a wide window of 1000 samples is subtracted from the original data to eliminate long-term trends. Second, the detrended signal is standardized by dividing it by a moving standard deviation with a window of 500 samples, thereby reducing non-stationary variance. Third, the resulting series is normalized to a standard Gaussian distribution to prepare the data for geostatistical simulation. Following the simulations, the data are transformed back into their original units by inverting the preprocessing steps.

Uncertainty in GHR is treated differently using multiple point geostatistics [26], which is well suited to capture complex patterns such as diurnal cycles. This approach is particularly appropriate for GHR, since it has values of zero during nighttime and strictly positive values during daytime. In addition, GHR calculated in EnergyPlus by the combination of direct normal radiation (DNR) and diffuse horizontal radiation (DHR) according to the following relationship [27] :

$$GHR = DNR \cdot cos(\theta_z) + DHR \tag{1}$$

where θ_z is the solar zenith angle. Hence, the multiple point geostatistics method employed is applied to these two variables.

Simpler or more direct geostatistical algorithms often fail to reproduce non-Gaussian and time-dependent behaviors such as the diurnal and seasonal variability of GHR (also seen in DNR and DHR). To overcome this limitation, the direct sampling method of Oriani et al. [28] was used here. This approach introduces latent variables that explicitly consider cyclical patterns, thereby conditioning the simulations to reflect both daily and seasonal dynamics. In this study, two latent variables are defined: (1) a cosine function representing the seasonal trend, with maximum amplitude at the summer solstice and minimum at the winter solstice, and (2) a categorical variable distinguishing between nighttime (0) and daytime (1). By using these latent variables, the geostatistical simulations are guided to reproduce the expected diurnal and seasonal structures. This strategy follows the framework of Oriani et al. [28], who successfully applied a similar approach to rainfall time series. The reader is referred to their work for further methodological details.

2.3. Ground heat exchanger modeling

To size a GHE, the building's thermal loads must first be converted into ground thermal loads, as expressed by:

$$Q_g = Q_b\left(1 \pm \frac{1}{COP(T_{out})}\right) \tag{2}$$

where Q_g and Q_b are the ground and building thermal loads, respectively, and $COP(T_{out})$ represents the coefficient of performance (COP) of the heat pump, which depends on the entering fluid temperature (i.e., the GHE outlet fluid temperature). Once the ground loads are determined, GHE sizing is carried out by matching the mean borehole fluid temperature, T_f, to the operating temperature limits of the system [13]. The general formulation for T_f is as follows:

$$T_f - T_0 = \frac{Q_g(t)}{L}R_b^* + \frac{\sum_{i=1}^{n}\left(Q_g(t_i) - Q_g(t_{i-1})\right)}{L} \cdot g(t - t_{i-1}) \tag{3}$$

where T_0 is the undisturbed ground temperature, R_b^* the effective borehole thermal resistance, L the total borefield length, k_s the ground thermal conductivity, and g the g-function of the GHE. Here, the g-function represents the ground's thermal response to a unit heat pulse of 1 W/m at the borehole wall (BC-II boundary condition as defined by Cimmino and Bernier [29]) and is calculated using the FLS model of Claesson and Javed [15]. A more concise and computationally efficient representation of Eq. 3 can be obtained using convolution such as:

$$T_f - T_0 = \frac{Q_g(t)}{L}R_b^* + \frac{1}{L}(f * g)(t) \tag{4}$$

where $f = Q_g(t_i) - Q_g(t_{i-1})$. This formulation enables the convolution to be solved in the frequency domain as a simple multiplication using the Fourier transform (and its inverse), which significantly accelerates computation and allows efficient evaluation even for hourly simulations. GHE sizing is then the process of determining the total borehole length (L) that ensures that T_f remains within the operating fluid temperature limits (i.e., 0 °C for heating and 30 °C for cooling), denoted as T_{lim} . By rearranging Eq. 4 to isolate the borehole length, the sizing expression becomes [17] :

$$L = \frac{(f*g)(t) - Q_g(t)R_b^*}{T_{lim} - T_0} \tag{5}$$

which must be solved for the lower and higher operating temperature limit of T_f. The retained length is then the maximum of the two.

Stochastic approaches such as Monte Carlo simulations or Bayesian inference can be applied to GHE modeling to quantify the influence of parameter variability and uncertainty on predicted fluid temperatures. In this study, the work of Pasquier and Marcotte [30] is used as a reference to provide a realistic characterization of uncertainty in key GHE parameters. In their study, a thermal response test was analyzed within a Bayesian framework to derive probability distributions considering autocorrelation in the temperature signal measured in the test at a site near Québec City, Canada [30]. It is worth noting that the inferred distributions allow reproducing the measured temperature with an accuracy close to the temperature sensor accuracy. In the present work, the distributions inferred by Pasquier and Marcotte [30] for the ground thermal conductivity

(k_s), ground volumetric heat capacity (C_s), grout thermal conductivity (k_g), and shank spacing (s) (i.e., the distance between the two legs of the U-loop) are used in our stochastic framework. The distributions are shown below in Figure 2.

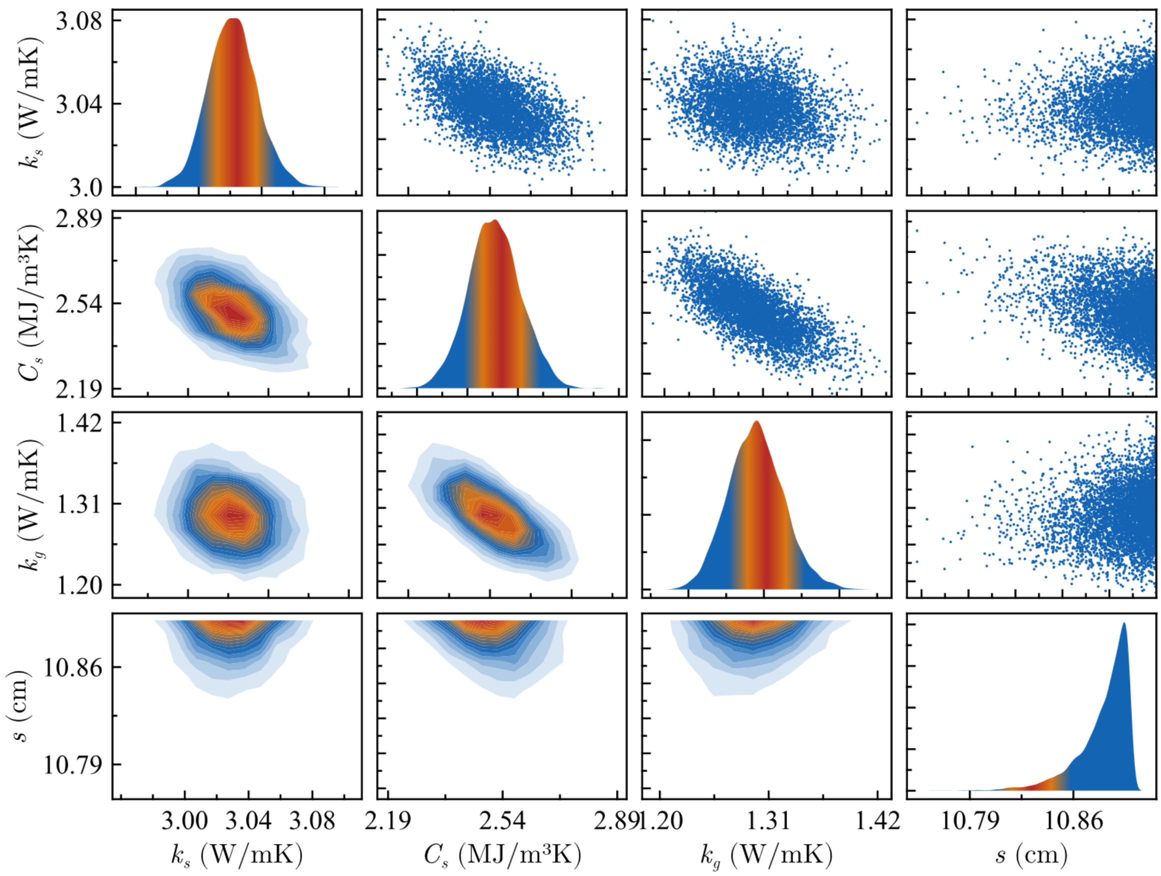

Figure 2. Distributions of ground and borehole parameters retrieved from Pasquier and Marcotte [30]. The main diagonal shows parameter distributions. The lower triangle panels (below the main diagonal) show zones of joint distributions, and the upper triangle panels (above the main diagonal) show scatter plots of the 5000 samples.

2.4. Stochastic combined BES and GHE sizing

For this part of the study, we provide insights into GHE sizing by considering realistic uncertainties in both weather variables and ground and borehole properties. To achieve this estimation of the sizing, the BES are first carried out, using the chosen building model together with the geostatistical simulation of the weather data described above. Next, GHE sizing is performed with the probability distributions reported by Pasquier and Marcotte [30] considering the ground and borehole properties. The procedure for performing the BES entails retrieving the building thermal loads, converting them to ground load, and finally performing GHE sizing. The process is repeated 5000 times to follow the length of the Markov-Chain vector available from the reference paper [30]. For each of the 5000 runs, the total borehole length (L) required to satisfy the ground thermal loads is recorded and subsequently used in the convergence analysis.

3. Stochastic sizing of GHE

Eleven scenarios are defined to evaluate the combined and individual impacts of the eight parameters for which uncertainty is considered. The first three scenarios are designed to assess the overall impact of multiple uncertainties on GHE sizing, while scenarios 4 to 11 are undertaken to support a sensitivity analysis of each individual parameter. Scenario 1 considers that all eight parameters vary simultaneously. For scenarios 2 and 3, two groups of variables are isolated. In Scenario 2, only the four weather variables are varied while the GHE parameters are fixed at their mean values from the 5000 samples shown in Figure 2. In Scenario 3, only the four parameters associated with the GHE are varied while the weather variables are fixed to the CWEC dataset.

In scenarios 4 to 7, the effect of varying each weather variable individually is studied, with all other variables held constant, whereas scenarios 8 to 11 follow the same approach for each GHE parameter. Table 1 provides a summary of the 11 scenarios, as well as sizing results defined by fitting a normal distribution over the sizing lengths of each scenario.

Table 1. Normal distribution parameters fitted on the sizing length distributions for each scenario.

Scenario	1	2	3	4	5	6	7	8	9	10	11
	Full	**Weather**	**GHE**	**Dry bulb T**	**Atm. P**	**Wind speed**	**GHR**	k_s	C_s	k_g	s
μ	165.5	165.4	165.9	165	167.6	169.5	170.3	165.9	165.9	165.9	165.9
σ	11.4	11.2	1.9	11.1	1.8	2.7	2.3	0.1	0	1.9	0.3
x_5	146.7	146.9	162.8	146.8	164.6	165	166.5	165.6	165.8	162.8	165.4
x_{95}	184.2	183.9	169	183.3	170.6	174	174	166.1	165.9	169	166.3

For the sizing process, fixed COPs are used in the conversion from building to ground thermal loads using Eq. 2. COP values of 3.5 and 4.5 are applied for the heating and cooling modes, respectively. The GHE is sized to cover 80% of the peak ground thermal loads. Figure 3 illustrates an example of the ground loads simulated, along with the 80% cutoff at the peak loads. Using 80% of the peak loads reduces the required heat pump size, leading to a reduction in construction costs, while still providing 99.7% of the building's total energy demand. The remaining energy demand is typically met by an auxiliary system added to the GSHP system, which is not studied here.

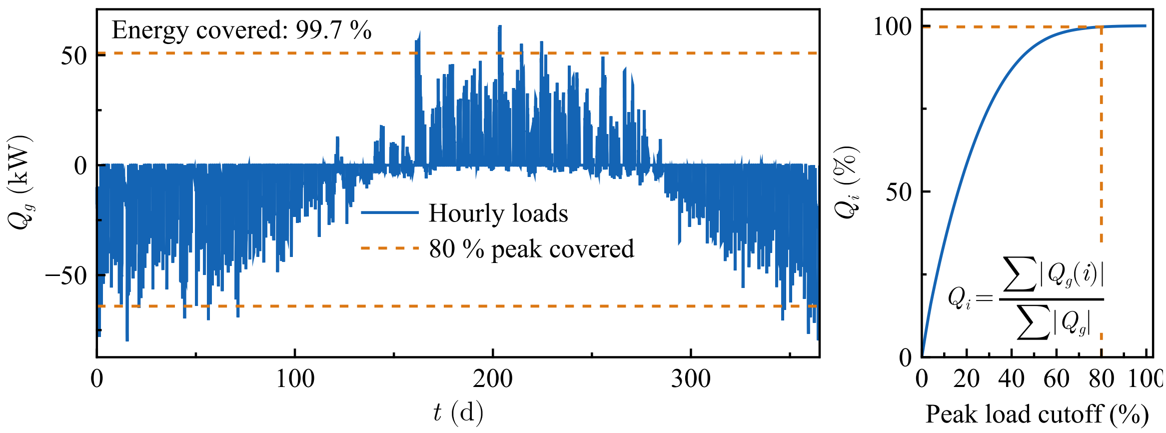

Figure 3. Thermal loads obtained from the BES using the building model and one of the simulations for weather data. (Left) Ground thermal loads (converted with Eq. 2). (Right) cumulative fraction of annual energy demand as a function of the cutoff applied to peak thermal loads. Dashed lines indicate the 80% cutoff of the peak load.

The GHE configuration in this study consists of three boreholes arranged in a line and spaced 8 m apart. The sizing procedure is applied 5000 times for each of the 11 scenarios, yielding distributions of borehole lengths. Figure 4 presents the distributions for scenarios 1 to 3, where either all variables, only the weather variables, or only the parameters of the GHE are varied. A normal distribution is fitted to each scenario, and the corresponding statistical properties (mean, standard deviation, and 5th and 95th percentiles) are summarized in Table 1.

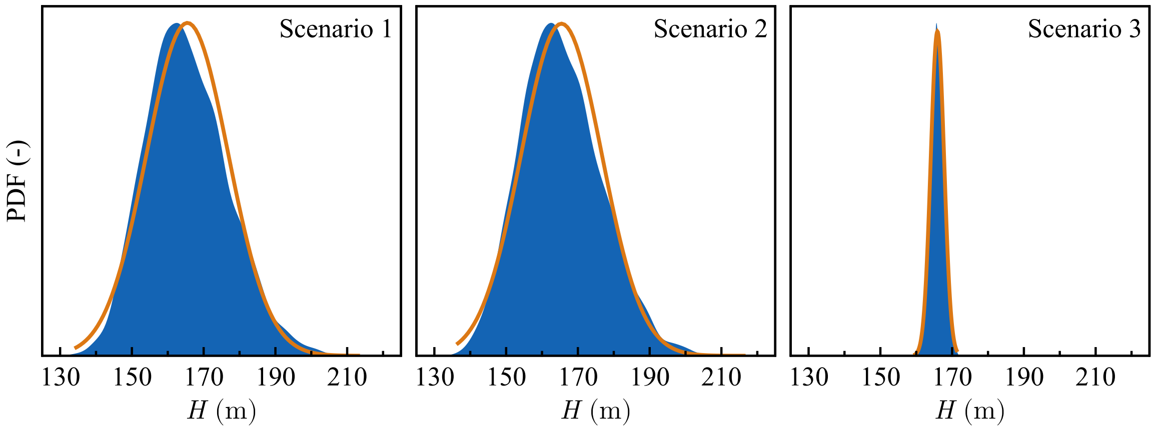

Figure 4. Distributions of borehole lengths (blue) with fitted normal distributions (orange) for the first three scenarios: (left) variation of weather and ground and borehole parameters, (middle) variation of weather variables only, and (right) variation of ground and borehole parameters only.

Across all first three scenarios, the mean borehole lengths (μ) is consistently close to 165 m. However, the distributions differ significantly in their spread. Scenarios 1 and 2 exhibit standard deviations (σ) and percentile ranges (x_5, x_{95}) that are similar to each other but substantially wider than Scenario 3. This indicates that uncertainty in weather variables has a much stronger influence on borehole length than uncertainty in GHE parameters. The difference reflects the relatively narrow variability of ground properties obtained by Bayesian inference compared to the broader fluctuations in weather data observed over two decades included in the CWEED dataset. As a result, weather-related uncertainty leads to variations of about 40 m per borehole (120 m for the bore-field), whereas uncertainty due to GHE parameters leads to an uncertainty of roughly 6 m per borehole (18 m for the bore-field). It is worth noting that the ground and borehole parameters inferred through a Bayesian framework yielded low variation for the thermal conductivity, which may not be representative of all geological sites.

To assess the influence of individual parameters on the sizing process, borehole length distributions were also calculated for scenarios 4 through 11, which are for individual parameters. The results are shown in Figure 5 using violin plots, where the first three scenarios provide an alternative visualization of the distributions shown in Figure 4. The remaining scenarios are grouped by weather variables and ground and borehole parameters. Among the weather variables, the dry bulb temperature appears to be the dominant variable, with a standard deviation (σ) of 11.1 m; a value close to the 11.4 m obtained when all eight parameters are varied simultaneously in Scenario 1. In contrast, the other three weather variables have comparatively narrow distributions, with normal fit characteristics close to one another. For the parameters of the GHE, grout thermal conductivity (k_g) shows the strongest influence, accounting for nearly all the variability observed. This is evidenced by the nearly identical standard deviations ($\sigma = 1.9$ m) between Scenario 3 (all parameters of the GHE varied) and Scenario 10 (only k_g varied). Overall, these findings emphasize that while certain properties of the GHE exert a localized effect on uncertainty, weather variability, such as the dry bulb temperature, remains the primary factor of uncertainty in GHE sizing. Neglecting this aspect by relying on a single deterministic weather dataset, such as the CWEC, could therefore lead to overly optimistic and less robust GHE designs.

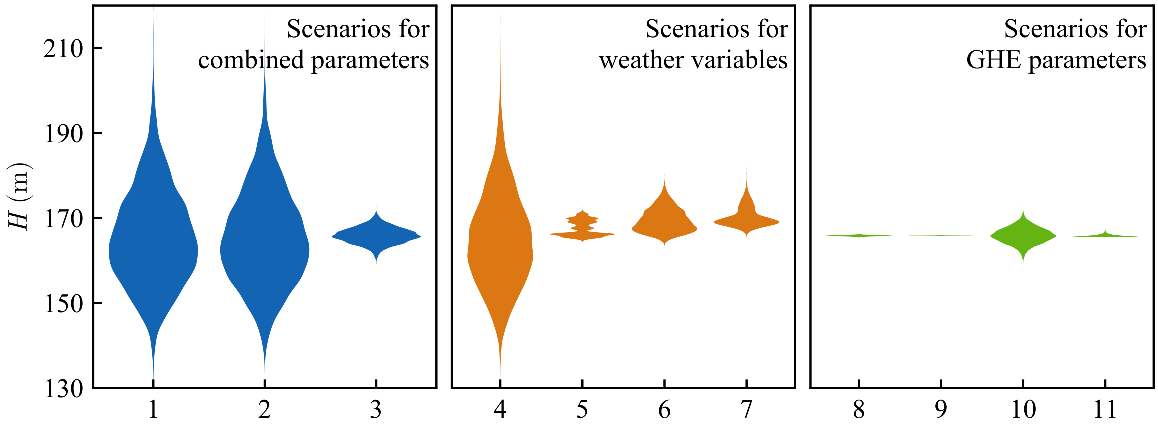

Figure 5. Violin distributions for the 11 scenarios that are grouped by scope: (left) combined parameters, (middle) weather variables, and (right) parameters of the GHE.

4. Discussion

In stochastic approaches, one can assess whether a sufficient number of simulations has been generated by examining the convergence (or stabilization) of the estimated variable as the number of iterations increases. This is achieved by calculating the cumulative average of the estimated borehole length as the number of simulations increases:

$$\widetilde{H}(j) = \frac{1}{j}\sum_{i=1}^{j} H(i);\ \forall j \in \{1, n\} \tag{6}$$

where $\widetilde{H}(j)$ denotes the cumulative average borehole length after j realizations, $H(i)$ is the borehole length estimated from the i-th simulation, and $n = 5000$ is the total number of realizations. Equation 6 was applied to all 11 scenarios, with the results shown in Figure 6. The figure indicates that most scenarios reach convergence relatively quickly. However, scenarios associated with the largest standard deviations (σ in Table 1), namely scenarios 1, 2, and 4 that include the dry bulb temperature, exhibit slower convergence. Although their cumulative averages eventually reach constant values, the slope remains slightly nonzero, even after 5000 stochastic simulations. Figure 6 also shows that most GHE parameters have negligible influence on convergence, as the lines for scenarios 8, 9, and 11 (k_s, C_s, and s) nearly overlap. Furthermore, the distributions for Scenario 3 (GHE parameters) and Scenario 10 (k_g) coincide, confirming that grout thermal conductivity is the only parameter with a discernible effect on convergence behavior.

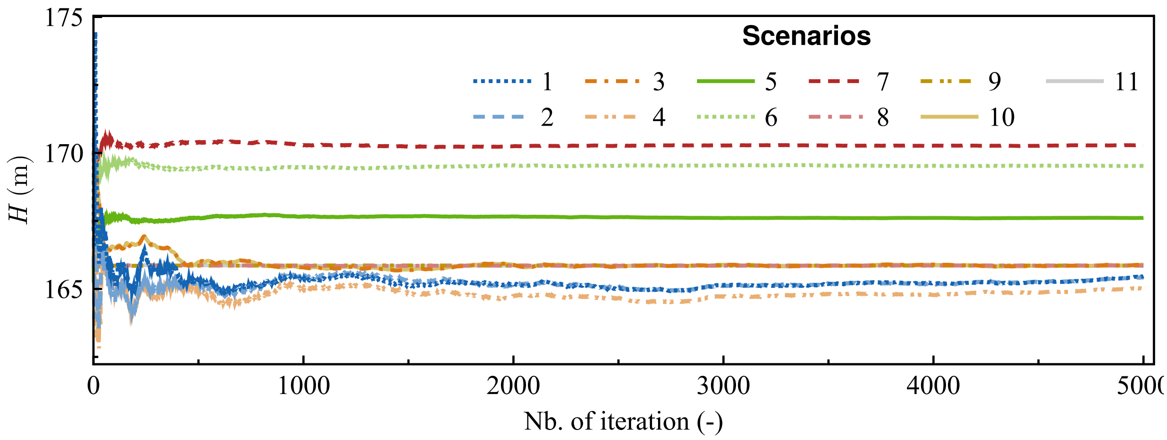

Figure 6. Average cumulative sum of the estimated borehole length calculated using Eq. 6 as the simulations progress to assess convergence across the 11 studied scenarios.

Figure 6 and Table 1 show that the average borehole length (μ) is between 165 m and 170 m across the scenarios. The largest variation in average length values is seen when sizing is based on individual weather parameters. This can be attributed to the fact that the resulting distributions deviate more significantly from normality compared to other scenarios. For instance, Figure 5 shows a hatched distribution for atmospheric pressure (Scenario 5) and off-centered distributions for wind speed and GHR (scenarios 6 and 7). Such deviations from a normal distribution may originate in the limited number of simulations, which in this study is constrained by the 5000-length Markov chains inferred in Pasquier and Marcotte [30].

5. Conclusion

This study introduces a stochastic framework for hourly ground heat exchanger (GHE) sizing that explicitly accounts for uncertainties in both weather data during building energy simulations (BES), as well as ground and borehole parameters used during the GHE simulations. The goal of this study is to quantify how grouped and individual sources of uncertainty influence borehole length distributions derived from an hourly sizing equation.

Uncertainty in four weather variables is modeled using geostatistical techniques to generate consistent time series across 5000 stochastic simulations, while variability in four parameters associated with the GHE is introduced through the stochastic analysis of a thermal response test in a Bayesian framework, ensuring physically realistic distributions.

A total of eleven scenarios are generated, and results show that borehole length distributions generally follow normal distributions across all scenarios, with weather uncertainty dominating the variability. Specifically, weather parameters produce a standard deviation of 11.2 m, nearly matching the 11.4 m when all parameters vary together. Among these, dry bulb temperature is the most influential (11.1 m), whereas for ground and borehole parameters, grout thermal conductivity contributes the most, but the combined GHE uncertainty remains relatively modest (1.9 m). Overall, weather uncertainty introduces deviations of up to 40 m around the mean borehole length of 165 m, while GHE uncertainty is limited to about 6 m. It is worth mentioning that the ground parameter uncertainties were not large for the studied site, which could lead to different results in other geological contexts.

Convergence analysis revealed that scenarios involving weather variability converge more slowly after 5000 stochastic simulations. This indicates that additional simulations may be necessary for full convergence. Ultimately, these findings highlight the critical role of weather variability in GHE sizing and emphasize the importance of incorporating stochastic approaches to improve the robustness and reliability of ground source heat pump design.

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