A Net Present Value-at-Risk Objective Function for Uncertainty Mitigation in the Design of Hybrid Ground-Coupled Heat Pump Systems

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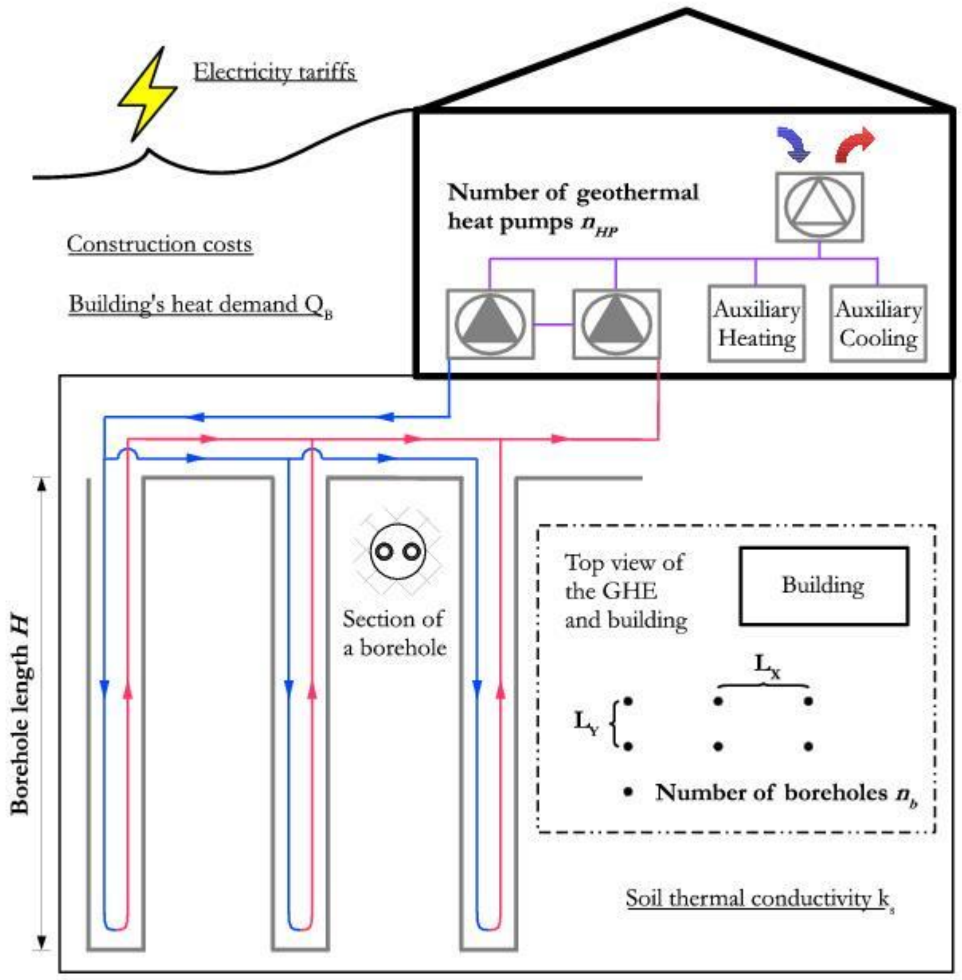
INTRODUCTION

Ground-coupled heat pump systems are on of the most efficient heating and cooling means for buildings (Omer, 2008). To reduce their high construction costs, it is quite common to coupled auxiliary systems with them. The design through optimization of the resulting **hybrid ground-coupled heat pump** (Hy-GCHP) systems is complicated because it involves multiple parameters, some of which can only be guessed or estimated.

Therefore, professionals face the very real prospect of **under or oversizing the Geothermal Heat Exchanger** (GHE) part of the Hy-GCHP system as a result of these uncertain parameters. This likely leads to (Nguyen et al., 2014):

- Higher upfront costs
- Higher operating costs
- Less energy savings

Traditionally, **sensitivity analyses** (Pianosi et al., 2016) are used by designers as a way to evaluate the impacts of uncertainties on their designs and prepare them against unforeseeable circumstances. This operation of course can only be done once the sizing is completed. This way of operating however **cannot lead to changes in design** to take uncertainties into account once the sizing is done.



Schematic representation of a hybrid ground-coupled heat pump system where the design variables considered in this work (H, n_b, n_{HP}, L_X, L_Y) are in bold and where the uncertain parameters are underlined.

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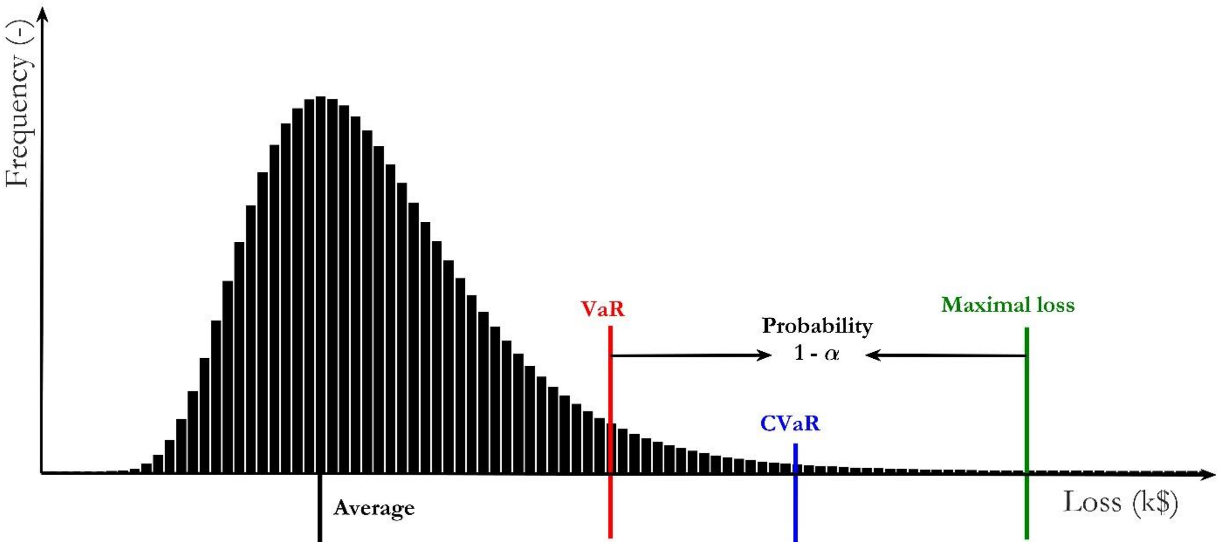
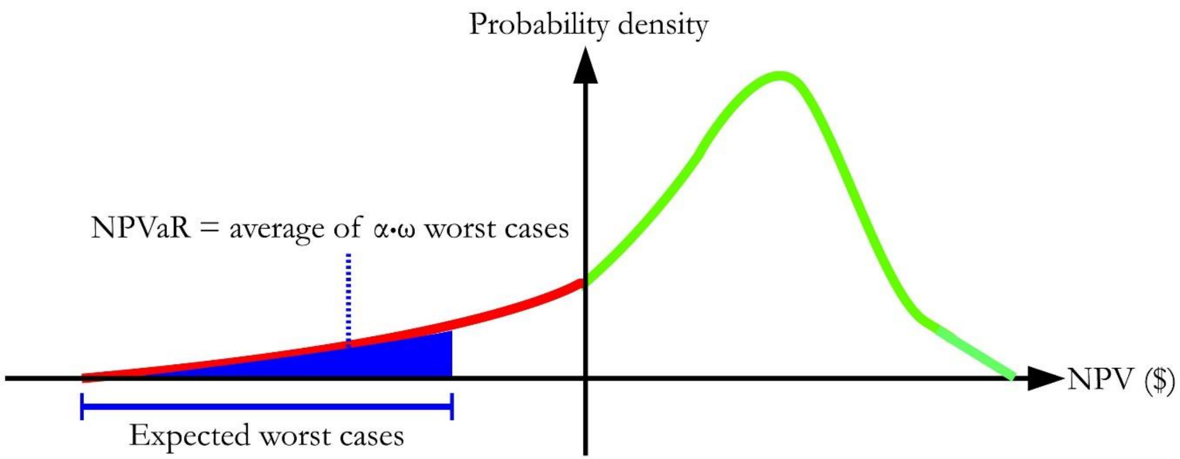
INTRODUCTION

Traditional stochastic methods, like Markov chain Monte Carlo, can handle uncertainties during the sizing, but come at a **high computational cost** paid for in millions of simulations.

Alternative stochastic design methodologies are exploited in other fields with great success that do not require nearly as many simulations. This is the case for the **conditional-value-at-risk** (CVaR, left) in the financial sector (Rockafellar and Uryasev, 1999),



Relation between the Value-at-risk (VaR) and the CVaR. The CVaR constitutes the average of the worst cases that occurred between the VaR and the worst possible outcome.



The NPVaR is assembled using the average of the worst fraction (α) of a NPV distribution composed of a population of ω samples.

and for the **net present value-at-risk** (NPVaR, right) in civil engineering (Ye and Tiong, 2000). Both involve **distributions of uncertain parameters** but only focus on the tail of distributions. This results in quicker optimizations than considering all possible outcomes but also leads to more conservative designs. This way, the proposed designs remain profitable even when faced with extremely unfavorable conditions.

INTRODUCTION

Problematic:
As of today, not muck work is published regarding the design by optimization of GCHP systems under uncertainty. Therefore, a methodology is required to weave directly uncertainties throughout the design phase instead of simply assessing their impacts on the optimum afterward.

Goal of this research:
In that regard, this work proposes the use of the NPVaR, a stochastic financial indicator that focuses on the minimization of loses, by adapting it for the design by optimization of hybrid GCHP systems. The goal is to put forward a methodology and to showcase how it can lead to the sizing of systems that are more economically robust when they are under uncertainty.

Outline of presentation:

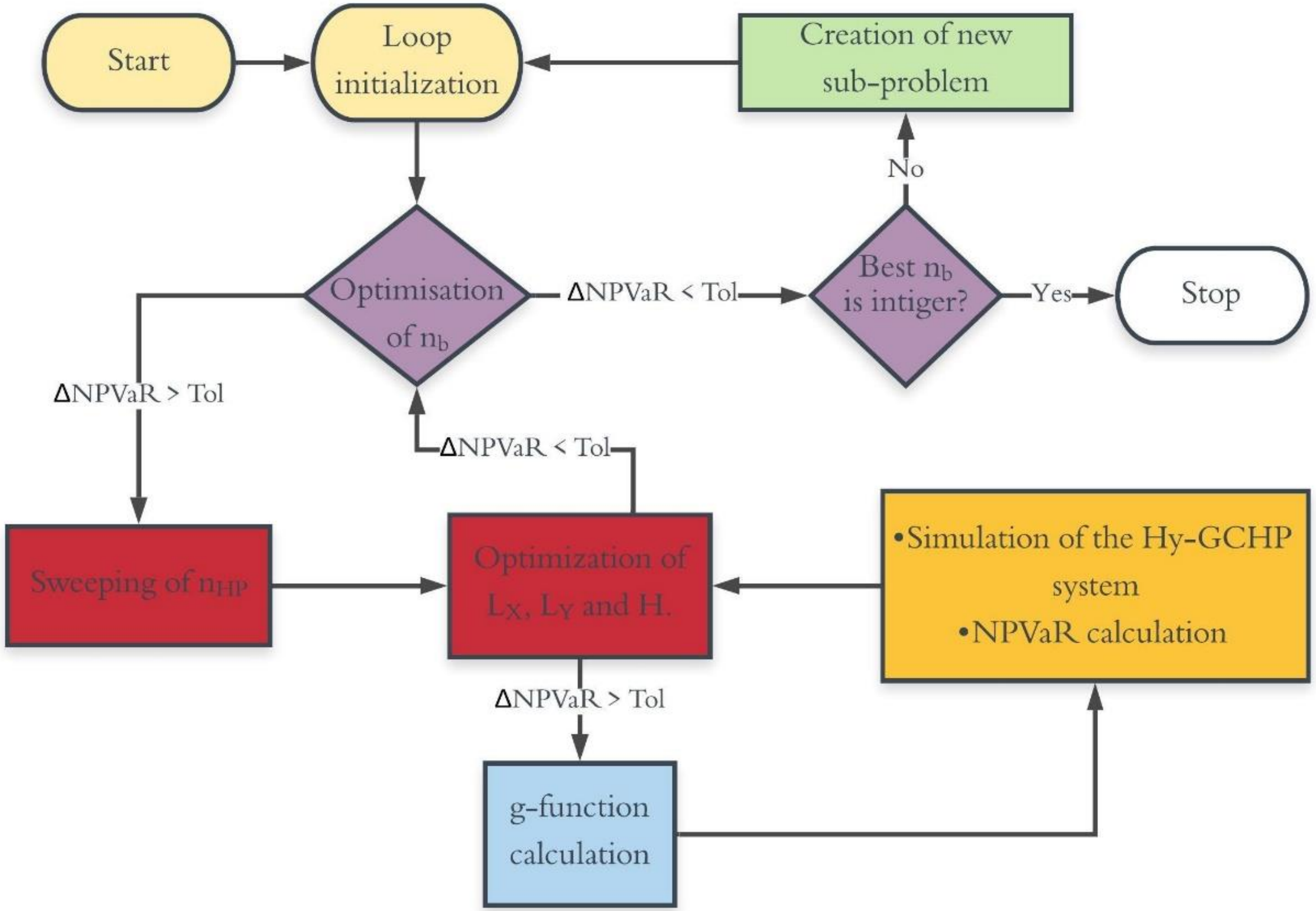
- First, this presentation goes over the optimization and simulation strategies that are used to model a CGHP system's operation. It also presents the elements that are considered by the model during the calculation of the NPVaR.
- Second, all the parameters, values and constants that are needed in the case study are presented.
- Third, the case study's results are presented. A brief discussion of the results follows.
- Finally, presentation concludes with a summary and outlines the main contributions of this research.

ALGORITHM DEVELOPED

The developed algorithm uses the **NPVaR** of the Hybrid GCHP system as **objective function** and a tolerance (*Tol*) on its variation through iterations as a stopping criteria in order to size the system.

In **PURPLE**, a first optimization of the number of borehole n_b is performed. Although n_b is an integer variable, this **optimization is relaxed** into a continuous one and relies on a **constrained nonlinear optimization algorithm**.

In **GREEN**, if the outcome of the optimization on n_b is fractional, a **branch-and-bound** (Lawler and Wood, 1966) scheme is utilized in order to constraint future sub-problems of the original one to converge towards integer solutions.



Simplified flow-chart of the algorithm used to optimize the NPVaR with a breakdown by color of its different parts.

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ALGORITHM DEVELOPED

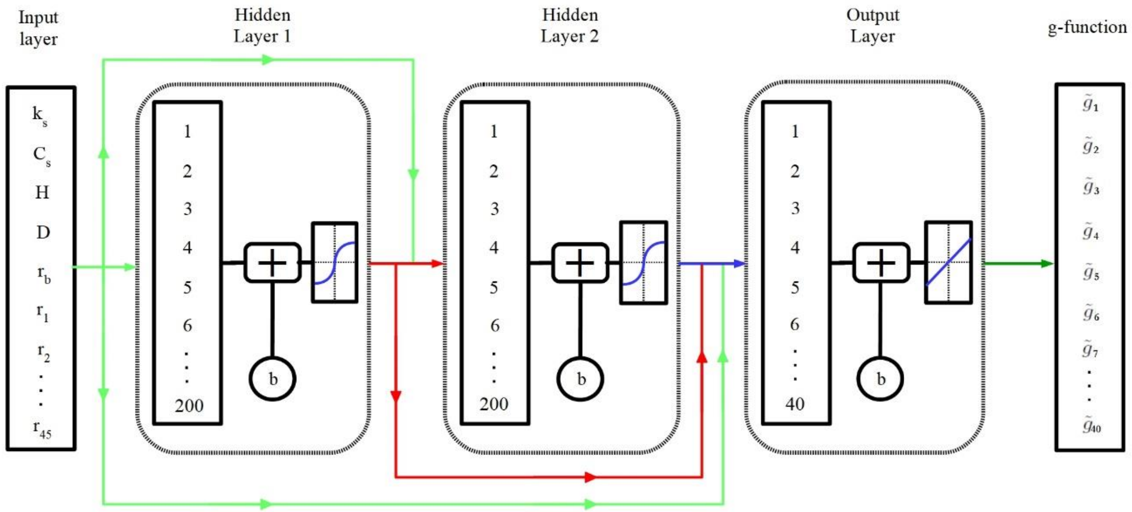
In **BLUE**, the g-function of the boreholes field tried out by the two optimization loops are calculated using :

1. an **Artificial Neural Network** (Dusseault and Pasquier, 2019; left), if $n_b \leq 10$, or

2. a **Block Matrix Formulation** (Dusseault et al., 2018; right) otherwise.

$$\begin{bmatrix} \hat{\mathbf{G}} & \hat{\mathbf{I}} \\ \hat{\mathbf{I}}' & \mathbf{0} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{f}} \\ -(\mathbf{T_b} - T_g) \end{bmatrix} = \begin{bmatrix} \hat{\mathbf{0}} \\ \mathbf{\Lambda} \end{bmatrix} \quad \text{Eq. 1}$$

$$g = 2\pi k_s n_b (\mathbf{T_b} - T_g)/\tilde{q} \quad \text{Eq. 2}$$



Artificial neural network used for the approximation of long term g-functions (source: Dusseault and Pasquier, 2019). It contains two fully connected hidden layers with 200 neurons each.

In **RED**, the other four design variables are optimized. All possible numbers of heat pump n_{HP}, which is also an integer variable, are tried out using a **sweeping scheme based on the current value of** $\boldsymbol{n_b}$. This proved to be quicker that using branch-and-bound on both integer variables.

The other three variables, H, L_x and L_y, are subjected to a second continuous optimization loop that uses the same **constrained nonlinear optimization** algorithm.

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ALGORITHM DEVELOPED

Finally in **ORANGE**, the objective function of both optimization loops, the NPVaR, is calculated using the following equations and related costs (in Table 1). *CF(k=0)* are the **construction costs**, *CF(k>0)* are **the revenues generated** by operating the hybrid system instead of an all-electrical reference system. Operating costs are calculated using **local electricity tariffs**.

Eq. 3 $$NPVaR = \frac{1}{\lceil \alpha \cdot \omega \rceil} \sum_{j=1}^{\lceil \alpha \cdot \omega \rceil} < NPV >_j$$

Eq. 4 $$NPV = \sum_{k=0}^{n} \frac{CF(k)}{(1+i)^k}$$

Eq. 5 $$CF(0) = -CF_{GHE} - CF_{Mec} + CF_{Ref}$$

Eq. 6 $$CF_{GHE} = n_b \left[H(c_1 + 1.816 c_4) + (c_2 + c_3 + c_7 + L_Y\, c_5\, c_6)\right] + L_X\, c_5\, c_6 \lceil n_b/5 \rceil + c_8$$

Eq. 7 $$CF_{Mec} = (c_9 + c_{10})\, max(|Q_G|) + c_{11}\, max(Q_{Aux}) + |c_{12}\, min(Q_{Aux})|$$

Eq. 8 $$CF_{Ref} = c_{11} \cdot max(|Q_B|) + |c_{12} \cdot min(|Q_B|)|$$

Item	Variables	Values
Borehole drilling ($/m)	c_1	50
Geothermal vault ($/borehole)	c_2	1666
Borehole commissioning ($/borehole)	c_3	200
Heat-carrying fluid ($/L)	c_4	1.75
Trench, volume ($/m3)	c_5	60
Trench, width ($/m)	c_6	2
GHE commissioning ($/borehole)	c_7	400
Thermal response test ($)	c_8	10000
Geothermal heat pump ($/kW)	c_9	733
Additional costs ($/kW)	c_{10}	366
Electric heating ($/kW)	c_{11}	50
Electric cooling ($/kW)	c_{12}	586

Table 1 - All costs (in Canadian currency) that are considered in this work regarding the construction of an hybrid GCHP system (Hénault et al., 2016).

Where Q_G (kW) is the total ground thermal load, Q_{Mec} (kW) is the power consumption of the auxiliary systems and mechanical equipment and Q_B (kW) is the heat demand of the building.

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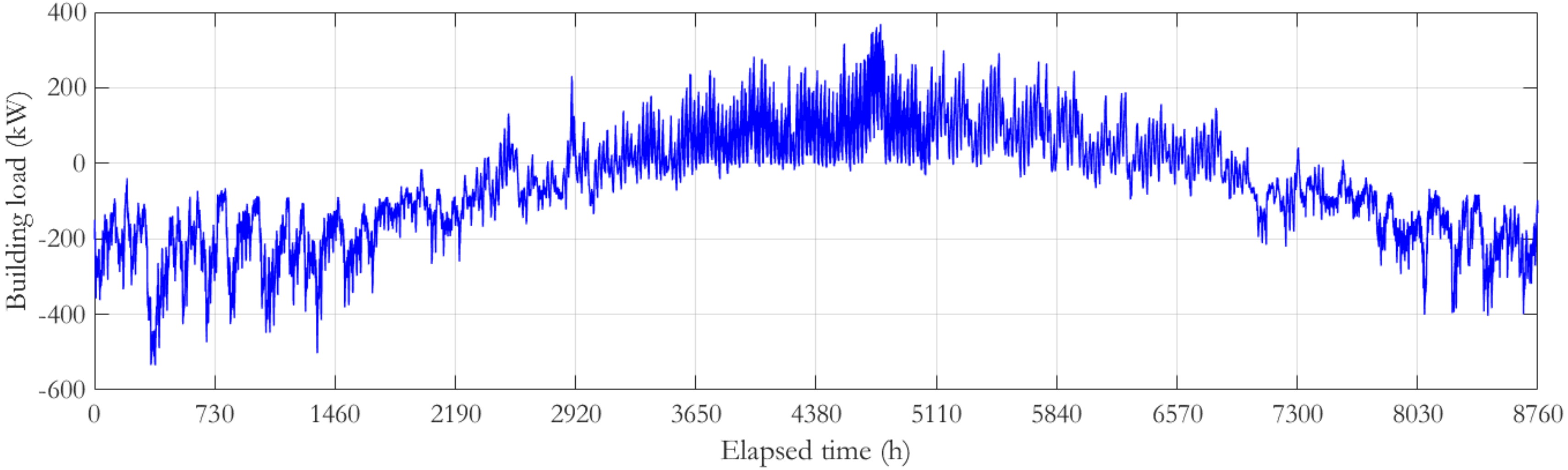
CASE STUDY

The algorithm that was just presented will now be used to design through optimization **two hybrid GCHP systems**: one with the **NPV as objective function**, and the other using the **NPVaR**. The goal of this case study is to compare the two resulting designs during a 10 years operation in 1000 random scenarios in term of return on investment. Each scenario corresponds to a different batch of the four uncertain parameters (heat loads, construction and electricity costs and soil thermal conductivity).

The building's heat demand is represented by the synthetic load showed below which corresponds to a **five-storey long-term care center** (each storey of 2322 m^2) . This building was modelled in the *Simeb* (Millette et al., 2011) software under typical climate and construction conditions for the city of **Montreal, Canada**.

- Peak loads of 534.6 kW in heating and 368.8 kW in cooling.
- 7.826 GWh of energy in heating and 2.996 GWh of energy in cooling annually.
- Sharp peak loads, both in heating and cooling.



The modelled building's hourly heat demands for a typical year of operation that begins January 1^{st}. Negative values are for heating and positive ones are for cooling.

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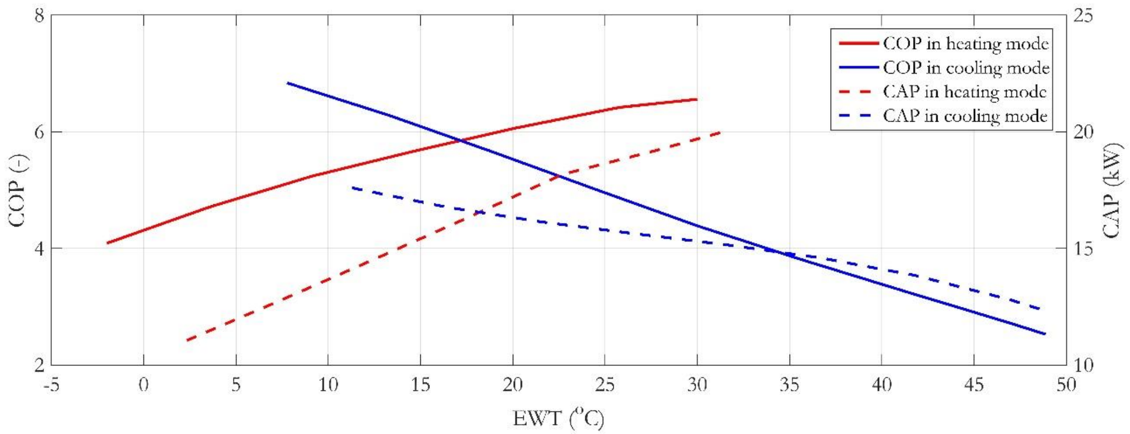
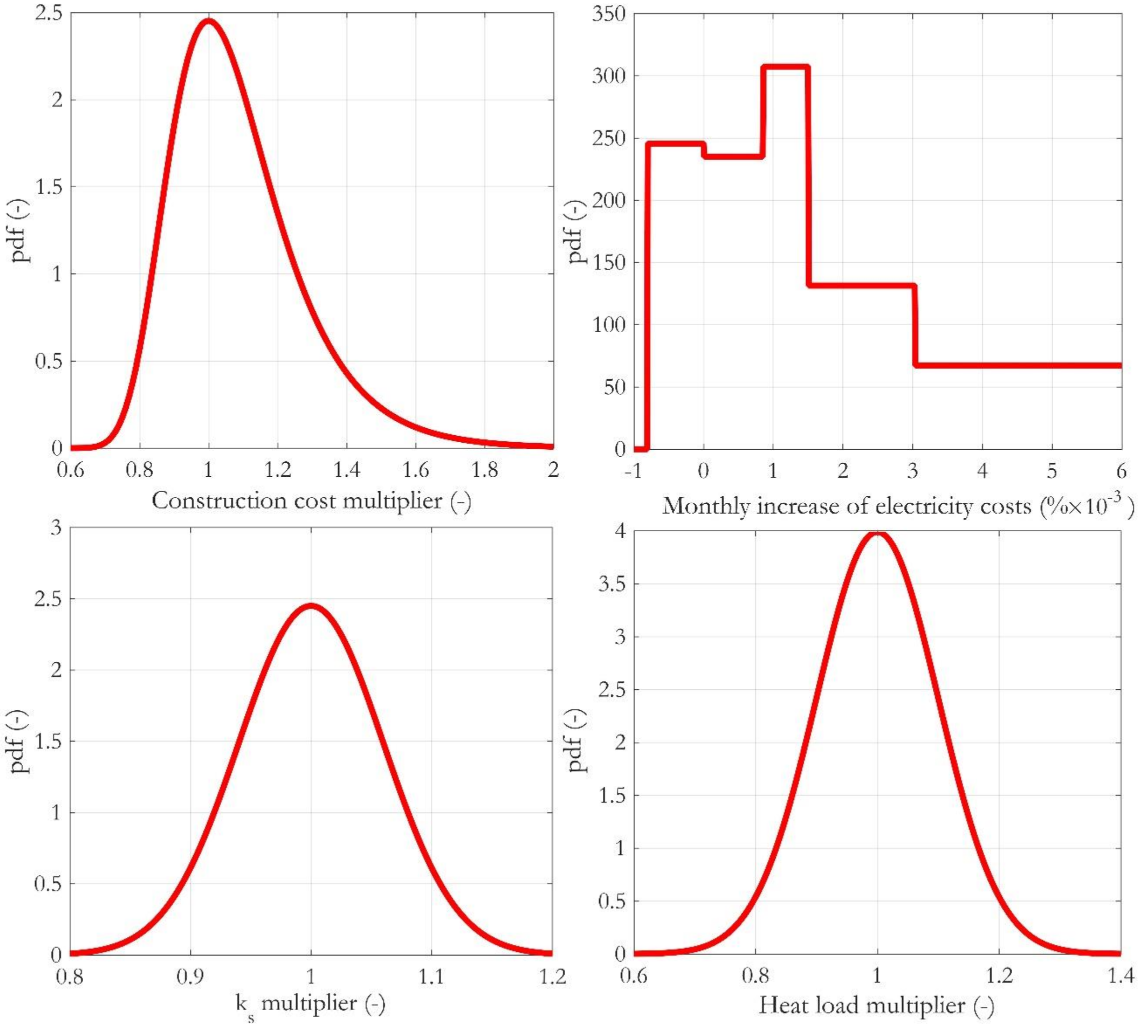
The **heat-pumps** behave according to the following graphic (left) in terms of **coefficient of performance** (COP) and **capacity** (CAP) with regard to their entering water temperature (EWT).



Coefficients of performance (COP) and capacities (CAP) of individual GCHP used in all simulations.

The **four uncertain parameters** (construction costs, increases of electricity costs, soil thermal conductivity and heat demand) have the following **probability density functions** (right).



Probability density functions of the four uncertain parameters. The PDFs express, apart from the monthly electricity cost, the probability that the corresponding base case scenario values are multiplied by a random constant.

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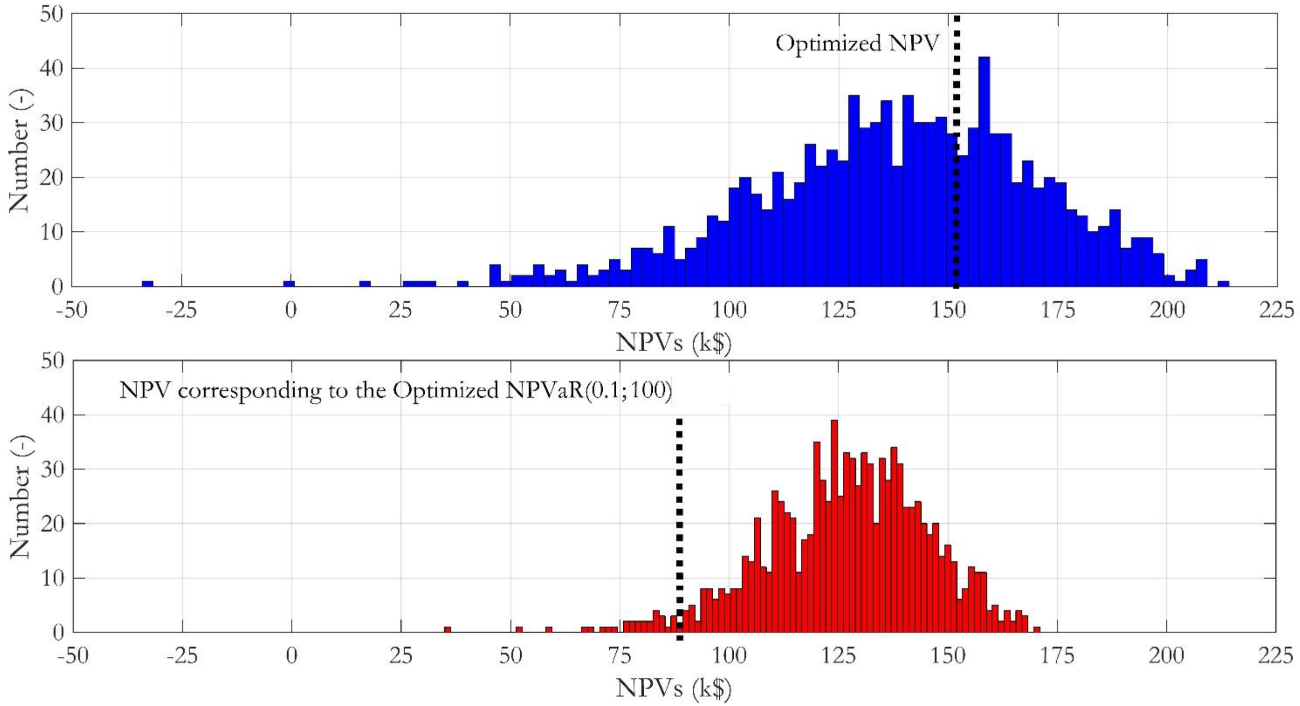
RESULTS

Here is a side by side comparison of the **1000 operation scenarios of both systems in post-design**, field conditions. All the returns on investment that are shown, the differential NPVs, are presented with respect to a reference solution that uses all-electrical heating and cooling systems.

	Sized using NPV	Sized using NPVaR
Optimized NPV (k$)	150.8	89.3
n_b (-)	16	9
n_{HP} (-)	10	6
H (m)	150	150
L_X (m)	8.83	7.28
L_Y (m)	5.27	4.73
Optimization time (hours)	3.8	48.2

Table 2 - Proposed designs and computational times for the optimizations that used the NPV and NPVaR as objective function.



These histograms were assembled using 1000 NPVs each that correspond to 10 years of operating each Hybrid GCHP systems. They were calculated using the NPV based design (blue), and the NPVaR based design (red) using α = 0.1 and ω = 100.

- The **blue histogram is much wider**. It is also **centered left** with regard to the return on investment that was forecasted during the design phase (the dashed vertical black line).
- The **blue histogram's tail of distributions**, that contains the worst returns, **is also longer**, stretching all the way into financial losses territory.

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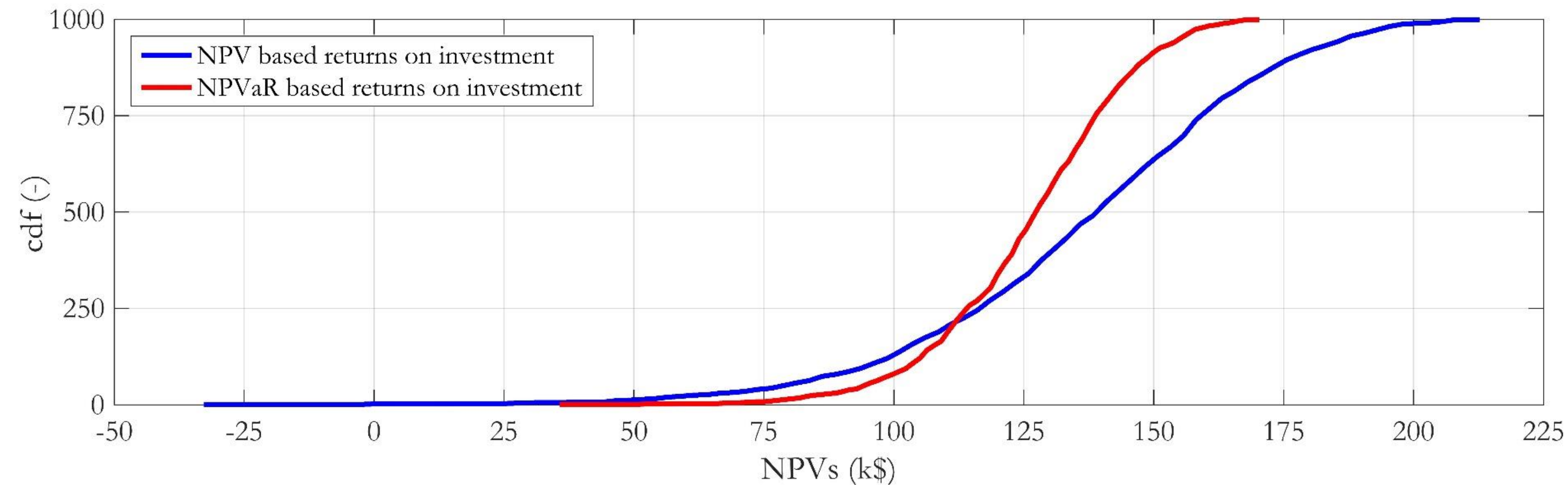
RESULTS

- In **the upper quartile**, the **NPV** based design is worth **25 k$ more on average** than the NPVaR based design. This amounts to 15.72 % superior gains.
- This difference drops to **11.03 % in the second quartile** and even further **in the third quartile** to **5.53 %**.
- The profitability of both systems finally inverts **in the bottom quartile in favor of the NPVaR** to **9.22 %**. Therefore, the differences in net present values across the 1000 scenarios show that the NPVaR outperforms the NPV under the most unfavorable circumstances.



This figures shows the cumulative distribution functions of net present values of both systems across the 1000 random scenarios. It was constructed using both histograms introduced earlier.

- The average **NPVaR system's worth** is **two and a half times that of the NPV** when looking at the **bottom 10 cases**.
- Considering only the worst case, the NPVaR transforms major losses into similar gains. This results in the sizing by **NPVaR never losing money** even in the harshest of circumstances.

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CONCLUSION

1. We demonstrated how a stochastic financial indicator called the **net present value-at-risk** (NPVaR), when used as an objective function, can help **offset the consequences of uncertainties** associated with the design of hybrid GCHP systems. This is better than traditional methods which only aim to quantify the impacts of uncertainties using sensitivity analyses after the sizing is completed.

2. This methodology is implemented **in design phase** as part of the optimization process. The benefits of this methodology are brought to light in a **case study that compares two designs** : one proposed using the NPVaR and the other sized with the more traditional net present value (NPV).

3. In this case study, **four parameters and factors** are represented as **statistical distributions** instead of fixed values: the construction costs, the building's heat loads, the electricity costs and the soil thermal conductivity.

4. Our results indicate that the **NPVaR yields better returns on investments** when considering **conditions less beneficial to geothermal energies**. Moreover, it **greatly shields against unpredictable financial losses** when looking at the worst possible construction and operational conditions.

5. This methodology for design is **radically different than existing methods** who rely on non stochastic algorithms and then rely on **sensitivity analysis in hindsight** to assess the robustness of their sizing.

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[1] Omer AM. Ground-source heat pumps systems and applications. Renewable and Sustainable Energy Reviews 2008; 12 (2): 344 - 371. https://doi.org/10.1016/j.rser.2006.10.003.

[2] Nguyen HV, Law YLE, Alavy M, Walsh PR, Leong WH, Dworkin SB. An analysis of the factors affecting hybrid ground-source heat pump installation potential in North America. Applied Energy 2014; 125: 28 - 38. https://doi.org/10.1016/j.apenergy.2014.03.044

[3] Pianosi F, Beven K, Freer J, Hall JW, Rougier J, Stephenson DB, Wagener T. Sensitivity analysis of environmental models: A systematic review with practical work flow. Environmental Modelling & Software 2016; 79: 214 - 232. https://doi.org/10.1016/j.envsoft.2016.02.008.

[4] Rockafellar RT, Uryasev S. Optimization of conditional value-at-risk. Journal of Risk 1999; 2: 21 - 41.

[5] Ye S, Tiong RLK. NPV-at-Risk Method in Infrastructure Project Investment Evaluation. Journal of Construction Engineering and Management 2000; 126 (3). https://doi.org/10.1061/(ASCE)0733-9364(2000)126:3(227).

[6] Lawler EL, Wood DE. Branch-and-Bound Methods: A Survey. Operations Research 1966; 14 (4): 699 - 719. https://www.jstor.org/stable/168733.

[7] Dusseault B, Pasquier P. Efficient g-function approximation with artificial neural networks for a varying number of boreholes on a regular or irregular layout. Science and Technology for the Built Environment Published online: 08 Aug 2019. https://doi.org/10.1080/23744731.2019.1634932.

[8] Dusseault B, Pasquier P, Marcotte D. A block matrix formulation for efficient g-function construction. Renewable Energy 2018; 121: 249 - 260. https://doi.org/10.1016/j.renene.2017.12.092.

[9] Claesson J, Javed S. An Analytical Method to Calculate Borehole Fluid Temperatures for Time-scales from Minutes to Decades. ASHRAE Transactions 2011; 117 (2): 279 - 288.

[10] Hénault B, Pasquier P, Kummert M. Financial optimization and design of hybrid ground-coupled heat pump systems. Applied Thermal Engineering 2016; 93: 72 - 82. https://doi.org/10.1016/j.applthermaleng.2015.09.088.

[11] Millette J, Sansregret S, Daoud A. Simeb: Simplfied interface to DOE2 and EnergyPLus - A User's perspective - Case study of an existing building. Proceedings of Building Simulation: 12th Conference of International Building Performance Simulation Association, Sydney 2011.