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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Ground-coupled heat pump systems are one 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.
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), 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.
Problematic:
As of today, not much 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 losses, 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.
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.
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.

\[
\begin{bmatrix}
\hat{G} \\
\hat{I}
\end{bmatrix}
\begin{bmatrix}
\hat{f} \\
\hat{I} - (T_b - T_g)
\end{bmatrix}
= \begin{bmatrix}
0 \\
A
\end{bmatrix}
\]  
Eq. 1

\[
g = 2\pi k_b n_b (T_b - T_g)/\bar{q}
\]  
Eq. 2

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 \( n_b \)**. This proved to be quicker than 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.
Finally in \textbf{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 \textbf{construction costs}, $CF(k>0)$ are the \textbf{revenues generated} by operating the hybrid system instead of an all-electrical reference system. Operating costs are calculated using \textbf{local electricity tariffs}.

\begin{align}
\text{Eq. 3} & \quad NPVaR = \frac{1}{[\alpha \cdot \omega]} \sum_{j=1}^{[\alpha \cdot \omega]} < NPV >_j \\
\text{Eq. 4} & \quad NPV = \sum_{k=0}^{n} CF(k) (1+i)^k \\
\text{Eq. 5} & \quad CF(0) = -CF_{GHE} - CF_{Mec} + CF_{Ref} \\
\text{Eq. 6} & \quad CF_{GHE} = n_b [H(c_1 + 1.816c_4) + (c_2 + c_3 + c_7 + L_Y c_5 c_6)] + L_X c_5 c_6 [n_b/3] + c_8 \\
\text{Eq. 7} & \quad CF_{Mec} = (c_9 + c_{10}) \max(|Q_G|) + c_{11} \max(Q_{Aux}) + |c_{12} \min(Q_{Aux})| \\
\text{Eq. 8} & \quad CF_{Ref} = c_{11} \cdot \max(|Q_B|) + |c_{12} \cdot \min(|Q_B|)|
\end{align}

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).

<table>
<thead>
<tr>
<th>Item</th>
<th>Variables</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Borehole drilling ($/m$)</td>
<td>$c_1$</td>
<td>50</td>
</tr>
<tr>
<td>Geothermal vault ($/borehole$)</td>
<td>$c_2$</td>
<td>1666</td>
</tr>
<tr>
<td>Borehole commissioning ($/borehole$)</td>
<td>$c_3$</td>
<td>200</td>
</tr>
<tr>
<td>Heat-carrying fluid ($/L$)</td>
<td>$c_4$</td>
<td>1.75</td>
</tr>
<tr>
<td>Trench, volume ($/m^3$)</td>
<td>$c_5$</td>
<td>60</td>
</tr>
<tr>
<td>Trench, width ($/m$)</td>
<td>$c_6$</td>
<td>2</td>
</tr>
<tr>
<td>GHE commissioning ($/borehole$)</td>
<td>$c_7$</td>
<td>400</td>
</tr>
<tr>
<td>Thermal response test ($)</td>
<td>$c_8$</td>
<td>10000</td>
</tr>
<tr>
<td>Geothermal heat pump ($$/kW$$)</td>
<td>$c_9$</td>
<td>733</td>
</tr>
<tr>
<td>Additional costs ($$/kW$$)</td>
<td>$c_{10}$</td>
<td>366</td>
</tr>
<tr>
<td>Electric heating ($$/kW$$)</td>
<td>$c_{11}$</td>
<td>50</td>
</tr>
<tr>
<td>Electric cooling ($$/kW$$)</td>
<td>$c_{12}$</td>
<td>586</td>
</tr>
</tbody>
</table>

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.
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 m²). 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 1st. Negative values are for heating and positive ones are for cooling.
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).

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

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

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.
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.

<table>
<thead>
<tr>
<th></th>
<th>Sized using NPV</th>
<th>Sized using NPVaR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimized NPV (k$)</td>
<td>150.8</td>
<td>89.3</td>
</tr>
<tr>
<td>$n_b$ (-)</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>$n_{hp}$ (-)</td>
<td>10</td>
<td>6</td>
</tr>
<tr>
<td>$H$ (m)</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>$L_x$ (m)</td>
<td>8.83</td>
<td>7.28</td>
</tr>
<tr>
<td>$L_y$ (m)</td>
<td>5.27</td>
<td>4.73</td>
</tr>
<tr>
<td>Optimization time (hours)</td>
<td>3.8</td>
<td>48.2</td>
</tr>
</tbody>
</table>

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

- 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.
• 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.

![Cumulative distribution functions of net present values](image)

*This figure 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.
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.
CONCLUSION - REFERENCES


