Assessing the sustainable application of Aquifer Thermal Energy Storage

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ABSTRACT

Aquifer Thermal Energy Storage (ATES) can yield significant reductions in the energy use and greenhouse gas (GHG) emissions of larger buildings, and the use of these systems has been rapidly growing in Europe – especially in the Netherlands, where over 3000 systems are currently active in urban areas. However, the successful management of this technology poses a range of policy challenges, due to its reliance on subsurface resources and to the possibility of thermal interactions across adjacent systems. In particular, recent research suggests that ATES planning policies should acknowledge a potential trade-off between the total energy or GHG savings which can be obtained by ATES systems within a given area, and the economic returns realized by individual system operators. To better understand this compromise, this paper follows a simplified version of the multi-objective robust decision making framework (Kasprzyk et al., 2013), using an idealized agent-based model of ATES adoption and operation coupled with a geohydrological subsurface model. This simulation approach was used to investigate suitable options for the spatial planning of ATES systems, by exploring the behaviour of the coupled system under a set of socio-technical and geohydrological uncertainties. A multi-objective evolutionary optimization algorithm was then applied to search for ATES well layout parameters which perform well in relation to the assessment criteria. The optimization identified a set of planning parameters which describe a Pareto-efficient trade-off between the individual and collective performance of ATES systems under uncertainty.

1. INTRODUCTION

Aquifer Thermal Energy Storage (ATES) is an increasingly popular type of shallow geothermal energy, which relies on aquifers to seasonally store thermal energy for the heating and cooling of buildings. The Netherlands are currently a world leader for ATES technology, due to a combination of easily accessible aquifer resources, dense urban development, and increasingly stringent building energy standards. The use of ATES in the country has thus rapidly grown over the last decade; as defined by total pumped volume, ATES systems could in fact become the largest user of groundwater in the Netherlands by 2020 (Bonte, 2013). This rapid adoption should be carefully monitored, given the complex interactions of the technology with aquifer resources: for instance, although ATES systems do not cause a net extraction or injection of groundwater, they create local thermal disturbances which should be managed appropriately.

Public authorities will therefore need to find a compromise between favouring the adoption of ATES technology to contribute towards goals for GHG reductions, and managing the potential impacts of large-scale thermal storage in the subsurface – particularly given the broader international potential of ATES (Bloemendal et al., 2015). The rapid development of ATES has underlined some areas of concern: for instance, current approaches for the operation and planning of ATES systems (and shallow geothermal energy in general) lack the flexibility to manage the uncertainties which are inherent to ATES adoption and use. As a reaction to these uncertainties, design guidelines are typically highly conservative, for example to avoid thermal interactions between neighbouring systems. Consequently, in the Netherlands, ATES adoption may become limited by the availability of subsurface space in urban areas (Bloemendal et al., 2014).

In order to better understand these challenges, this work focuses on the implications of ATES spatial planning parameters for the individual and collective performance of the technology. The following section summarizes ATES technology; Section 3 then structures the problem through a XLRM approach (Lempert et al., 2003) to describe relevant models and relationships, performance measures, uncertainties, and policy levers. In Section 4, this framework is combined with a coupled simulation environment to explore idealized dynamics of ATES operation under uncertainty, with a simplified application of multi-objective robust decision making (Kasprzyk et al., 2013). This approach is used to identify an efficient trade-off between individual economic returns and collective energy-saving performance. Finally, Section 5 discusses these results in the broader context of future challenges for the planning of ATES technology.

2. PROBLEM BACKGROUND

ATES systems are used to seasonally store thermal energy in aquifers, which – in combination with a heat pump – can significantly reduce the energy demand of buildings for heating and cooling in temperate climates. These systems usually use a pair (or more) of coupled wells to inject and extract groundwater at different locations or depths of the aquifer; in winter conditions, relatively warmer water is thus extracted from one well and passed through a heat exchanger for heating, then re-injected into a "cold" well at a lower temperature (typically 5-10°C). Conversely, in summer conditions, the flow across the wells is reversed so that the cooler water injected in winter is used for cooling, then reinjected into the "warm" well at a temperature of 15-25°C. This process is illustrated in Figure 1 a). This eventually creates thermal zones around each well, which can have a radius of a few dozen meters (Figure 1 b).

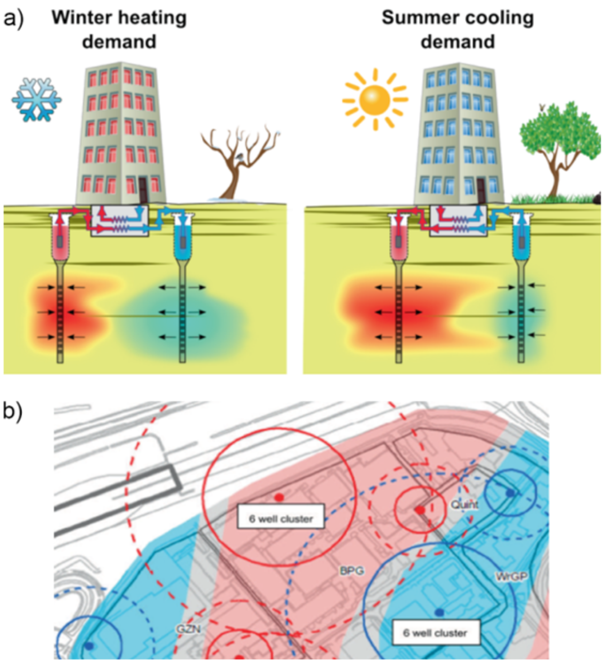


Figure 1: a) Basic functioning of Aquifer Thermal Energy Storage (Bonte, 2013); b) Plan view of ATES thermal zones in a urban layout

The characteristics of these thermal zones are crucial for the performance and management of ATES systems. They are affected by local geohydrological conditions, such as the porosity of the aquifer or the presence of a regional groundwater flow; in addition, thermal interferences between neighbouring systems can reduce thermal recovery if "cold" and "warm" wells are located too closely, while wells of similar temperatures can have beneficial interactions (Bakr et al., 2013). These geohydrological and operational factors cause significant uncertainties regarding subsurface conditions and the resulting performance of ATES systems. Furthermore, at the building level, the demand for heating or cooling is difficult to forecast due to variations in building occupancy and weather conditions. The actual use of ATES systems can therefore differ significantly from the expected pumping rates which are used for permitting and design; although the "cold" and "warm" wells would ideally be used symmetrically over the seasons for cooling and heating, ATES systems used in the Netherlands often have a significant level of thermal imbalance in practice (Willemsen, 2016).

Given that local temperature disturbances can persist in the subsurface over a period of decades, this can cause unforeseen long-term changes in aquifer temperature distributions – which, in turn, can affect the performance of ATES systems, and eventually their continued adoption by building owners. Thermal imbalances and interactions are therefore a particularly sensitive aspect of ATES development. The risk of negative thermal interferences between neighbouring wells especially introduces additional constraints on the planning of ATES systems in dense urban areas, which need to accommodate various existing subsurface functions such as groundwater extraction.

3. PROBLEM FORMULATION

The problem described above can be defined as a complex adaptive system, which is driven by the interactions between environmental conditions in the subsurface and the use of ATES systems. The performance of ATES systems is thus affected by aquifer temperature distributions, which are themselves influenced by the operation of existing systems and by the construction of new wells by building owners. These dynamics are mediated by the spatial layout of ATES systems, and further affected by geohydrological and socio-technical uncertainties (for instance, aquifer heterogeneity, building energy demand, or the energy prices which influence the investment behaviour of potential ATES users). Following the definition of Lempert et al. (2003), some of these uncertainties can be qualified as *deep* -- in the sense that it would be impossible to precisely define the causal relationships and probability distributions associated with some of these parameters, such as future energy prices. To better understand plausible scenarios for the development of ATES as well as performance trade-offs, a modelling framework which acknowledges the complexity and the uncertainty of the underlying systems is therefore required.

The many-objective robust decision making (MORDM) framework described by Kasprzyk et al. (2013) offers a suitable starting point. Rather than attempting to optimize the performance of a complex environmental system by aggregating multiple measures into a single metric (e.g. through cost-benefit analysis), this framework uses a multi-objective problem formulation to investigate key trade-offs across performance indicators. Quantitative methods like multi-objective evolutionary optimization can be used within this framework to identify solutions (for instance, ATES layout parameters) which perform efficiently for these trade-offs across a broad range of uncertainties, e.g. which are *robust*. Techniques for scenario discovery can support the analysis by identifying the ranges and combinations of uncertain parameters which are most relevant in regards to the model outcomes. Figure 2 summarizes the MORDM approach.

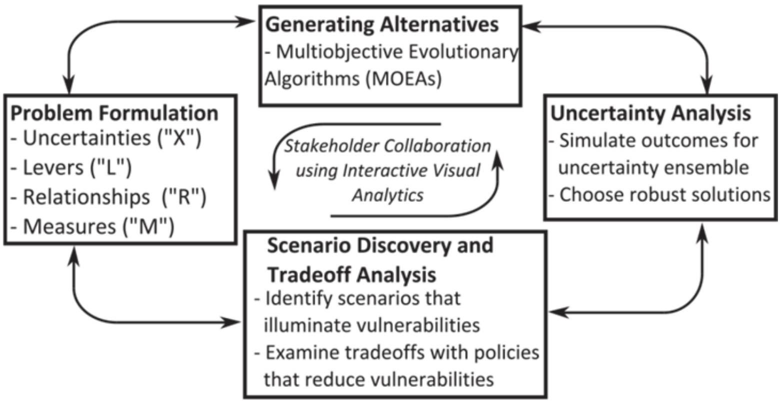


Figure 2: Many-objective robust decision making framework (Kasprzyk et al., 2013)

Table 1: XLRM problem formulation

Models and relationships	Measures
Agent-based model of ATES adoption • Adoption dynamics based on empirical data for acceptable ROI on general energy-efficiency investments Geohydrological model (SEAWAT) • 1000m x 1000m aquifer model; monthly time resolution Control model (Matlab) • ATES well flows computed based on climate data and building energy demand	Main performance indicators: • Average system ROI (payback period) • Cumulative GHG and energy savings Secondary indicators: • Average ATES thermal efficiency • Number of active ATES systems • Fraction of subsurface volume used for storage

Uncertainties	Policy levers
Socio-technical • Electricity price • Gas price • Discount rate used by investors Geohydrological: • Aquifer properties (conductivities, porosity)	Distance between ATES wells of opposite type Distance between ATES wells of same type

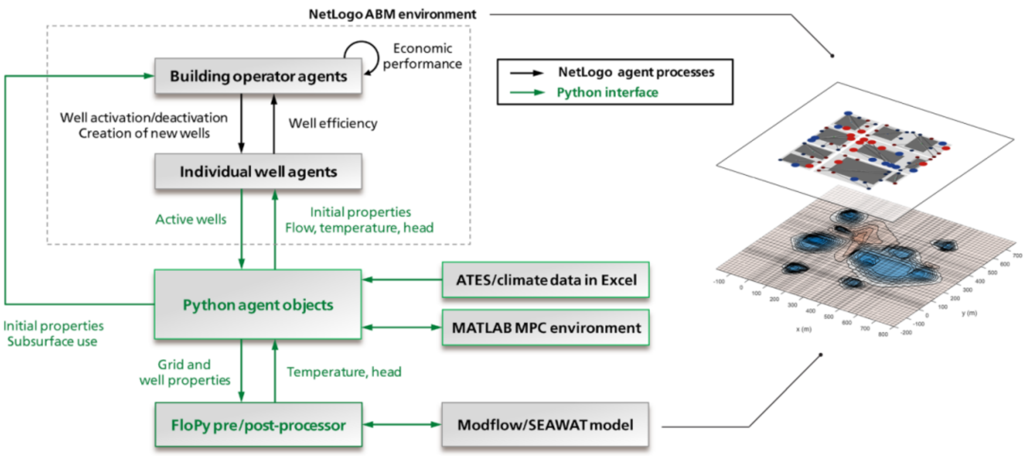


Figure 3: Coupled simulation architecture

As a first step, Table 1 summarizes the definition of the problem using the XLRM framework (Lempert et al., 2003). The subsections below detail the models and relationships (R) used to represent the problem, the measures (M) which track the performance of different ATES layout policies, the uncertainties (X) which affect the outcomes, and the layout parameters which can be used as policy levers (L).

3.1 Models and relationships

This analysis relies on idealized simulation models for ATES adoption and operation (described in more detail in Jaxa-Rozen et al., 2015), which represent 10 simulated ATES systems interacting with a 1000m x 1000m x 20m confined aquifer over a time frame of 240 months. The geohydrological dynamics are modelled using the MODFLOW / SEAWAT codes, while an agent-based model for ATES adoption and operation is implemented using NetLogo. These model components are linked through an object-oriented architecture using the Python language, in which Python objects are used as a common interface between the model layers. Figure 3 illustrates the basic architecture and data exchanges. The coupled models are executed using the EMA Workbench package for exploratory modelling (Kwakkel, 2015).

The simulated ATES operators are modelled from representative data for ATES systems in the Netherlands; at the initialization of the simulation, two of the operators are assumed to be actively operating ATES wells, and the other systems can activate or build wells (within imposed spatial constraints) based on expected economic performance. This behaviour is modelled by assigning a randomly distributed adoption threshold to each agent, which is defined as the expected payback period which the simulated operators consider to be acceptable for ATES technology relative to a conventional energy system; the expected economic returns are derived from the realized performance of the active simulated ATES systems. The distribution of adoption thresholds is based on empirical data for firm-level investments in energy efficiency in the Netherlands (Blok et al., 2004).

3.2 Measures

A particular challenge for ATES planning in the Netherlands is the lack of a consistent framework which could be used to assess the performance and sustainable use of urban ATES systems, and therefore to define metrics and objectives for the analysis. Several methods have been applied to assess the thermal and economic performance of single ATES systems (Rosen, 1999; Rosen and Dincer, 2003; Sommer et al., 2015). However, an integrated approach to assess the long-term efficiency and sustainable use of an aquifer with ATES systems has not yet been implemented in practice. This is becoming an increasingly important issue for the public actors involved in ATES management (typically municipalities, as well as provincial authorities in the case of large-scale ATES projects which may impact groundwater extraction activities); these actors have a twofold interest in maximizing the energy-saving potential of ATES technology, while preserving the long-term integrity of aquifer resources. As a starting point, this analysis considers two main performance objectives, based on the dynamics outlined previously:

• The average economic performance of ATES systems at the end of the simulation, which should minimize the payback period relative to a conventional energy system;

• The contribution of ATES systems towards collective targets for GHG reductions, which should maximize the cumulative GHG emissions avoided relative to conventional building energy systems, over the time of the simulation.

Additional intervening outcomes are also recorded to track the number of active systems over time, as well as their thermal efficiency and the use of subsurface resources for thermal storage (defined as the fraction of aquifer volume in which the temperature is affected beyond an arbitrary threshold of 1°C, at the end of the simulation).

3.3 Uncertainties

Each of the model components is affected by given uncertainties, presented in Table 2. The uncertainty ranges for socio-technical and geohydrological parameters were based on data representative of typical ATES/aquifer conditions where available. The table also provides ranges for the spatial planning parameters, which will be sampled in the experimental design along with the uncertainties. Given that the agent-based model uses simplified decision heuristics, this component is primarily driven by deeply uncertain external values for energy prices, which are assumed to remain constant over the time frame of the simulation. The analysis therefore ignores structural uncertainties regarding the decision-making process of ATES adopters. Due to runtime constraints, more detailed technical uncertainties in the ATES control model (which could for instance lead to variable thermal imbalances over time) are also excluded at this stage.

Table 2: Model uncertainties

Socio-technical	Min.	Max.	Unit
Electricity price	0.15	0.3	€/kWh
Gas price	0.3	0.8	€/m3
Discount rate	0.02	0.1	-
Geohydrological			
Aquifer porosity	0.2	0.4	-
Hydraulic conductivity (horiz.)	10	60	m/day
Hydraulic conductivity (vert.)	2	20	m/day
Dispersivity	0.5	5	m
Policy levers			
Min. dist. for wells of same type (D_{same})	1.75	3.5	R_{th}
Min. dist. for wells of opposite type ($D_{opposite}$)	1.75	3.5	R_{th}

3.4 Policy levers

Under current approaches for the permitting and planning of ATES systems in the Netherlands, the main policy levers available to public authorities are based on spatial planning parameters. These parameters typically relate to the minimal required distance between neighbouring wells, which is itself defined as a multiplier of the average thermal radius R_{th} (illustrated in plan view in Figure 4). This value corresponds to the expected radius of thermal influence, based on the analytical solution for heat transport in porous media; the prevailing Dutch guidelines for ATES system design require a distance of 3 R_{th} to avoid thermal interactions.

However, recent research suggests that these guidelines may be overly conservative (Sommer et al., 2015). The analysis will thus explore a broader range of design parameters, distinguishing distances between "warm" and "cold" wells, and wells of similar temperatures.

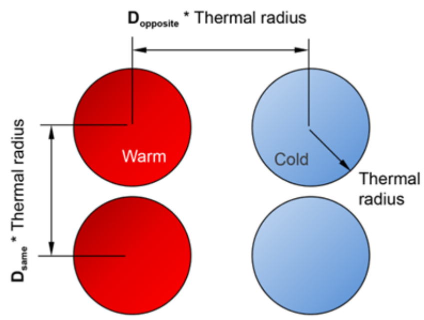


Figure 4: ATES well layout parameters

4. CASE GENERATION AND EXPLORATION

The next step of the analysis is to explore the behaviour of the coupled models under uncertainty, and to evaluate the relative impact and interactions of the various uncertainties and policy levers. The scatter plots below present the values of the two key indicators (economic performance and GHG savings), as well as subsurface use, at the final time of the simulation (240 months). The markers show an ensemble of 1500 experiments sampled from the uncertainties listed in Table 2 using a Latin Hypercube design, including the ranges of plausible spatial layout parameters.

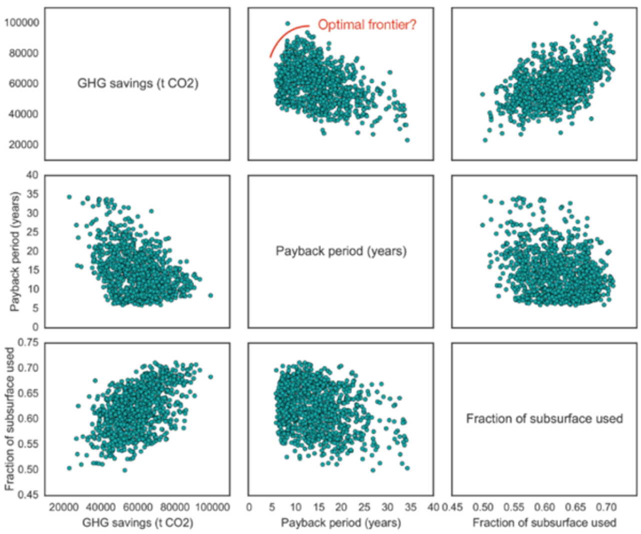


Figure 5: Model results under uncertainty

The red curve provides an indication of the optimal (i.e. Pareto-efficient) frontier which should be feasible for the trade-off between individual and collective performance, by revising the spatial layout parameters. To understand the conditions under which this frontier could be achieved, techniques for scenario discovery were then applied to the full ensemble of results. In the context of quantitative model-supported decision analysis, scenario discovery can be used to identify the combinations of assumptions and uncertainties which may lead to a given policy-relevant outcome – for instance, the conditions under which a policy could be successful or not.

Although scenario discovery often uses explicit performance thresholds to identify a subset of cases of interest (Bryant and Lempert, 2010), the exploratory nature of this analysis would make it more difficult to select unambiguous thresholds across the selected indicators. As suggested by Gerst et al. (2013), multidimensional clustering may instead provide a more flexible way to generate scenarios by identifying groups of experiments which yield similar behaviours and outcomes. For the purposes of this analysis, the scikit-learn Python library was therefore used to fit a Gaussian mixture model (GMM) to the model results, across the two main indicators. This technique essentially assumes that the samples of interest are generated by a mixture of an arbitrary number of Gaussian distributions; expectation maximization can then be used to assign each sample to the distribution to which it most likely belongs, generating a finite number of clusters. A GMM with 6 components was selected, using the Bayesian information criterion to assess the quality of fit of the possible models. This process resulted in the following groups, shown on normalized axes:

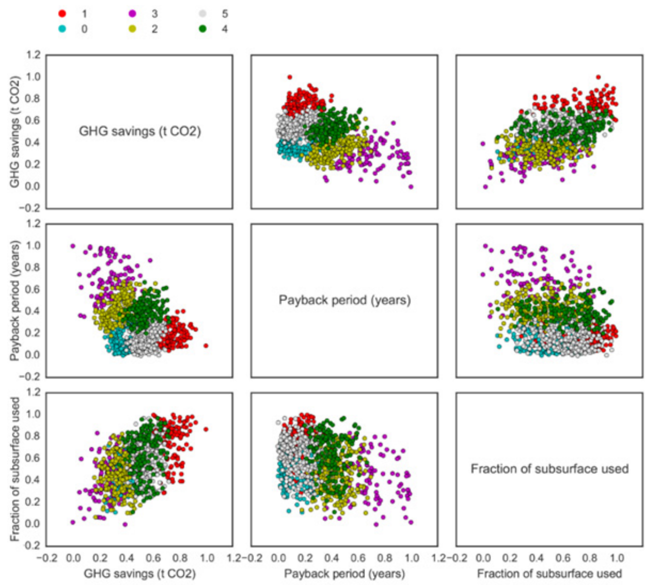


Figure 6: GMM clustering results

The clustering algorithm appears to perform well on the dimensions corresponding to GHG savings and payback period, which provide visually consistent clusters. These clusters can then individually be studied by using the Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999) to identify the combinations of uncertainties which lead to a given cluster classification. Expressing the model output as $y = f(x)$, with x corresponding to a vector of uncertain input parameters of length M, the sets of cases of interest corresponding to each cluster C can be defined as $I_j = \{x^I \mid f(x^I) \in C_j\}$ (Bryant and Lempert, 2010). Each of these sets of cases of interest can be described by one or more sets of limiting constraints $B_k = \{a_n \leq x_n \leq b_n, n \in L_k\}$, applied to the ranges of a subset of the input parameters: $L_k \subseteq \{1, ..., M\}$. Each set B_k then corresponds to a "box" within the multidimensional input space which is associated with a given output set of cases of interest. The set of boxes B can in turn be interpreted as a "scenario".

This definition assumes that the cases of interest are entirely described by a (hyper-) rectangular region of the uncertainty space, which is rarely the case in practice. To support the identification of interpretable scenarios, the PRIM technique thus aims to maximize the *coverage* and *density* of a box set B. The coverage equals the ratio between the total number of cases of interest within a box set, and the total number of cases of interest; the density corresponds to the ratio between the total cases of interest in a box set, and the total number of cases in the box set. Following Bryant and Lempert (2010), this can be noted as:

$$Coverage = \frac{\sum_{x_i \in B} y_i}{\sum_{x_i \in x^I} y_i} \quad ; \quad Density = \frac{\sum_{x_i \in B} y_i}{\sum_{x_i \in B} 1}$$

$$\text{with} \begin{cases} y_i = 1 & if\ x_i \in I \\ y_i = 0 & otherwise \end{cases}$$

These two indicators typically present a trade-off, so that a box set with high coverage may have relatively low density, and vice versa. This trade-off can be assessed using a "peeling" trajectory which indicates the progress of the PRIM algorithm, and which lets the analyst select an appropriate box set for the purposes of the analysis.

Table 3 presents representative box sets for two of the clusters displayed in Figure 6: cluster 3 (in purple), which provides the worst performance in terms of both average payback period and GHG savings, and cluster 5 (in light grey), which performs relatively well on GHG savings and has the lowest average payback period. The *Min* and *Max* table columns correspond to the ranges of the uncertain parameters which are associated with each of these box sets, while the *quasi-p* column gives a measure of the significance of each parameter. As an example, the results for cluster 3 can be interpreted as follows: 53% of the cases which were grouped in cluster 3 are associated with the combination of a gas price between 0.3 and 0.49 €/m^3, an electricity price between 0.23 and 0.3 €/kWh, and a $D_{opposite}$ value between 1.75 and 2.8 R_{th}.

Table 3: PRIM results

Cluster 3 (coverage 53%, density 58%)	Min.	Max.	Quasi-p
Gas price	0.3	0.49	1.2e-05
Electricity price	0.23	0.3	0.047
$D_{opposite}$	1.75	2.8	0.058
Cluster 5 (coverage 48%, density 64%)			
Gas price	0.56	0.8	1.4e-09
D_{same}	2.02	2.64	9.5e-06
$D_{opposite}$	2.12	3.48	3.5e-05
Electricity price	0.15	0.26	0.0029

As indicated by the coverage and density values, the PRIM algorithm does not perform particularly well, which may be due to the relatively low sample size. Nonetheless, the boxes describe reasonably consistent scenarios: in the first case (cluster 3), an unfavorable combination of energy prices leads to poor economic performance, as a low gas price reduces the attractiveness of ATES compared to conventional energy, while a high electricity price increases the operational costs of the ATES heat pump. In parallel, the distance between ATES wells of different temperatures is constrained to a relatively low range, which tends to accelerate the development of thermal interferences and reduces thermal efficiency – and therefore has an additional negative impact on economic performance. Cluster 3 thus corresponds to a "worst-case" scenario.

In the second case (cluster 5), a relatively high gas price is combined with mid-range values for the distance between ATES wells of similar temperatures, and relatively high values for the distance between wells of different temperatures. These ranges could be expected to be beneficial for both economic performance and GHG savings, by controlling negative interactions between wells of different types while allowing for a greater number of wells to be built.

4.1 Trade-off analysis and policy search

The PRIM results indicate that spatial planning parameters are a significant driver for the model outcomes, in combination with exogenous uncertainties on energy prices. The next step is therefore to specifically search for planning parameters which perform well on the performance indicators across the same uncertainties. This can be accomplished by using robust multi-objective optimization to generate alternative solutions. A key concept for this analysis is the notion of Pareto optimality: most problems are unlikely to present a single "optimal" solution; however, multi-objective optimization can be used to approximate a Pareto frontier of non-dominated solutions, which describe a trade-off between objectives.

Following Hadka and Reed (2012), a vector $u = (u_1, ..., u_m)$ can be said to Pareto-dominate another vector $v = (v_1, ..., v_m)$ for a minimization problem if and only if $\forall i \in \{1, ..., M\}$, $u_i \leq v_i$, and $\exists j \in \{1, ..., M\} \mid u_j < v_j$. This is noted as $u \prec v$. For a given multi-objective problem F(x) with decision variables x over a decision space Ω, the Pareto optimal set is then $P^* = \{x \in \Omega \mid \nexists x' \in \Omega, F(x') \prec F(x)\}$.

In the context of robust multi-objective optimization, candidate solutions are typically generated by a multi-objective evolutionary algorithm (MOEA), with the robustness of these solutions being assessed *a posteriori*. For the purposes of this analysis, the problem can be defined as follows, using a simple robustness metric provided by Eker and van Daalen (2015):

$$min\ R(P) = (-r_{GHG}, r_{ROI})$$

$$\text{with } P = [D_{same}, D_{opposite}]$$

$$1.75 \leq D_{same} \leq 3.5 \quad ; \quad 1.75 \leq D_{opposite} \leq 3.5$$

$$r_{GHG} = \frac{\mu(GHG)}{\sigma(GHG)} \qquad r_{ROI} = \mu(ROI) \cdot \sigma(ROI)$$

GHG and *ROI* correspond to the model outcomes as previously defined (cumulative GHG savings and average payback period, at the end of the simulation), over an ensemble of experiments sampled from the uncertain input ranges. The disadvantage of these robustness metrics is the lack of insight into the trade-off between the mean and standard deviation of the outcome ensembles; these values would ideally be treated as separate optimization objectives. However, due to the relatively high runtime of the geohydrological model, such an approach would result in excessive computational complexity for the purposes of this analysis.

This problem was implemented using the Borg multi-objective evolutionary algorithm (Hadka and Reed, 2012), using ensembles of 96 experiments, an initial population size of 20 solutions, and approximate ε values of 0.1 over the normalized output space. Although the analysis was constrained by runtimes using a 48-core server, the algorithm was able to attain a reasonable level of convergence over 200 function evaluations, and identified the three solutions shown in Figure 7. Figure 8 shows convergence as expressed by ε-improvements, i.e. the total number of improvements to the Pareto set over time.

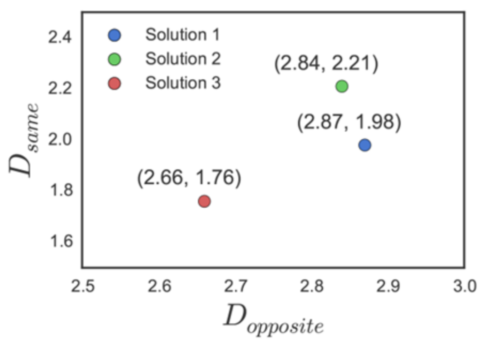


Figure 7: Optimization solutions

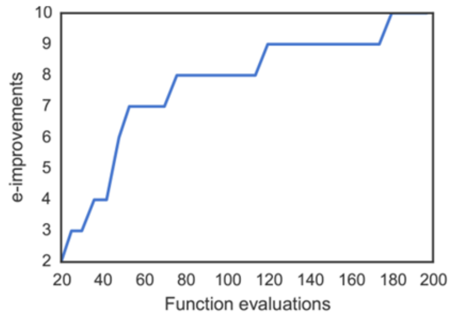
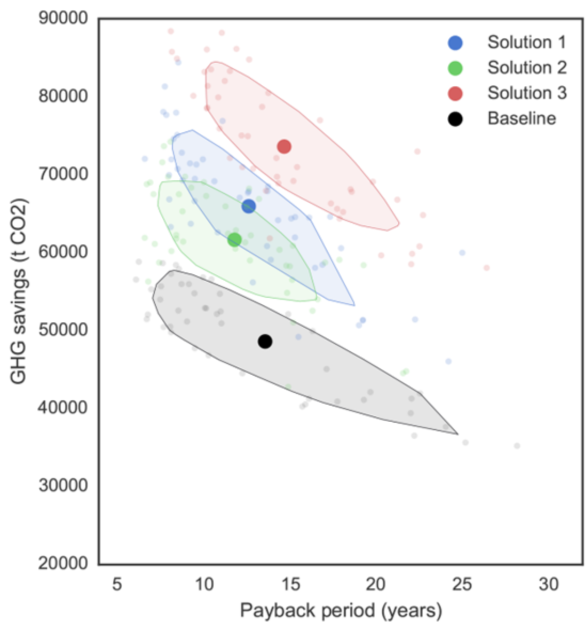


Figure 8: Optimization convergence

The scatter plot shown in Figure 9 compares these solutions with a baseline policy which would attempt to minimize thermal interactions between neighboring systems, with a distance of 3 R_{th} between wells; the plot shows the centroids and bag plots (Rousseeuw et al., 1999) for each policy option across GHG savings and payback period, over 48 experiments. The table provides detailed results for the two indicators.



Measure		Solution 1	Solution 2	Solution 3	Baseline
Payback period (yrs)	μ	12.68	11.85	14.72	13.63
	σ	4.60	3.96	4.66	7.06
GHG savings (tCO2)	μ	65949	61563	72472	48612
	σ	8586	6945	8573	7573

Figure 9: Performance of solutions

As such, the three solutions identified by the Borg algorithm seem to describe a more efficient trade-off between GHG savings and economic performance: solution 1 yields an improved mean payback period compared to the baseline policy, along with a mean increase of 35% in GHG savings. The other solutions trade off a certain amount of environmental performance and economic returns, leaving decision-makers with a set of options. All three solutions decrease the standard deviation of the average payback period, suggesting that these policies are less affected by energy prices; this is caused by the beneficial thermal interactions between wells of similar temperatures, which are less significant in the baseline case but which allow for an increase in thermal recovery (as previously described by Bakr et al., 2013). An additional PRIM analysis could here be performed to study specific vulnerabilities.

5. CONCLUSIONS

This work presented a simplified application of multi-objective robust decision making for the problem of urban ATES planning under uncertainty. The combination of clustering techniques and scenario discovery proved useful to explore the different plausible modes of behaviour of the model. In addition, the Borg multi-objective evolutionary algorithm was helpful in better understanding the trade-off between the collective energy-saving potential of ATES, and the economic performance of individual systems. In particular, this showed the beneficial role of positive thermal interactions between ATES wells of similar temperatures, compared to a case which would attempt to minimize any thermal interactions between systems.

From a broader perspective, while robust optimization was a useful technique for analysing the effect of spatial planning parameters and their interactions with exogenous uncertainties, the large-scale management of ATES systems may call for an altogether different approach to planning to maximize the benefits of the technology. Current planning methods rely on local permits and master plans, which essentially take a static view of ATES management under uncertain future conditions. For instance, permits do not incorporate feedback from operational performance which could account for thermal imbalances or variations in well flows, as well as variable adoption dynamics. As an alternative, Bloemendal et al., (2014) summarily evaluate the potential of a self-organized approach for ATES governance. As described by Ostrom (2009), empirical evidence indicates that such self-organization mechanisms – in which cooperative institutional arrangements replace hierarchical planning – may offer an effective route for the management of common-pool resources. Bloemendal et al.’s analysis suggests that self-organization could be appropriate for ATES development in urban areas, notably due to a relatively small spatial scale, slow resource dynamics, and the high economic benefits of efficient ATES operation. The design of corrective feedbacks and compensation arrangements would be crucial to preserve the sustainability of the subsurface under a self-organized approach, and would in turn require advancements in the technical control systems of ATES systems to facilitate their cooperative management. However, such a “bottom-up” organization could perhaps offer a more genuinely robust option for the successful management of urban ATES systems under uncertainty.

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