Using Decision Support Models to Analyse the Performance of EGS Systems

J.D. Van Wees¹,²,a, D. Bont², R. Bertani³, A. Genter⁴
¹TNO, Utrecht, Netherlands, ²Vrije Universiteit, Amsterdam, Netherlands, ³ENEL, Rome, Italy, ⁴GEIE, Kutzenhausen, France
abcorresponding author: jan_diederik.vanwees@tno.nl

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ABSTRACT
In this study we present a techno-economic performance assessment model for deep geothermal projects. These models are a public deliverable of the European project Enhanced Geothermal Innovative Network for Europe (ENGINE), which has been completed spring 2008. The models have been implemented in EXCEL and as part of dedicated decision support system, using best practices for asset evaluation from the Oil and Gas industry. This approach allows to take into account natural uncertainties and decision trees to evaluate sensitivities and different scenarios.

In the model approach, fast model calculations for the techno-economic evaluation are used to calculate the performance of the geothermal systems, investigating sensitivities of the performance due to both natural uncertainties beyond control (e.g. flow characteristics, subsurface temperatures), engineering options (bore layout and surface facilities options) and economic uncertainties (e.g. electricity price, tax regimes). Fast models for the temperature evolution of the water in the well and fractures are based on fast analytical solutions, based on streamline approximations. This allows to calculate in a matter of seconds the performance and its sensitivity to uncertainties and the effect of various engineering options.

For doublet systems in deep (enhanced) geothermal systems we use analytical methodologies developed for the Soultz project. Results show that the performance of the system is primary sensitive to subsurface temperature, flow rates which can be sustained in the fractured rock, and the number of fractures involved in the fluid flow. We also are capable to forecast effects of improved explorative approaches and technological performance as well as governmental incentives on viability of prospects. The tools are available at http://engine.brgm.fr/DecisionSupportSystem.asp.

1. INTRODUCTION
In the capital intensive oil and gas industry it has been long recognized that many Exploration and Production (E&P) projects failed to deliver the performance they promised as a result of underestimation of risks (e.g. Bratvold and Begg, 2008). Studies by Merrow (2003) showed that one in eight E&P projects with capital expenditure ranging from $1 million to $3 billion dollar were disasters, where disaster is defined as the project failing on two out of the following three metrics:

- not more than 40% cost growth
- not more than 40% time slippage
- first year operability at least 50% of plan

Over the years the oil and gas industry has developed quantitative frameworks for better decision making regarding the allocation of resources, when faced with uncertainty beyond human control (cf. Floris and Peersmann, 2001, Bos, 2005). Evidence exists that adopting such frameworks has improved performance of companies (Jonkman et al., 2000).

This paper gives an introduction to such a quantitative framework and describes how it can be used for EGS projects, with emphasis on the exploration, at which stage most can be gained by risk analysis and improved decision making under uncertainty. The tools which have been used in this paper have been published as deliverable from the EU-project “Enhanced Geothermal Innovative Network for Europe (ENGINE)” and are freely available from the Engine website (ENGINE website, 2009).

We will show that taking advantage of quantitative risk and decision analysis techniques, one is capable to understand the causes for risks and integrate risk mitigation actions into project planning. In this context, especially the potential positive influence of staged exploration strategies is discussed. In future, optimized and novel exploration technologies, can considerably aid in minimizing risk and can increase economic success. Shared risks for groups of prospects can have a major impact on the prospects expected return when costs for risk mitigation and results are shared. Dependencies may not only be related to critical characteristics shared between nearby prospects, but can also be related to conceptual breakthroughs in physical processes in prospects, tested through pilot projects.

2. METHODOLOGY
For Economic performance assessment of projects prior to exploration activity, the forecast of Net Present Value (NPV) is generally used.

NPV is defined as the total present value (PV) of a time series of cash flows. It is a standard method for using the time value of money to appraise long-term projects. Used for capital budgeting, and widely throughout economics, it measures the excess or shortfall of cash flows, in present value terms. To calculate NPV the cash flow is discounted back to its present value (PV).

\[
PV = \frac{R}{(1+i)^t}
\]

where

t - the time [year] of the cash flow relative to the start of the project
i - the discount rate (the rate of return that could be earned on an investment in the financial markets with similar risk)
$R_t$ - the net cash flow (the amount of cash, inflow minus outflow) at time $t$

Then they are summed into the cumulative discounted cash flow (CDF) and the NPV is the sum of all yearly terms.

Figure 1 gives an example of the calculation of NPV for a geothermal project during its exploration and production lifetime. The details of the project are further delineated in the following section. Cumulative Discounted Cash Flow (CDF) at the end of the lifetime of the project (3.1 mln euro).

In case the project would have been aborted due to legal problems in year 3, the NPV would be -34 mln. The CDF is the accumulation of the discounted cash flow (DCF). The DCF equals the Undiscounted Cash Flow (UCF) corrected for the discount rate. The UCF is the sum of revenues, capital expenditure and operating expenditure (CAPEX and OPEX), corrected for tax.

Figure 1: Cash Flow calculation of a project. NPV for the project corresponds to the forecasted

Figure 2: integrated value-chain probabilistic fast-model capable of assessing the impact of uncertainty in technical and economic parameters on an asset’s key performance indicators. The model integrates a number of different physical compartments.

Uncertainty and Risk

Financially, risk is defined by the downside, which equals the average returns below the target of NPV $>0$ (cf Markowitz, 1952, Sharpe, 1964). The probability of a negative project outcome is related to the probability density function of forecasted NPV prior to a project-phase execution. The value-chain integration models, as introduced in the previous sections allow to assess the impacts of uncertainties in technical and economic parameters in expected NPV distributions, with multiple runs and using monte-carlo sampling (Fig. 2).

Figure 3 gives an example of an NPV distribution adopting various subsurface uncertainties. Its performance at 30% expectation corresponds to the cash-flow shown in Fig. 12. The average performance is positive, but due to the uncertainties there is probability of 43% that forecasted NPV is less than 0. The resulting calculated risk is 1.5 mln Euro.

Portfolio Analysis

Portfolio theory (e.g. Markowitz, 1952, Sharpe, 1964) allows to rationally benchmark prospect performance, under uncertainty. In this approach projects are plotted in a portfolio plot, with risk on the horizontal axis and the average NPV as expected return on the vertical axis (Fig. 4). When multiple projects are plotted, these can be ranked relative to each other. Best projects are marked by maximum expected return at minimum risk. They are located at an imaginary line along the upper left edge of plotted prospects and is known as the efficient frontier.

Portfolio plots also allow to quantitatively benchmark the robustness of the project development strategy, through evaluating the effect of alternative workflow options to mitigate financial risks. This involves an optimisation of risk mitigating actions in the project, their staging in the project execution and associated decision tollgates. Its general aim is to lower downside, and at the same time increase expected return. Staged exploration strategies are a clear example. Here more information (data and/or analysis) is gathered to reduce uncertainty. In case of negative results of exploration (e.g. demonstrating very low flow rates with associated negative NPV) the project will be aborted at relatively low cost. Note that doing so the probability of having a negative project result is generally not altered.

Figure 3 and 4 show an example of the effect of adopting an improved exploration workflow. The default workflow performance is marked by a downside of ca 1.5 mln Euro, and an expected return of 1 mln Euro. An exploration phase allows to abort the project at relatively low cost, resulting in a reduced downside of 0.6 mln Euro and an increase of expected return up to 1.72 mln Euro. In this simple example the exploration phase is considered to yield perfect information for NPV forecast. This allows to mitigate downside costs in excess of the exploration costs. The costs made during exploration are limited to 2 mln Euro, without any
additional costs to the project execution when the exploration phase is successful.

**Figure 4: Portfolio plot of imaginary set of projects (small grey dots). Large grey and black dots represent forecasted Risk and expected return corresponding to default and staged exploration project workflows respectively (Fig. 3).**

### 3. A CASE STUDY

In the example given above it had been assumed that exploration gives direct information on NPV. In fact this is hardly ever the case. In fact, through exploration -and other risk mitigating actions- one reduces the uncertainty of specific parameters, which affect indirectly NPV. In order to understand which parameter uncertainties have a negative impact on NPV, sensitivity analysis is performed (e.g. Bratvold and Begg, 2008).

Decision trees (c.f. Koller, 2000) are subsequently used to represent and calculate quantitatively the effects of adjusted workflows under uncertainty. The latter is achieved through an integration of decision tree logic and probabilistic integrated value chain models for NPV (Floris and Peersmann, 2002).

The techno-economic value chain model used in the case study has been described in detail on the Engine website (ENGINE website, 2009). The model is derived from Heidinger et al., (2006) and builds on experiences from Soutz-sous-Forêt. Here pre-existing natural fractures zones appear to play a key role in fluid flow transport from an injector to producer well. Following Heidinger et al. (2006) the natural fracture zones have a large areal extent in the order of ca 3 km² surface area, capable of connecting injector and producer wells. The fractures are relatively thin in the order of few cm resulting in progressive cooling of production water (thermal short cut). However as shown by tracer tests by Sanjuan et al (2006) only a limited portion (approximately 30%) of the produced water originates from the injector well. Consequently the cooling effect of production water is limited to this fraction.

In the example focus is on dealing with various subsurface uncertainties it is assumed that significant uncertainty exists regarding the sustainable flow rate (80-120 l/s), the number of fracture zones (1, 2, or 3), the fraction of produced water (30-50%) which will originate from the injection well and the initial reservoir temperature (205-210°C).

The subsurface uncertainties in this project are not solely dependent on the effect of continuous distributions. The number of connecting fractures is this discrete. Such discrete uncertainties are represented in the decision tree with an event node (Figure 5). The predicted distribution is calculated from a merger of samples from the various branches underlying the event node, in which the selected number of branch-specific samples is weighted for the probability of the particular branch. Figure 6 shows the NPV distributions at the end nodes and the merged NPV distribution. The merged distribution is marked by an expected outcome of NPV of -1.07 mln euro, with a downside of approximately 3 mln euro. Consequently the decision should be not to develop the project.

#### Sensitivity Analysis

The NPV distribution of the default project (Fig. 6) is marked by a negative expected return of -1.07 mln. However there is considerable positive NPV in the distribution. If the downside could be mitigated the project’s performance would be improved. In this case this could be accomplished through exploration activities to reduce uncertainties of the subsurface parameters. Sensitivity analysis allows to target exploration activity to obtain information on parameters which have the largest impact on NPV.

#### Monte Carlo Simulation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sustainable flowrate</td>
<td>80-120 l/s</td>
</tr>
<tr>
<td>% inflow from connected fracture</td>
<td>30-50%</td>
</tr>
<tr>
<td>Temperature</td>
<td>205-210°C</td>
</tr>
</tbody>
</table>

**Figure 5: Default decision tree of the example case to execute doublet development, given subsurface uncertainties. Circles denote event nodes, squares decisions. Decision should be to abort the project as the expected return is -1.07 mln euro.**
Figure 6: NPV distribution at end nodes and merged distribution at the event node in Fig. 5, which is a merger of end node results, weighted according to probabilities of the end nodes in the decision.

Figure 7: correlation diagrams of subsurface uncertainty parameters (table 5), and NPV. Correlation factors (r) show that number of connected fractures has the highest impact on NPV.
The sensitivity analysis uses the merged value-chain modelling results for the project (Fig. 6). From the monte carlo samples correlation factors are produced of the input parameters and NPV (Fig. 7). The parameters with strongest correlation – in absolute value- are the parameters which have the most significant impact on the project’s NPV. Consequently these parameters are to be further explored to reduce uncertainty.

**Exploration Approach to Minimize Downside and Maximizing Expected Return**

As has been shown by the sensitivity analysis, the “One fracture” scenario is marked by strongly negative NPV ruining the project. It is supposed that the first well drilled can detect the “one fracture” scenario. Evidently the project would be aborted if the well demonstrates this scenario. It is assumed that the costs of an exploration well to the investor will be limited to 2 mln Euro, thanks to a government incentive scheme.

The decision tree accounting for making the additional go-no-go decision on the project is displayed in fig. 8. The decision to be made today is to drill or not to drill an exploration well. The exploration has 70% chance for a negative “one fracture” scenario and 30% chance for a positive result proving a two or three fractures scenario. Since a significant portion of the downside of the default project has been mitigated by avoiding high costs of production development (Fig. 10), the expected return of the project is increased to 0.06, however the downside of the project is still significant: 1.5 mln euro.

The downside can be further reduced by staged decisions and associated exploration phases. This is demonstrated through extending the exploration. Exploration techniques which are cheaper and can be done before drilling the first doublet well may increase the economic performance of the project. Here it is assumed that we can apply well-seismic in a nearby existing oil and gas well which can give additional information prior to drilling the geothermal exploration well (Fig. 9). The seismic can give an indication for the number of natural fracture zones in the rock (cf Cuenot et al., 2007 – Soultz-sous-forêts) prior to drilling the doublet wells. The costs of this seismic exploration phases is 0.1 MLN. Costs for abortion after the seismic and drilling an exploration well is 2.1 MLN. In order to update probabilities of the subsequent exploration drilling phase, it is assumed that it cannot rule out with certainty the existence of a particular fracture scenario. This imperfect information is generally modeled with conditional probabilities based on experience with similar exploration cases (e.g. Koller, 2000; Van Wees et al., 2008). In this case we assume that in 90% of the cases in which the “one fracture” scenario is indicated by the seismic it is really found, whereas for the “two fracture” and “three fracture” scenarios it is less perfect, capable of proving both in 60% of the cases.

From the conditional probabilities, the probabilities for the outcomes of the seismic exploration phase and the exploration well are calculated as well as the probabilities for the underlying one, two and three fractures scenario outcomes. The sum of the one, two and three fracture scenario probabilities over the various branches in the tree equate back to the original probabilities of 0.7, 0.15 and 0.15 respectively.

Evaluation of the tree demonstrates the capability to increase the probability of a positive outcome at the stage of drilling the exploration well up to 72% at relative little costs (0.1 mln). This has a strongly positive effect on the NPV expectation curve for the project, which is marked by a less pronounced downside (Fig 10). The expected return of the project is now increased to 0.66 mln and the downside has decreased to 0.31 mln. This increase of NPV relative to the default exploration is called Value of information (VOI) which is 0.6 mln for including the seismic exploration.

The decision tree approach moves the prospect towards the efficient frontier (Fig. 11), thanks to an inexpensive exploration study prior to doublet drilling. The NPV of the prospect can possibly be further enhanced by additional decision toll-gates and exploration phases.

**Figure 8: Decision tree with an exploration well phase. The decision tree contains two go-no go decisions, one at the start of the project to drill an exploration well and one decision after exploration to develop the doublet for production.**
Figure 9: Decision tree of fig. 22 preceded with an seismic exploration activity. The decision tree contains three go-no go decisions, one at the start of the project (to explore or not to explore with seismic), the second decision to drill an exploration well, and the third to develop the doublet for production.

Figure 10: The expectation curve of the NPV of executing the project at the first go-no go decision in the default tree (Fig. 5), the exploration well tree (Fig. 8) and the exploration seismic tree (Fig. 9).

Figure 11: Portfolio plot, plotting progressive improvement of staged exploration approach. Default (light grey), exploration well (dark grey), exploration seismic (black). Other features as in fig.4.

Figure 12: Decision tree of fig. 9 in which exploration results are used for the development for two production doublets as they are both believed to share perfectly correlated underground uncertainties.
Shared Risks in Prospects
If critical factors for risk of individual prospects are shared (e.g. regional factors such as flow rates for natural fault zones, temperature) than at the costs of a single exploration well we are capable to mitigate risk for a group of prospects.

The positive effect of this prospect dependency can be simple demonstrated considering the development of group of two prospects in which the natural fractures are shared. Furthermore the doublets share the same plant.

The evaluation of the decision tree is displayed in Fig. 12. The expected return of the project has increased significantly to 1.56 mln Euro, which is much higher than the cumulative value of two independent prospects which would add up to 1.32 mln (cf Fig. 9).

4. CONCLUSIONS
We have shown that taking advantage of quantitative risk and decision analysis techniques, one is capable of understanding the causes for risks at one is able to take a quantitative and unbiased view to risk mitigation actions.

In future, optimized and novel exploration technologies, can considerably aid in minimizing risk and increase the expected return. Shared risks for groups of groups of prospects can have a major impact on the prospects expected return when costs for risk mitigation and results are shared. Dependencies may not only be related to critical characteristics shared between nearby prospects, but can also be related to conceptual breakthroughs in physical processes in prospects, tested through pilot projects.

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Markowitz, 1952


Sharpe, 1964