Risk Assessment for Geothermal Wells— A Probabilistic Approach to Time and Cost Estimation

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Keywords

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ABSTRACT

In the last five years about 30 deep geothermal wells have been drilled in the Southern German Molasse Basin. 16 of them have been planned and/or supervised by ERDWERK GmbH who supports the operator as a consultant throughout the project. One of the main duties of a consultant like ERDWERK GmbH is cost planning and time schedule forecasting for the well construction process. To date, these estimates have been based on a historic average time for the main operations which have been added up to the total well construction time. Uncertainties have been taken into account by adding a contingency factor. This approach has the advantage of being simple, fast and easy to communicate. However, it does not give any idea about the variability of the estimate and the risks involved, which limits its application. Therefore, the aim of the work presented in this paper was to establish a well construction model based on statistical methods to allow probabilistic time and cost estimation.

Firstly, a literature review on probabilistic methods in well planning was performed. Then a model to determine the total well construction time was set up. Offset data of 16 wells was gathered and analyzed to determine a probability function for the duration of each process. Morning reports were the main data source for this task but also rig sensor data was used. The model was fed with the gathered data and verified by comparison with real historic results. Trends observed in the offset data were implemented to model the performance mean and its variation over time. Then a multi-well model was established. Finally, the model was extended by adding costs.

With the presented approach of well construction modeling, one can deliver risk assessment for geothermal wells to investors, insurance companies and decision makers. This will aid proper budgeting and the calculation of insurance premiums. Moreover, the modeled technical limit or best historic performance can be used as technical performance reference. Based on the results of the sensitivity analysis, the key driving forces can be identified. Therefore, optimization strategies can be steered into the right direction.

Introduction

Hydrothermal energy has been used in the Southern German Mollasse Basin for decades to supply spas with warm water. However, geothermal exploration has also targeted district heating and power generation on a larger scale over the last ten years. Since 2007, activities have boomed and about 30 geothermal wells have been drilled in the last five years. [1]

Depending on the temperature and production rates, the thermal energy is used for power generation coupled with heating or, in case of lower temperatures, for heating only. A typical well doublet, used for a coupled system, can support 5-50 MW for direct use (heating) and has an electrical capacity of 5-10 MW.

ERDWERK planned and supervised 16 of those geothermal wells so far, which are approximately 2500 to 4500 m deep and are divided into 4 sections of different diameters. We can distinguish between two categories of wells:

- Category 1, where the first section starts with 23” followed by 17.1/2”, 12.1/4” and 8.1/2” bit diameter.
- and Category 2, where the first section starts with 17.1/2” followed with 12.1/4”, 8.1/2” and 6.1/8” bit diameter;

The geology in this area is generally well known (mainly due to data and literature from previous oil and gas exploration). However, drilling down to the reservoir can be challenging and drilling performance has been uneven in the past. To counter this, Rotary Steerable Systems have been applied in recently drilled wells (cf. [2]) and a lot of effort has been put into well designs which honor the lessons learned. These measures have led to a significant decrease in well delivery time and costs. However, the variability is still high and there is great potential for improved performance and saving costs.

Problem Definition

To date, cost planning and time schedule forecasting have been based on historical performance data of offset wells, whereas outstandingly strong or weak performance has been rejected and an average estimated time for the main operations has been summed up to the total well delivery time. By multiplying with the respective costs and adding the fixed costs, total well costs have been identified. Uncertainties have been taken into account by adding a contingency factor whose value has been based on the engineer's subjective degree of optimism.

This approach has the advantage of being simple, fast and easy to communicate. However, it does not give any idea about the uncertainty of that estimate which limits its application: For example, the estimated time schedule was used for both, budget planning and as technical reference for the drilling contractor. But from the engineer's point of view it was too conservative and no incentive for the well construction team. On the other hand, if drilling problems occurred, costs could increase rapidly and the forecast was too optimistic. Now one could estimate two or more cases (e.g. best-case, business-case or worst-case) again with the same deterministic method (scenario based approach). However, it does not deliver the probability of each case and quantitative risk assessment is still not possible.

Therefore, the goal of this work was to establish a probabilistic well construction model**,** which allows the simulation of a time schedule forecast and the well delivery costs on a statistical basis. It should allow risk assessment by giving a distribution, their expected value, the probability of a certain value and the range of outcomes.

Literature Review

In the oil & gas industry probabilistic techniques for time and cost planning of wells are well established. However it started by improving deterministic approaches by splitting up the well construction process in smaller operations, by defining how their duration and costs depend on input variables and by simulating an estimate for a new well by combining the operations again whilst applying actual design parameters.

For example, in 1987 Thorogood [3] described "a mathematical model for analyzing drilling performance and estimating well times" in the North Sea. In 1990 Shilling and Lowe [4] published a paper about the development of an "automatic cost estimating and tracking system" in the Gulf of Mexico.

Although this approach might result in a more accurate prediction it does not deliver the uncertainty in the planned well construction costs and time. Therefore probabilistic estimations are necessary and there are several papers on this topic: Murtha (1997) [5], Williamson et al. (2004) [6] and Akins et al. (2005) [7] refresh concisely the theoretical background of probabilistic techniques. They proposed how Monte Carlo simulation can be used for well planning and explained its strengths, weaknesses and the pitfalls. Examples for practical studies are Peterson et al. (1993) [8], Peterson et al. (1995) [9], Kitchel et al. (1997) [10], Zoller et al. (2003) [11], Hariharan et al. (2006) [12], and Adams et al. (2009) [13]. The ideas and methods described in these papers provided the theoretical basis of this work.

Modeling Drilling Time

The output variable of this first model is the *Total Well Construction Time* of one single well. This covers all processes between spud and logging the reservoir section. Therefore, it does not include for example rig-up times, stimulation, running the pre-holed liner, well testing and rig-down time. The *Total Well Construction Time* is broken down into sequential steps which will be called *processes* from this point on. The duration of some of these processes are derived from *input variables* and *well design parameters.* Figure 1 shows an overview of the models architecture.

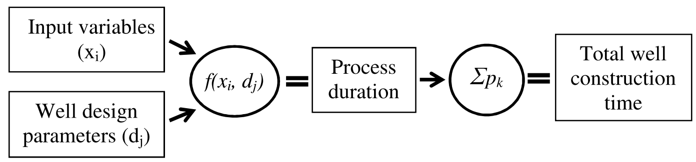

Figure 1. Concept of modeling the total well construction time.

Before the model is described in detail some definitions are made regarding the nomenclature used in this paper for different drilling and completion activities. The term "flat time" is used in this paper to address time during which no depth is made. "Non-productive time" is used for lost time due to troubles or unplanned events, i.e. unnecessary flat time. These definitions are made following the terminology defined by Spörker et al. in their paper about unplanned and invisible lost time [14, p. 1]. "On-bottom time" (OBT) is used for the time when depth is made (the drill bit is on bottom, it is rotated and mud is circulated), i.e. the total well construction time minus the flat time.

Processes

The processes defined are: *Drilling Hole, Logging, Conditioning Trip, Running Casing* or *Running Liner, Cementing, WOC/BOP and Drilling Cement/Shoe*. Repeatedly connecting these seven processes for each section describes the typical well construction process without any gaps.

Figure 2 shows one sequence of these parameters in a time vs. depth graph. During the process *Drilling Hole* some flat time occurs as well (making connections, reaming, changing the bit or

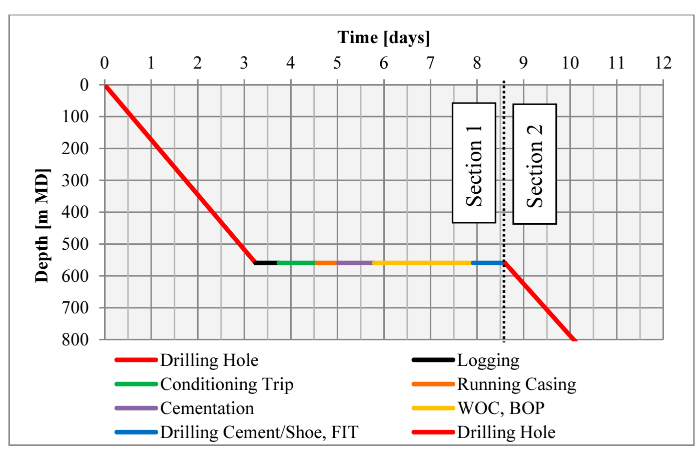

Figure 2. Process sequence in a time vs. depth graph.

BHA components, trouble time etc.). However, this flat time is not visualized because the model does not consider the exact depth and duration of each flat time occurrence. It is averaged over the whole section and therefore the graph shows a straight line which includes both, OBT (On bottom time) and DFT (Drilling flat time).

The duration of these processes is different for each section. The typical geothermal well considered in this paper has 4 sections. Therefore, for each section a separate process duration has to be defined (e.g. *Drilling Hole Section 1, Drilling Hole Section 2*, etc.). Each of these processes has a certain start and end where they are linked together. The processes are chosen so that their starting and finishing points can be determined with morning reports and that no gaps between certain processes will arise.

Input Variables and Well Design Parameters

For most of the processes the model does not consider any dependencies on input variables. Only the process *Drilling Hole* is a function of the input variable ROP (Rate of Penetration) and DFT (Drilling Flat Time). They are defined as follows:

- ***ROP [m/h]*** is the net rate of penetration. So the ROP is measured only when the bit is on bottom whilst it is rotated and mud is circulated.
- ***DFT [h/100 m]*** is the time consumed for all operations except drilling during the drilling process normalized to 100 m. With the knowledge of ROP and the total time to drill a section the DFT can be calculated. Due to the limited data granularity of the morning reports used to determine DFT it is not possible to extract individual sub-processes or to distinguish between non-productive time and necessary flat time.

In addition well design parameters have to be defined. These are:

- ***Casing Setting Depths*** (and the resulting section lengths).
- ***Type of the Second Casing*** (liner, casing to surface or liner with tieback).

Gathering Data

The aforementioned processes and input variables, except ROP, have been gathered manually for each section and every well from morning reports. These reports have a coarse level of detail and the duration of different jobs are often rounded to the quarter, half or even full hour. In addition they are written manually and therefore may be prone to some degree of error. However, for this paper it is the only data available. For further work on this model also processed rig sensor data could be used (cf. [15]).

The input variable ROP [m/h], which is the average ROP for each section, was determined on the basis of rig sensor data. Although the ROP is part of the morning reports, deriving the ROP from them is not reasonable because the quality of these daily "averaged" values is generally not reliable.

Then the DFT [h/100 m] was calculated by knowing the total time t [h] to drill the section i (derived by morning reports), the average ROP [m/h] (derived by rig sensor data) and the length L [m] of this section:

$$t_i = \frac{DFT_i \cdot L_i}{100} + \frac{L_i}{ROP_i} \qquad \text{Eq. (1)}$$

As already mentioned, all other variables have been derived directly from the morning reports.

Evaluating the Deterministic Model

The next step was the evaluation of the still deterministic model. Therefore, the total time to drill all four sections is calculated for each well based on the model defined and the offset data gathered. After modeling the drilling time the results were compared with the real data. Figure 3 shows the modeled time vs. depth curve and the real data of one well.

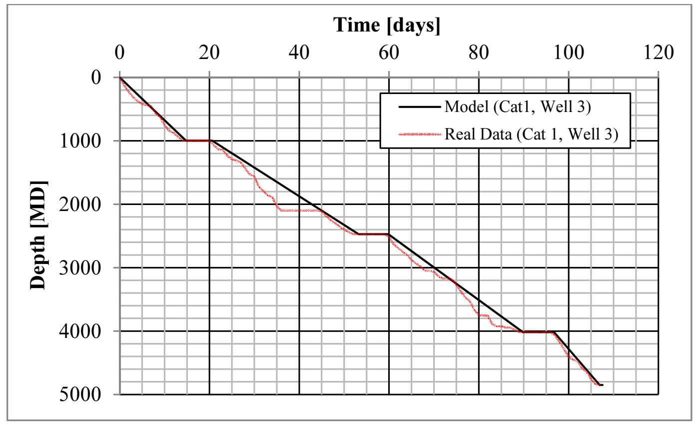

Figure 3. Modeled time vs. depth curve and real data of Well 3 of Category 1.

The model should match the starting and end point of every section, which is fulfilled quite well in the example shown. Between the starting and end point of a section, the real data cannot be matched because in the model ROP and DFT are averaged for each section.

This quality check has been performed for each well. This assessment confirms both: The model set up and the data gathering leads to reasonable results.

Defining Input Distributions

The next step was to assign a distribution function to every input variable by fitting a theoretical distribution to the respective data set (parametric fit). Therefore, a software tool was used.

Incorporating Learning with Correlation Coefficients

Learning trends over time were implemented by assigning a correlation coefficient between the well number and the respective input variable like ROP or DFT.

Figure 4 shows the result of the correlation for the input parameter ROP of the reservoir section. Trend and variance changes along the time scale.

Correlation coefficients have not been assigned to variables for which learning is not reasonable. For example, even if *Running Casing* would correlate with the *Well Number*, it would not be reasonable because the rig and crew changed from project to project.

Therefore, only ROP and DFT have been considered for assigning correlation coefficients. As the correlation coefficients are derived from a limited set of data their uncertainty should be considered as well. This uncertainty was implemented by performing a bootstrap [16].

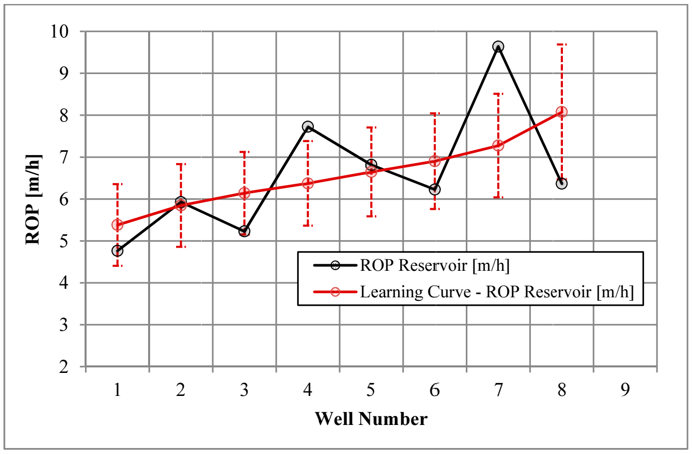

Figure 4. Real data and assigned learning curve with its standard deviation derived by correlation for the input parameter "ROP Reservoir" (Category 1).

Correlations

During the sampling process of the Monte Carlo simulation it is important to account for correlations between input variables. This means that if two variables are related to each other, the sampling of a relatively high value for one input variable should lead to a high value (or low value in case of negative correlation) for the second variable.

A relationship which has been investigated is the ROP between different sections because correlation between them is reasonable: Some design elements and also the skills of people involved stay rather constant throughout all sections. However there are other influencing parameters as well, which will cover these effects if they are stronger. To identify correlations in offset data the Spearman rank correlation coefficient was calculated between the ROP of different sections.

The uncertainty of the correlations is taken into account by implementing a bootstrap on the data (by analogy to the correlations used for the learning trends).

Other relationships like ROP-DFT or DFT-DFT were investigated, but no significant correlation was to be found.

Modeling Multiple Wells

So far, only the single-well model has been discussed. By modeling multiple wells an additional consideration has to be taken into account, which is the correlation between several well outcomes. Therefore, correlations between wells within former projects have been studied and assigned to the model.

Modeling Drilling Costs

Modeling Time-Dependent Costs

The total time-dependent costs can be determined easily by multiplying the time-dependent costs of each process with the respective process duration. However, this implies that the time-dependent costs stay constant during a process, which can be assumed for the processes defined.

For each process different cost positions are assigned. For example, during the process *Drilling Hole Section 1* the following positions are added up:

- Rig dayrate
- Project coordination fee
- Mud engineering costs
- Directional BHA and service cost of section 1

To give another example, during the process *WOC/BOP* the following positions are added up:

- Rig dayrate (waiting mode)
- Project coordination fee
- Mud engineering costs

During a simulation run, in each iteration step, the costs are multiplied with the respective process duration. The costs are assumed to be deterministic for the purpose of this paper. This makes sense if the project is already in a phase where offers to the tender are available or contracts are already made. In this case the uncertainty of the cost position's value will be small. However, in an earlier stage of a project also costs should be handled as probability distributions rather than fixed values.

Modeling Time-Independent Costs

The time-independent costs are summarized and assigned to the respective section. For this paper also the costs for completion and testing are handled as time independent costs because the time model covers only the well construction process. Therefore, the planned time schedule was used to determine the time-dependent costs which then stay constant during the simulation.

Results

Probability Distribution

Based on the model described above a Monte Carlo simulation was run. Figure 5 shows the resulting probability distribution of the total well construction time of a simulated future example well of Cat 2.

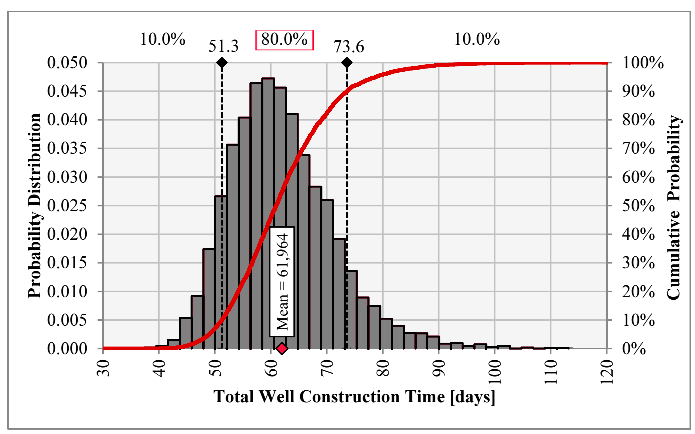

Figure 5. Probability distribution and cumulative probability of the total well construction time (Category 2).

Time vs. Depth Curves

The model results can also be transferred to a time vs. depth curve. This is especially useful for a single well forecast. Figure 6 shows a time vs. depth diagram for a well of Category 2. There are 6 different curves on the diagram:

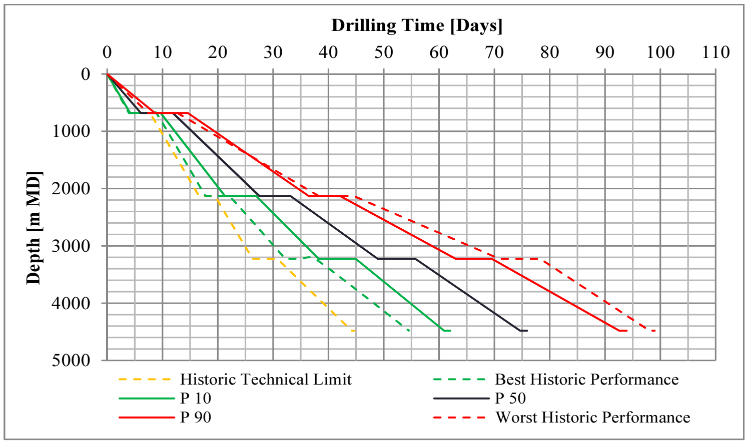

Figure 6. Historic and modeled time vs. depth curves (Category 2).

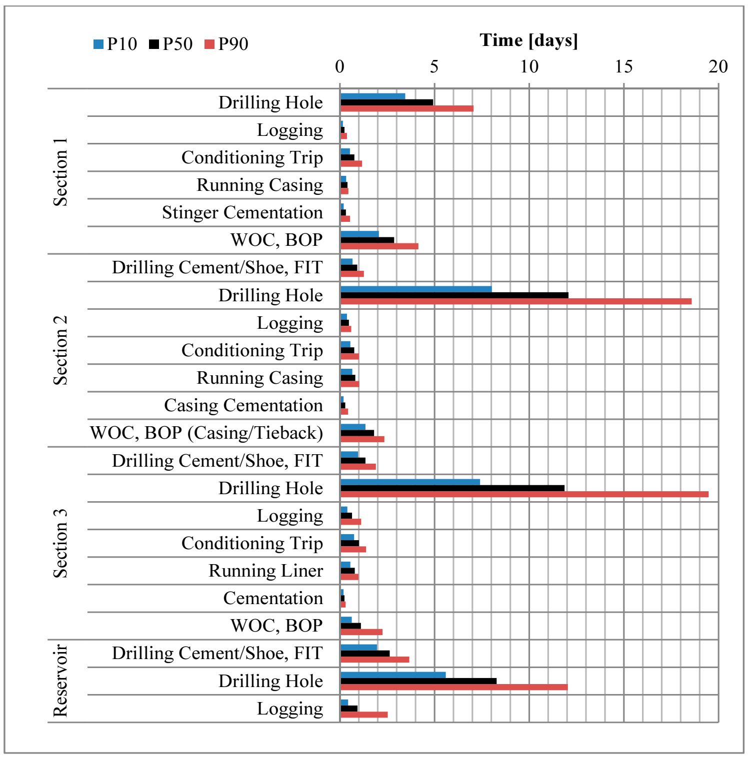

Figure 7. Process durations for the result of Category 2 wells.

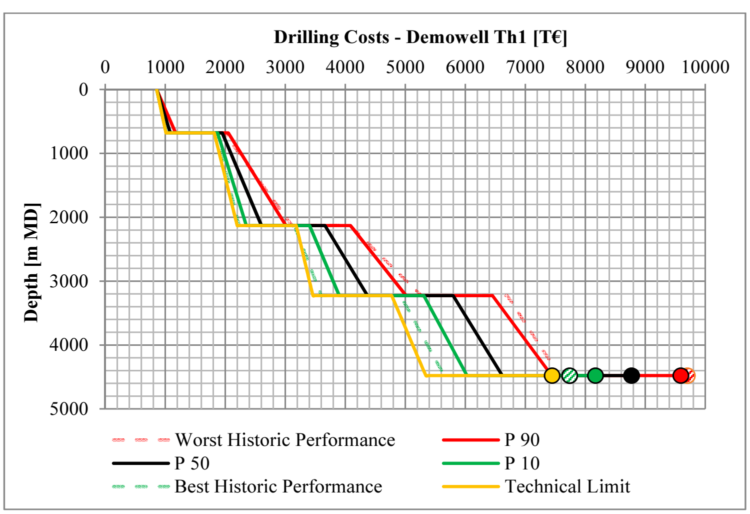

Figure 8. Drilling Costs vs. Depth curve of Demowell Th1.

Firstly, the "historic technical limit": It is the sum of the best historic process duration of all wells. Therefore, for each process (e.g. *Drilling Hole*), the minimum value of the offset data is gathered and stacked together. So this curve is a mixture of processes from different wells.

Then, the "best historic performance" curve is displayed, which is the time vs. depth curve of the well with the best overall outcome (normalized to the modeled casing setting depths). This well does not necessarily have the best performance in all sections. Only the overall outcome was the best in this category.

The next three curves are the modeled P10, P50 and P90 values as a function of depth. From the spread between these curves, the risk involved is indicated.

Finally, the "worst historic performance" is displayed. It is, in analogy of the "best historic performance", the time vs. depth curve of the well with the worst overall outcome (normalized to the modeled casing setting depths).

Process Statistics

To get further insight into the simulation results, each process can be analyzed separately. Figure 7 shows the P10, P50 and P90 values of the modeled process durations. It illustrates clearly that the process drilling hole of Section 2 and 3 has the highest variability and duration.

Single Well Cost Estimation

In analogy to the time vs. depth curve discussed above, the simulation results can be displayed in a drilling cost vs. depth curve (Figure 8). The time-independent costs of each section are displayed at the respective casing setting depths together with the time-dependent costs of the flat time processes.

The costs before spud are displayed at a depth of 0 m and represent the costs for the rig site and rig up. Then the section costs are added up until the final depth is reached. Then costs for completion and testing are added.

Multiwell Cost Estimation

To estimate the total project cost the outcome of all wells have to be added up as discussed above. For this example, two wells have been simulated with a correlation coefficient of 0.6 between them. Figure 9 shows the probability distribution and the cumulative distribution function of the simulated total project costs.

Conclusions

The following main conclusions can be made:

- With the presented approach of well construction modeling, decision makers can evaluate the risk involved in the well construction process. Uncertainties are acknowledged and the variety of expected outcomes can

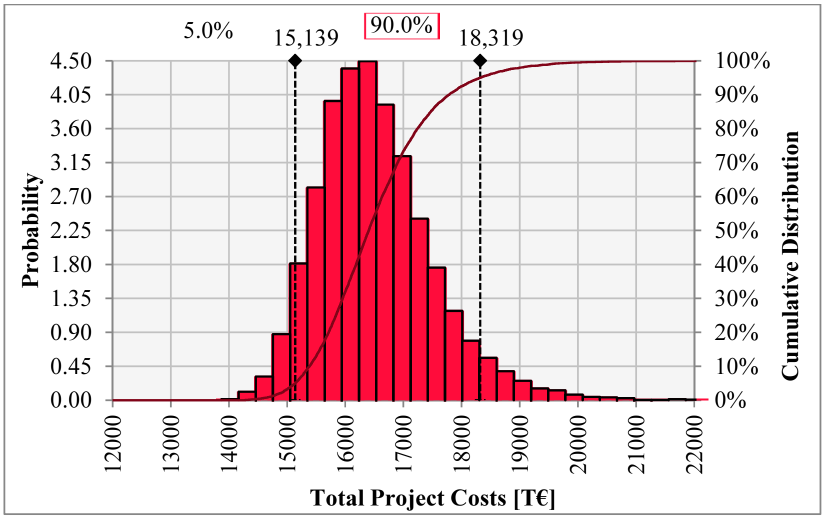

Figure 9. Probability distribution of the total project costs.

be communicated more effectively. The awareness of risks and opportunities is improved.

- Moreover, the normalized technical limit or best historic performance can be used as technical performance goal which is separated from the drilling time used for budget planning. This is the foundation for performance improvement.
- It can also be easily assessed how good the current performance is compared to other wells. This is essential for effective performance management.
- Building a probabilistic model also stimulates the analysis of offset data and the actual operational time and cost data. It also gives the opportunity to perform a sensitivity analysis. Based on the results of the sensitivity analysis, the key driving forces can be identified. Therefore, optimization strategies can be steered into the right direction.

However, there are some key limitations:

- There are several assumptions made which should always be reported in conjunction with the model results.
- The general approach explained in this paper may need some individual adjustments to assess the risk for certain projects. For example, factors like the well path can be considered by limiting the input-data to wells with similar well paths.

Recommendations and Outlook

The model has already been applied for a current project (budgeting and risk assessment) and proved its applicability. However, some improvements should be made in future work:

- This model cannot deliver a high level of detail. To get a better understanding of how input parameters, like tripping speed, effect the output of the model, the data acquisition has to be changed or expanded. Morning reports only give a rough idea about these variables. Automated systems which recognize processes are available on the market (cf. [14]) and should be applied if a higher level of understanding is necessary.
- The influence of parameters like rig capacity or well path is not captured by this model due to limited data. If more data is available in the future the model should be expanded by these input variables.
- The sensitivity analysis showed clearly that DFT and ROP have the highest impact on the model result. Therefore, for drilling optimization, the focus should lie on the investigation of the reasons for high DFT and low ROP. Rig sensor data analysis can be implemented to identify reasons for non-productive time and benchmark the performance of each process (cf. [14]).

Nomenclature

BHA	Bottom Hole Assembly
ROP	Rate of Penetration
DFT	Drilling Flat Time
FIT	Formation Integrity Test
BOP	Blow Out Preventer
NPT	Non-Productive Time
MD	Measured Depth
OBT	On-Bottom Time
WOC	Wait on Cement
Cat 1	Category 1
Cat 2	Category 2

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