Measuring the impact of risk on LCOE (levelized cost of energy) in geothermal technology

Soojin Park[*] , Antony Langat, Kyuhwan Lee and Yongbeum Yoon

*Correspondence:
sugini1144@gmail.com
Department of Energy
Policy and Engineering,
KEPCO International
Nuclear Graduate School,
658-91 Haemaji-ro,
Seosaeng-Myeon, Ulju-gun,
Ulsan 45014, Korea

Abstract

Geothermal technology has a high level of uncertainty and, thus, requires thorough risk analysis for economic decisions. The levelized cost of energy (LCOE) is a basic economic analysis widely used in determining an investment or energy mix. Many reputable institutions and government agencies provide LCOE, to which they apply different levels of discount rates to reflect project risk. To this end, the weighted average cost of capital (WACC) is frequently used as a proxy for project risk-adjusted discount rate. However, whether using a higher discount rate for a riskier project is appropriate in calculating LCOE has not been scrutinized. The purpose of this paper is to propose a certainty equivalent method of LCOE as an alternative way for considering risk. We present a theoretical background and formula based on the utility theory, improving the probabilistic LCOE estimation methodology of previous studies. We also perform scenario analysis to show how the certainty equivalent model changes LCOE reflecting different level of risk of the individual variables, which traditional LCOE does not. Additionally, we suggest that the traditional LCOE should be used prudently, recognizing it can distort the result when an individual project has a different level of risk from the industry average.

Keywords: Geothermal technology, Levelized cost of energy, Certainty equivalent, Weighted average cost of capital (WACC), Monte Carlo simulation, Project valuation

Introduction

Geothermal technology is a renewable energy source that is the best substitute for those regions with considerable volcanic storage underground, and it is not dependent on the weather. This resource can be exploited from underneath the earth's surface reservoirs, containing high-temperature rocks saturated with hot brine or steam by drilling wells of approximately two kilometers below the earth's surface (Regenspurg and Schäfer 2017). The hot water and steam are then extracted from the underground reservoirs using pipes up to a geothermal power plant, where they are used to drive turbines coupled to electric generators to produce electricity. An enhanced geothermal system (EGS) was successfully realized by Los Alamos Scientific Laboratory (LASL) and European Projects based at Soultz-sous-Forêts. The Geodynamics plant in Habanero began to operate on a

large scale as a commercial EGS plant (Olasolo et al. 2016). The EGS involves a creation of reservoir, where there is hot rock, in order to increase permeability and extract the resulting steam to power a turbine: fluid is injected into the subsurface to cause fractures open and thus to increase permeability, which allows the fluid to circulate throughout the fractured rock and to transport heat to the surface where electricity can be generated (EERE 2012a).

There are many risks associated with geothermal projects that currently deter private sector investors from venturing into this energy source (Berman et al. 2018). Surface exploratory and drilling is among the highest risk associated with geothermal (Kolditz et al. 2013). Geothermal well viability is only proven after drilling has been completed. Well output is another risk that can significantly affect projected capital costs required and impact the feasibility of a geothermal power project. Although geothermal technology has a high capacity factor, wells drying out is a risk that prevents the plant from generating the maximum electricity required, affecting the projected revenue (The World Bank et al. 2014). The high level of risk profile in geothermal technology requires a thorough risk analysis and reflection concerning economic analysis.

The levelized cost of energy (LCOE) is often recommended to determine the competitiveness of an energy mix (EIA 2020b). It computes the unit cost of energy from the present value of costs incurred over the lifetime of the plant. Many reputable institutions and government agencies, such as the UK Department for Business and Industrial Strategy (BEIS 2020), U.S. Energy Information Administration (EIA 2021), International Energy Agency (IEA 2020), and International Renewable Energy Agency (IRENA 2020) produce LCOE data. Many of them apply different level of discount rates to reflect the level of project risk, which may be regarded as a surrogate for the Weighted Average Cost of Capital (WACC). For example, the UK Government Department for Business applies a discount rate of 8.9% for offshore wind projects and 7.8% for gas turbine projects, which are in agreement with the range for the cost of capital estimated by the Competition and Market Authority for integrated generation companies (Aldersey-Williams and Rubert 2019). The U.S. Energy Information Administration calculated LCOE values by applying the real WACC of 4.3%, which corresponds to 6.6% of the after-tax nominal rate for plants entering services in 2025 (EIA 2020b). The International Renewable Energy Agency applied a 7.5% discount rate for OECD countries and China, and 10% elsewhere (IRENA 2019).

However, whether using a higher WACC for a risky project is appropriate in calculating LCOE is not fully understood. For example, Manzhos (2013) argued that the most appropriate rate to use in comparing technologies is the risk-free rate. Further criticism may be raised based on Beedles (1978) and Lewellen et al. (1977). They showed that a lower discount rate should be used for riskier projects if the cash flow is negative.

Damodaran (2006) explains, "When cash flows are negative, using a higher discount rate will have the perverse impact of reducing their present value and perhaps increasing the aggregate value of the asset". The numerator in the LCOE is the discounted life-cycle cost, which is purely negative cash flow. Thus, we can infer that there may be something wrong if we increase the discount rate for risky projects.

As a result, determining how to reflect project risk properly in the LCOE calculation is among the most important concerns for geothermal technology. The purpose of

this paper is to propose an alternative way to reflect risk in LCOE and to compare the result with traditional methods used in geothermal technology. Instead of the discounting method with WACC, we propose a straightforward way to estimate and incorporate risk into the LCOE via a certainty equivalent method. We apply the probabilistic method with a Monte Carlo simulation to measure the certainty equivalent value of the LCOE. Additionally, we use research-based input data and distributions to draw a realistic LCOE estimation result for geothermal technology.

The rest of this paper contains the following five sections: literature review, research methodology, input data, case analysis, and conclusion.

Literature review

Numerous researchers have studied the weaknesses and technical improvements concerning the LCOE formula. However, few papers have covered the topic of discount rate in the LCOE. One prominent paper focused on the discount rate of the LCOE is Manzhos (2013), who concluded that different rates should be used between borrowing and discount rates in assessing the LCOE. He suggested that a risk-free rate should be used to discount when assessing and comparing different technologies. He assumed the life-cycle project cost to be financed, using a sequence of bonds that pay a principal and accrued interest at the end of the project. He also drew the present value of the future bond payment equation, whose value comprises the numerator part of the LCOE formula. Using this equation, he showed that the interest rate should differ from the discount rate to avoid the LCOE equation being independent of the interest rate. Further, he showed that the interest rate should become a risk-free rate based on the arbitrage transaction process. His approach increases the future value (in absolute terms) of the life-cycle cost proportional to the interest rate, which reflects the level of project risk. The absolute values of risky cash flows are evaluated as being larger, because the cost is negative cash flow. Therefore, it yields a similar outcome with the certainty equivalent cash flow method, reflecting the project risk directly to the corresponding cash flows.

Sklar-Chik et al. (2016) argued that the traditional LCOE does not consider inflation. Including inflation may produce contrary results between different energy technologies, resulting from different types of expenditures.

Other relevant research on the discount rate of the LCOE includes Aldersey and Rubert (2019). They sought a theoretical foundation of LCOE by comparing the alternative costs of energy metrics. The LCOE weaknesses centered on the discount rate, inflation effects, and sensitivity of results to uncertainty in future commodity costs. The authors maintained that the HM Government Department for Business used the 'hurdle rate', which may have skewed the LCOE estimation due to an inappropriate reflection of individual projects' risk in a particular way. They suggested applying a higher discount rate to gas turbines, considering the high level of historical commodity price volatility. Conversely, a lower discount rate should be applied to wind power due to technological stabilization. They also provided a comparison of the LCOE estimation results between traditional and probabilistic methods, concluding that the latter could offer a richer analysis with which to compare technologies. However, the authors did not propose an alternative way to determine an optimal discount rate, reflecting an individual project's risk or another framework to consider project risk, rather than risk-based discounting.

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Other streams of research introduced a probabilistic approach, using a Monte Carlo simulation to calculate the LCOE using a specific distribution of input variables and estimating the most probable value or statistical range of the LCOE under a pre-determined confidence level.

Geissmann and Ponta (2017) utilized a probabilistic model that accounts for endogenous input parameters. A Monte Carlo simulation showed that a correlation between input parameters had a significant effect on the outcome. The authors also discussed the role of hyperbolic discounting options, in which time preference rates decrease over time. However, the authors simply applied 8.25% of WACC for nuclear power and 7% for gas turbines during the whole project period.

In another paper, Tran and Smith (2018) proposed incorporating the carbon price into the traditional LCOE formula to address emission penalties. A Monte Carlo method can be utilized to perform global sensitivity analysis, which comprises four steps: interpreting distributions of input variables, generating random values based on the distributions, computing the LCOE with the input values, and aggregating the LCOE result. The discount rate in their study was part of the stochastic model and assumed a range of 3% to 10%. Their study is meaningful in that it considered a carbon price in the LCOE comparison via a probabilistic Monte Carlo approach.

Lee and Ahn (2020) also applied a stochastic approach to estimate the LCOE for solar photovoltaic (PV) in South Korea. They tried to derive a realistic analysis result by using actual data generated from solar PV projects. They also treated the discount rate itself as a variable with a 4.5–7.5% range of triangular distribution. They suggested that the discount rate was the second most critical factor, accounting for 18% of the variance in the LCOE estimation.

In the present article, we introduce a different perspective of economic theory to reflect project risk, directly corresponding to costs in calculating the LCOE, which may contribute a step forward from the previous researches. However, our probabilistic methodology of estimating risk equivalent LCOE derives from the previous researches.

Research methodology

First, we review theories to propose an alternative way to reflect project risk in the LCOE formula. We calculate the LCOE of geothermal technology both with traditional formula and alternative certanty equivalent model based on the same data. The former is a deterministic model using a risk-adjusted discounting approach; the latter is probabilistic and reflects risk directly to the expected cash flow(cost) of the LCOE. Next, we conduct a simulation analysis based on the variation in the risk level of critical variables based on the certanty equivalent LCOE model. We compare the simulation result to that of a traditional LCOE to draw implications.

Theoretical background
Risk-adjusted discount LCOE (LCOE$_{RAD}$)

Although there is much variation in the LCOE equation, a highly representative metric may be:

$$\mathrm{LCOE_{RAD}} = \left(\sum_{t=1}^{n} \frac{(C_t + O_t + V_t)}{(1 + R_{RAD})^t} \right) / \left(\sum_{t=1}^{n} \frac{E_t}{(1 + R_{RAD})^t} \right), \tag{1}$$

where t is the timing of cost or energy generation of the project's duration of n; C_t is the capital and decommissioning cost in period t; O_t is the fixed operating cost in period t; V_t is the variable operating cost in period t; E_t is the energy generated in period t; R_{RAD} is the risk-adjusted discount rate. This formula considers costs over the life of a project, deriving a lifetime cost per unit of energy (Aldersey-Williams and Rubert 2019).

We name the traditional LCOE Eq. (1) as 'LCOE$_{\mathrm{RAD}}$' and discount rate R as 'R_{RAD}' to distinguish them from the alternative model. We calculate the LCOE$_{\mathrm{RAD}}$ of geothermal technology case based on Eq. (1).

A risk-adjusted discount rate (R_{RAD}) is needed to derive the LCOE$_{\mathrm{RAD}}$, which is traditionally set as weighted average cost of capital (WACC) from comparable projects or industry averages as Eq. (2) (Bruner et al. 1998; Brotherson et al. 2013):

$$\mathrm{WACC} = W_\mathrm{d} \times K_\mathrm{d} \times (1 - t) + W_\mathrm{e} \times K_\mathrm{e}, \tag{2}$$

where W_d = weight of debt as percentage of total capital, W_e = weight of equity as percentage of total capital, K_d = cost of debt, K_e = cost of equity, and t = marginal tax rate

And again, we choose CAPM for estimating the cost of equity (K_e) as Eq. (3):

$$K_\mathrm{e} = R_\mathrm{f} + \mathrm{EMRP} \times \beta_\mathrm{e}, \tag{3}$$

where R_f = risk-free rate, EMRP = expected market risk premium, and β_e = equity beta.

Conceptually, Eq. (3) includes time value discounting (R_f) and risk discounting portion (EMRP $\times \beta_\mathrm{e}$) and it comprises the WACC together with cost of debt (K_d) in Eq. (2). Basically the equity beta should be (β_e) consistent with the systematic risk of free cash flow to shareholder (or expected dividend): in practice, proxy-beta, measured from similar companies or industry, is used. In the same context, the WACC is designed to discount free cash flow to the firm (FCFF) that belongs to both lender and shareholders. The principle is clear: discount rate should match with numerator in terms of degree of risk.

However, the WACC can barely be used for discounting life-cycle cost ($C_t + O_t + V_t$) in LCOE because the systematic risk of life-cycle cost is not consistent with that of after-tax operating cash flow. In the same context, it is awkward to discount generated energy (E_t). For example, if a degree of financial leverage increases, levered equity beta in Eq. (3) increases, resulting in higher cost of equity (Hamada 1972). Of course, as the weight of equity and debt changes, the WACC will be changed, too. However, the change in financial leverage has little connection with the degree of risk in life-cycle cost ($C_t + O_t + V_t$) or generated energy (E_t). Another problem lies in applying WACC for discounting purely negative cash flows ($C_t + O_t + V_t$) in the LCOE numerator. In this case, it does not always lead to the right decision (Zhang, 2010): if we apply higher discount rate to cost (negative cash flow) that has higher risk, the absolute value of cost shrinks more and thus the cost becomes more favorable. Anyway, we apply benchmarking discount rates of geothermal technology to provide the LCOE$_{\mathrm{RAD}}$ for comparison and sensitivity purpose.

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Certainty equivalent LCOE (LCOECE)

Another way of considering risk is to use a certainty equivalent and discounting with a risk-free rate. Previous studies on certainty equivalent theory are works by Hennessy and Lapan (2006), Eeckhoudt et al. (1996), Gollier and Pratt (1996), Kimball (1993), Becker and Sarin (1987), and Gordon (1986). The definition of certainty equivalent is "a guaranteed cash flow that we would accept instead of an uncertain cash flow" (Damodaran 2012). The concept of the certainty equivalent model stems from the expected utility theory. And the 'Fourfold Pattern' theory also explains people fear of loss (risk-averse) and tend to accept a less favorable settlement than the expected value when losses are expected with a low level of probability (Kahneman et al. 2011). It is consistent with the reason that people pay more for insurance or construction bonds than for an expected loss. Risk-averse people would accept a lower value of the certainty equivalent than the expected value from a given set of uncertain cash flows. The difference between the expected value and certainty equivalent equals the risk premium that risk-averse people are willing to pay to eliminate a given set of uncertainty.

Conceptually, the relationship between risk-adjusted discount, where CAPM is used, and the certainty equivalent model can be shown with one-year valuation example as below:

$$E(V) = \frac{E(\mathrm{CF}_1)}{1 + [R_\mathrm{f} + (E(R_\mathrm{m}) - R_\mathrm{f})\beta]} = \frac{E(\mathrm{CF}_1) - E(V)(E(R_\mathrm{m}) - R_\mathrm{f})\beta}{1 + R_\mathrm{f}} = \frac{\mathrm{CE}(\mathrm{CF}_1)}{1 + R_\mathrm{f}},$$

(4)

where $E(\mathrm{CF}_1)$ is an expected cash flow at year one, R_f is a risk-free rate, $E(R_\mathrm{m})$ is an expected market return, β is a systematic risk, and $\mathrm{CE}(\mathrm{CF}_1)$ is a certainty equivalent of CF_1.

In Eq. (4), the $E(V)(E(R_\mathrm{m}) - R_\mathrm{f})\beta$ is a risk premium (RP) that investor is willing to sacrifice to get rid of the uncertainty. So, the certainty equivalent can be expressed as an expected cash flow ($E(\mathrm{CF}_1)$) minus risk premium (RP). As a matter of course, the risk premium (RP) changes in different times of cash flows due to a compounding effect.

Applying Eq. (4), we can conceptually define the certainty equivalent LCOE ($\mathrm{LCOE_{CE}}$) equation as follows:

$$\mathrm{LCOE_{CE}} = \left(\sum_{t=1}^{n} \frac{E(C_t + O_t + V_t) + \mathrm{RP}(C_t + O_t + V_t)}{(1 + R_\mathrm{f})^t} \right) \bigg/ \left(\sum_{t=1}^{n} \frac{E(E_t) - \mathrm{RP}(E_t)}{(1 + R_\mathrm{f})^t} \right)$$
$$= \left(\sum_{t=1}^{n} \frac{\mathrm{CE}(C_t + O_t + V_t)}{(1 + R_\mathrm{f})^t} \right) \bigg/ \left(\sum_{t=1}^{n} \frac{\mathrm{CE}(E_t)}{(1 + R_\mathrm{f})^t} \right).$$

(5)

In Eq. (5), the C_t, O_t, V_t, E_t are no more constant numbers, but variables that have uncertainty. And so, the risk premiums of all variables are deducted to achieve the certainty equivalents. A noteworthy point is the numerator part, which comprises costs ($C_t + O_t + V_t$). They are negative cash flows, and thus the absolute value increase when we deduct risk premium. However, the quantity of energy generated (E_t) in denominator portion decreases in value when risk premium is deducted.

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For the purpose of estimating the LCOE_{CE} in Eq. (5), we will apply a probabilistic approach based on Monte Carlo simulation because a mathematical calculation may incur several problems. First of all, the mathematical approach needs an assumption of independency among the risk premiums in variables (C_t, O_t, V_t, E_t). Second, we need to know the value of LCOE_{CE} to calculate the risk premium (RP), which brings a circular problem. Third, we cannot get systematic risk (β) for individual variables (C_t, O_t, V_t, E_t). On the other hand, the probabilistic approach with Monte Carlo simulation can provide a practical solution to calculate the certainty equivalent value as well as risk premium under a statistical reliance level.

As there exists no 'completely certain future value' in the real world, we use a quasi-certainty equivalent. In this paper, we define a certainty equivalent as 'the maximum critical value that cumulative probability under which point does not exceed a pre-determined criterion (α%)' as illustrated in Fig. 1. From the positive point of view, it also means the maximum critical value that we can suggest a mean value with $(1 - \alpha\%)$ of confidence level. A certainty equivalent of cost locates below the expected value, and thus it is the sum of expected value and risk premium in absolute numbers, which relation is shown in Eq. (5).

Let us define a sample space Ω of cost (C_t), represented by a set of $\mathbb{R}$. Assuming the C_t be a probabilistic variable, we put a cumulative distribution function (CDF) of C_t as follows:

$$F(x) = \int_{-\infty}^{x} pC_t dC_t = P(C_t \leq x), \tag{6}$$

where $F: \Omega[0,1]$, $x \in \mathbb{R}$, and P is the corresponding CDF. In any case, the $\alpha < 50\%$ condition should be met to keep the assumption of risk averseness.
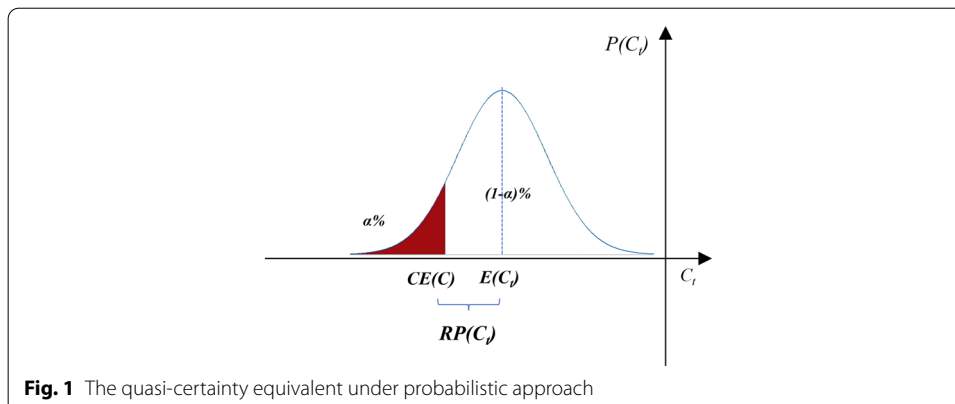
As a result, we can obtain the $\text{CE}(C_t)$ and $\text{RP}(C_t)$ formula under $(1-\alpha)\%$ of confidence level and $\alpha < 50\%$ condition as follows:

$$\text{CE}_{(1-\alpha)}(C_t) = -F^{-1}(\alpha), \tag{7}$$

$$\text{RP}_{(1-\alpha)}(C_t) = -F^{-1}(\alpha) - E(C_t). \tag{8}$$

The certainty equivalents of O_t, V_t will be measured in similar way to Eq. (7).

However, that of E_t should be in positive domain as follows:

Fig. 1 The quasi-certainty equivalent under probabilistic approach

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$$CE_{(1-\alpha)}(E_t) = G^{-1}(\alpha), \tag{9}$$

where $G(z) = P(E_t \leq z)$, G: $\Omega[0,1]$, $z \in \mathbb{R}$, and P is the corresponding CDF.

Equation (9) can be conceptually explained with the expected utility theory, too. Let a von Neumann–Morgenstern expected utility function $U : \Pi \rightarrow R$ be given as n cases of wealth (w_i) and assigned probability ($p_i \in \Pi$). The expected utility of wealth can be expressed as $E(U(w)) = \sum_{i=1}^{N} p_i U(w_i)$ and the utility of expected wealth be expressed as $U(E(w)) = U(\sum_{i=1}^{N} p_i w_i)$. Based on Jensen's inequality, a risk-averse person will have a preference as follows:

$$E(U(w)) < U(E(w)). \tag{10}$$

And this utility theory can be applied to express the certainty equivalent LCOE ($LCOE_{CE}$) as Eq. (11).

$$U(LCOE_{CE}) = E(U(LCOE)) \text{ or } LCOE_{CE} = U^{-1}[E(U(LCOE))]. \tag{11}$$

$LCOE_{CE}$ estimation and simulation

The estimation process is similar to that of previous researchers using probabilistic approaches. For applications involving multiple risk factors that affect the LCOE with non-normality, it is necessary first to define the dynamics of the fundamental process, which is made using the EXCEL software. Second, the distribution data of input variables in geothermal technology are determined based on historical data. Third, N sample paths are generated following the combined distribution of multiple variables with integrated probability. Finally, following the generated sample paths and hypothesized distribution function of variables, the value of the LCOE distribution function with the assigned probability is generated. We used the @RISK, which is a software tool for the Monte Carlo simulation process in drawing the LCOE distribution (Palisade 2021).

And we use a risk-free rate to discount both cost and quantity of energy because risk factors are directly incorporated in the cash flows. We also propose $LCOE_{CE}$ value different from previous researches which suggested the most probable value ($E(LCOE)$) as a result.

Input data

For the empirical analysis, we researched technical input data, assuming a geothermal plant that has a 50 MW system size, double flash type technology steam, and 25 years of economic life (IRENA 2018). The operational environment is also defined as a region with steam temperatures above 180 degrees centigrade. Life-cycle costs are categorized into capital expenditure, and operations and maintenance (O&M) costs. The main risks associated with geothermal energy are exploration, resource sustainability, financing, completion date, operational, offtake, price, and political considerations. These risks lead to uncertainty in the LCOE of the geothermal plant (Magnus and Victor 2012).

We gather technical geothermal data mainly from the three sources: International Renewable Energy Agency (IRENA 2018), U.S. Energy Information Administration (EIA 2019, 2021), Energy Sector Management Assistance Program (Magnus and Victor 2012). All monetary values are converted into real prices as of 2018 (CoinNews 2020). We

researched the mean value as well as the distributions of the major input data. The mean value is used to calculate $LCOE_{RAD}$, and the distribution is used for the Monte Carlo Simulation in estimating $LCOE_{CE}$.

The capital expenditure includes not only construction costs, but also development expenses incurred during the initial stage. A geothermal project requires high initial capital expenditures such as exploration, well drilling, infrastructure to build a power plant, and steam field development. Based on the collected data, the mean value of capital expenditure is 3729 USD/KW and ranges from 2000 to 5872 USD/KW. We selected a PERT (Project Evaluation and Review Technique) distribution for the capital expenditure because it can provide approximated 'feasible' minimum and maximum range of cost distribution with percentiles based on our collection of historical data (Clark 1962). The PERT distribution can identify the most likely value and closely resembles a realistic probability distribution, which also fits closely with normal or lognormal distributions.

The O&M involves costs to run and maintain a geothermal plant and the steam fields that ensure the highest capacity factor possible. The O&M costs also include broken or old equipment replacement, steam pipeline service, and replacement of nonproductive wells. However, geothermal technology rarely requires fuel cost and, thus, variable O&M costs are assumed to be negligible. The O&M costs vary among sites depending on the chemical structure of steam and brine as the geothermal fluid can be acidic and has the potential to corrode equipment. From the collected data, the mean value of annual O&M cost is approximately 129 USD/KW, and it varies from 75 to 224 USD/KW. The PERT distribution is also applied to O&M costs.

The capacity factor is the actual operating capacity recorded over the duration of project time compared against the designed capacity of a unit at its maximum operation. We pick 90% of the average initial capacity factor with 0.5% of annual degradation, which caters to the reduction in steam output. The initial capacity factor ranges from 85 to 92%. The distribution range is narrow, and we would like to place greater trust on the mean value; therefore, we assign a TRIANGLE distribution for the capacity factor.

A geothermal project requires extensive upfront costs in the early stages of the project before project viability can be confirmed. This uncertainty of the upstream process is the reason investors request steep returns as a countermeasure against the risk involved. We have selected 5.4% of real WACC as a reference discount rate based on the study of US Energy Information Administration (EIA 2021). This WACC is used in calculating the $LCOE_{RAD}$.
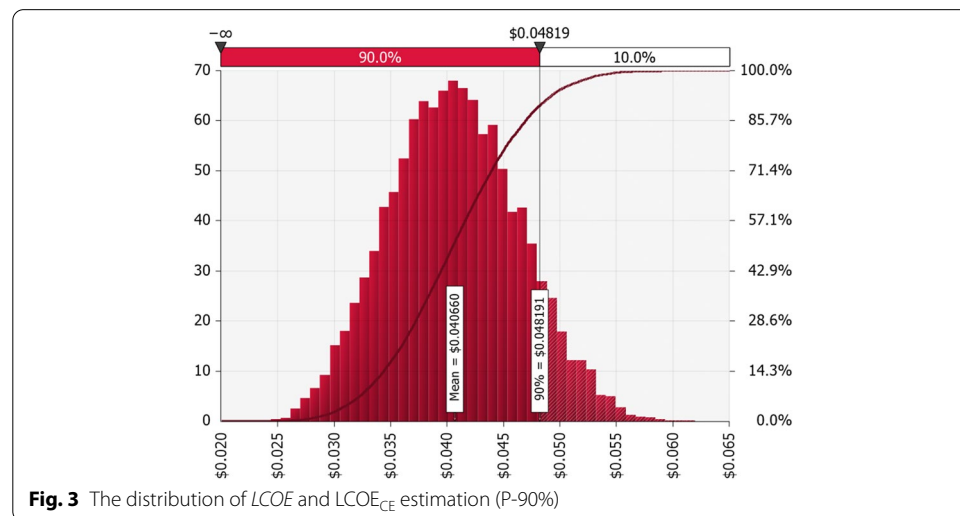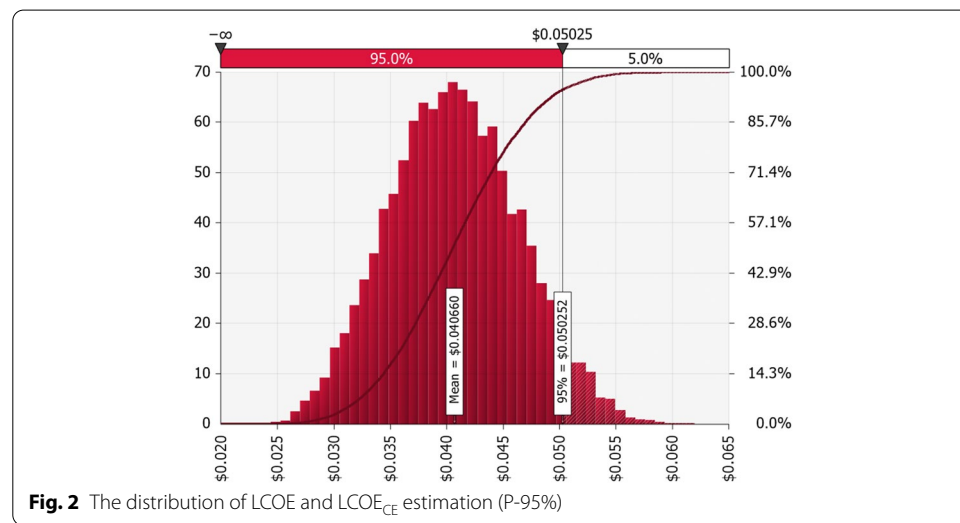
The estimation result
LCOE estimation
The $LCOE_{RAD}$ is estimated at 5.18 ¢/KW based on Eq. (1) and the mean input values of Table 1. The 5.4% of WACC is used in calculating $LCOE_{RAD}$. The system size of the geothermal case is assumed as 50 MW.

On the other hand, we performed Monte Carlo simulation with the input distributions of Table 1 on top of the non-linear LCOE model to establish the probabilistic distribution of LCOE, which is defined by Eqs. (7) and (9). We used 0.609% of real based risk-free rate, which is the average of the 20-year real Treasury Yield of United States from 2011 to 2020 (US Department of the Treasury 2021). The result is illustrated as follows.

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Table 1 Summary of input variables

Input variables	Mean value	Range (standard deviation)	Distribution	References
Capital expenditure (USD/KW)	3,729	2000–5872 (0.00749)	PERT	EERE (2012b), EIA (2019), IRENA (2019), Magnus and Victor (2012)
Annual O&M cost (USD/KW)	129	75–224 (0.00735)	PERT	EERE (2012b), EIA (2019), IRENA (2019), Magnus and Victor (2012)
Capacity factor (%)	N	85–92 (0.00742)	TRIANGLE	EIA (2020a), IRENA (2017)
WACC (in real, %)	5.4	N/A	N/A	EIA (2021)
Risk-free rate (in real, %)	0.609	N/A	N/A	US Treasury (2021)

Fig. 2 The distribution of LCOE and LCOE$_{CE}$ estimation (P-95%)

Fig. 3 The distribution of *LCOE* and LCOE$_{CE}$ estimation (P-90%)

Figures 2 and 3 are expressed in a reverse way to Fig. 1 because the cost is entered as a positive number following the general industry practice. The most likely LCOE point
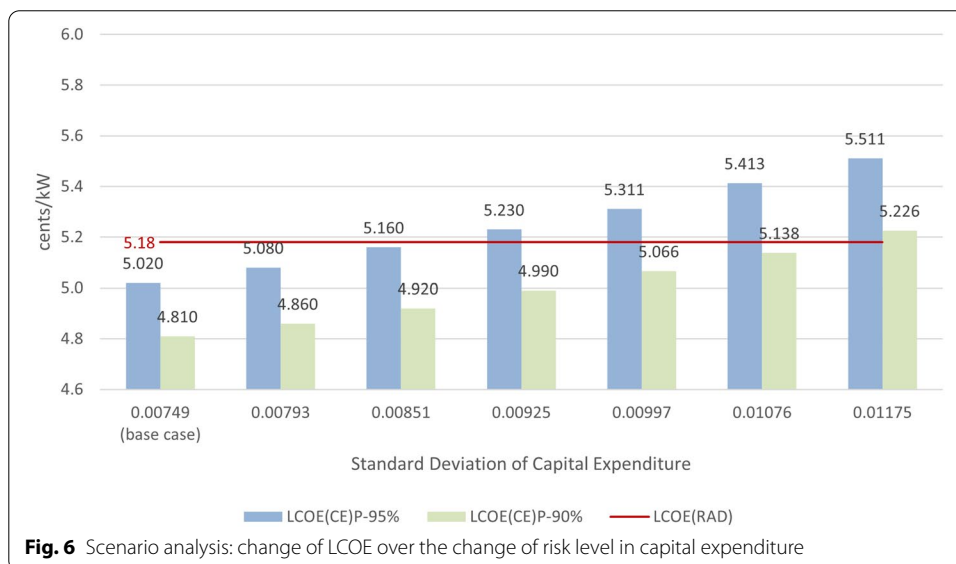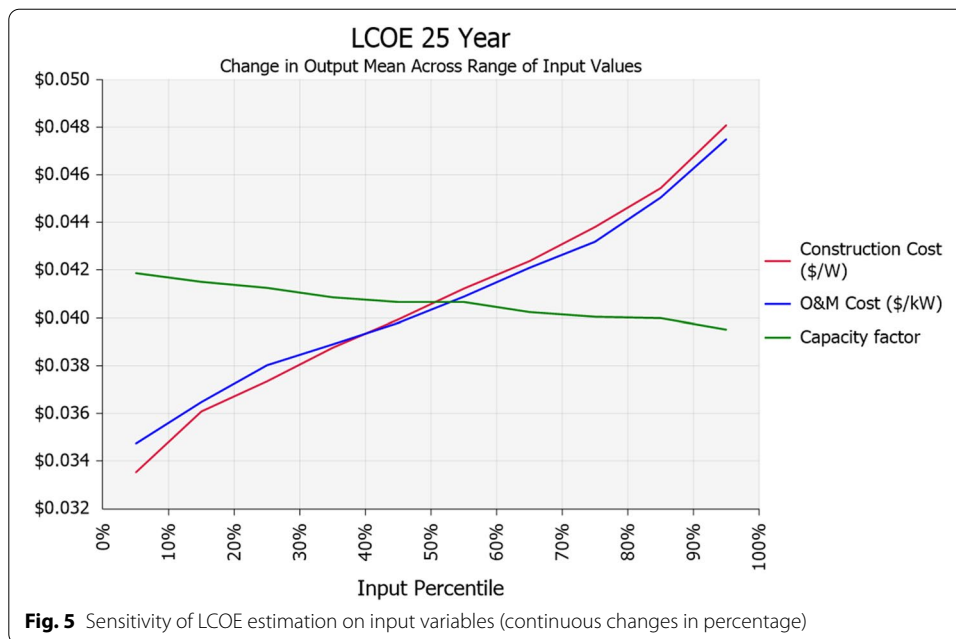
estimation value, not reflecting risk, is estimated at 4.06 ¢/KW. However, the CE values from the above distribution are selected following Eqs. (7) and (9) with 90% and 95% confidence levels, both of which meet risk-averse conditions ($\alpha < 50\%$): the $LCOE_{CE}$ are estimated at 4.81 ¢/KW under 90% confidence level (P-90%), and 5.02 ¢/KW under 95% of confidence level (P-95%). The result implies that people with higher risk averseness will accept a higher risk premium and thus, the absolute value of CE in LCOE becomes larger, which is the 95% of confidence level case in Fig. 2. In other words, a risk-averse person tends to evaluate an uncertain cost as being larger than others.

After the Monte Carlo simulation, we performed sensitivity analysis of the LCOE estimation result on major input variables, which result is illustrated in Fig. 4. We found that construction cost variable has the greatest impact on the LCOE value followed by the operation cost and capacity factor. The blue bars indicate positive proportional impacts between independent (input) and dependent (LCOE) variables, and the red bars mean the vice versa. Figure 4 shows that capital expenditure and O&M cost are positively correlated with LCOE, while the capacity factor is negatively correlated. Based on the most likely estimation value of 4.06 ¢/KW, if the capital expenditure increases one sigma, the LCOE value will increase 0.74 ¢/KW, whereas if the capital expenditure decreases one sigma the LCOE value will decrease 0.71 ¢/KW. When the O&M cost increases one sigma the LCOE value will increase 0.69 ¢/KW, whereas if the O&M cost decreases one sigma, the LCOE value will decrease 0.59 ¢/KW. In the case where the capacity factor increases one sigma the LCOE value will decrease 0.11¢/KW, whereas if the capacity factor decreases one sigma the LCOE value will increase by 0.12 ¢/KW. Figure 5 also shows the sensitivity of LCOE to the continuous changes in percentage.

Scenario analysis

We selected the three analysis variables based on the impact to LCOE, which is illustrated in Fig. 4. And we created four scenarios by changing the degree of risk in three major variables: capital expenditure, O&M cost, initial capacity factor, and all the three

Fig. 4 Sensitivity of LCOE estimation on input variables (change in sigma)

Fig. 5 Sensitivity of LCOE estimation on input variables (continuous changes in percentage)

Fig. 6 Scenario analysis: change of LCOE over the change of risk level in capital expenditure
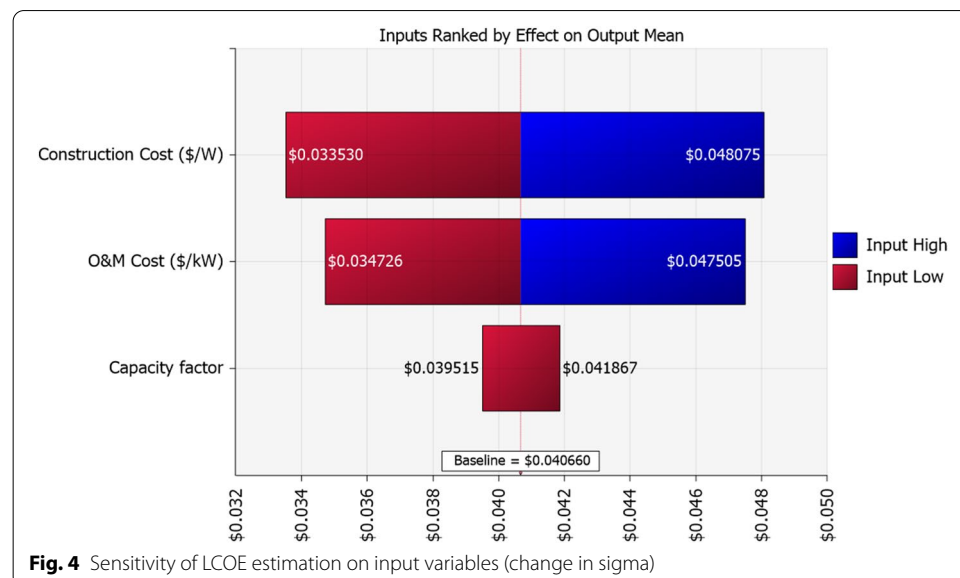
variables together. A statistical distribution method is used based on probability of 95% (5% one-sided tail) and 90% (10% one-sided tail), respectively.

The first scenario analysis is to increase the level of risk in capital expenditure, assuming all other conditions being equal. The purpose of the analysis is to test how the $LCOE_{CE}$ changes due to the change of standard deviation in the capital expenditure ($\partial LCOE_{CE}/\partial \sigma (CaPex)$).

As is expected, the $LCOE_{CE}$ increases as the standard deviation of capital expenditures increase both in 90% and 95% confidence levels, as illustrated in Fig. 6. The Y-axis represents ¢/KW, and the X-axis represents the standard deviation of the capital expenditure. At the base point, where the standard deviation ($\partial LCOE_{CE}$) is 0.00749, the $LCOE_{CE}$

(P-95%) is 5.02 ¢/KW, which is lower than the 5.18 ¢/KW of $LCOE_{RAD}$. However, it exceeds the $LCOE_{RAD}$ to become 5.51 ¢/KW when the standard deviation of capital expenditure reaches at 0.01175. The $LCOE_{CE}$ (P-90%) exceeds $LCOE_{RAD}$, too.

However, the $LCOE_{RAD}$ does not change in proportion to the increasing volatility of input variables because the mean values of input variables remain the same. If we were able to measure the accurate WACC, reflecting the increased risk of capital expenditure, we could have applied a revised WACC and obtained a similar result to $LCOE_{CE}$ theoretically. However, it is difficult to adjust in response to the change of specific risk factors because a benchmarking WACC is used. It also remains doubtful whether the increase in WACC accurately reflects the impact of project risk for the LCOE.

The second scenario analysis is to change the degree of risk in O&M costs, assuming all other things being equal. Through this analysis, we test how the change of standard deviation in the O&M costs ($\partial LCOE_{CE}/\partial\sigma$(O&M)) effect on the $LCOE_{CE}$.

Similar to the first scenario, $LCOE_{CE}$ increases as the standard deviation of O&M costs increase at both 90% and 95% confidence levels, as illustrated in Fig. 7. At the base case, the standard deviation is 0.00735, and $LCOE_{CE}$ (P-95%) is 5.02 ¢/KW. However, when the standard deviation of O&N costs rises to 0.0108, the $LCOE_{CE}$ (P-95%) goes over $LCOE_{RAD}$ and becomes 5.85 ¢/KW. The $LCOE_{CE}$ (P-90%) of 5.49 ¢/KW exceeds $LCOE_{RAD}$, too.

The third scenario analysis is to change the risk level in capacity factor, assuming all other things being equal. We test how the change in standard deviation in the capacity factor ($\partial LCOE_{CE}/\partial\sigma$(CaP)) affects $LCOE_{CE}$.

Likewise, $LCOE_{CE}$ increases as the standard deviation of capacity factor increases at both 90% and 95% confidence levels, as illustrated in Fig. 8. In the base case, the standard deviation is 0.00742, and $LCOE_{CE}$ (P-95%) is 5.02 ¢/KW. However, when the standard deviation of the capacity factor rises to 0.00837, $LCOE_{CE}$ (P-95%) approaches 5.316 ¢/KW. $LCOE_{CE}$ (P-90%) does not exceed $LCOE_{RAD}$ within our scenario.
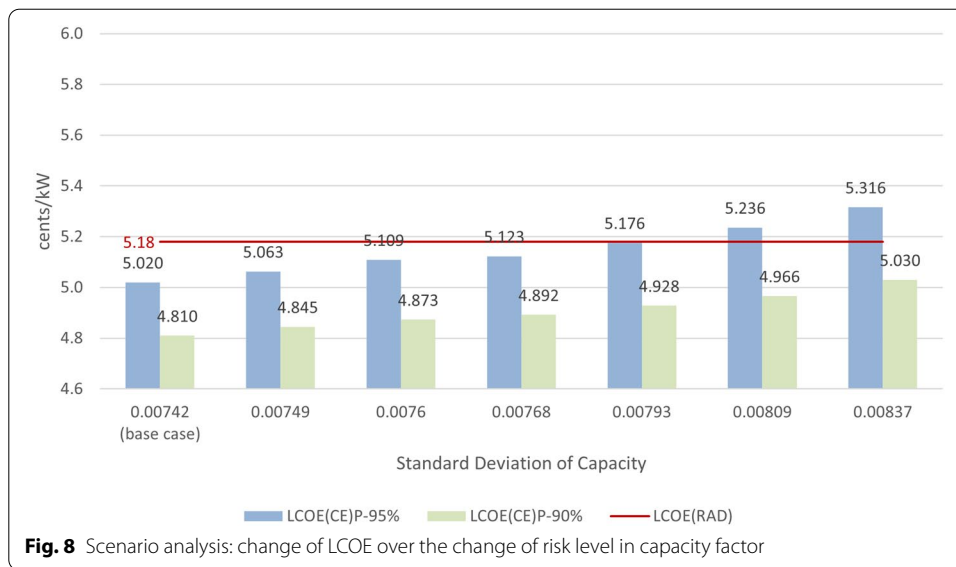

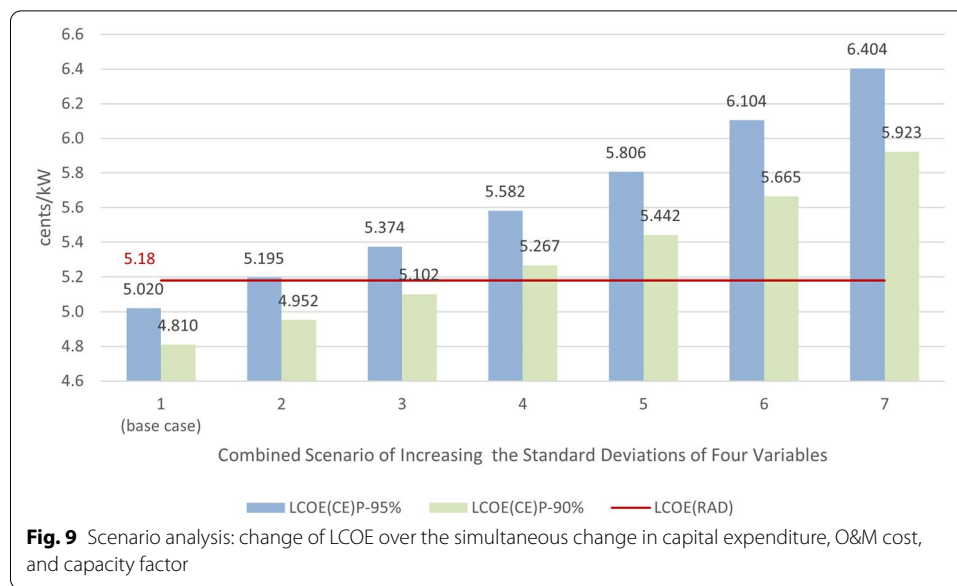**Fig. 7** Scenario analysis: change of LCOE over the change of risk level in O&M cost
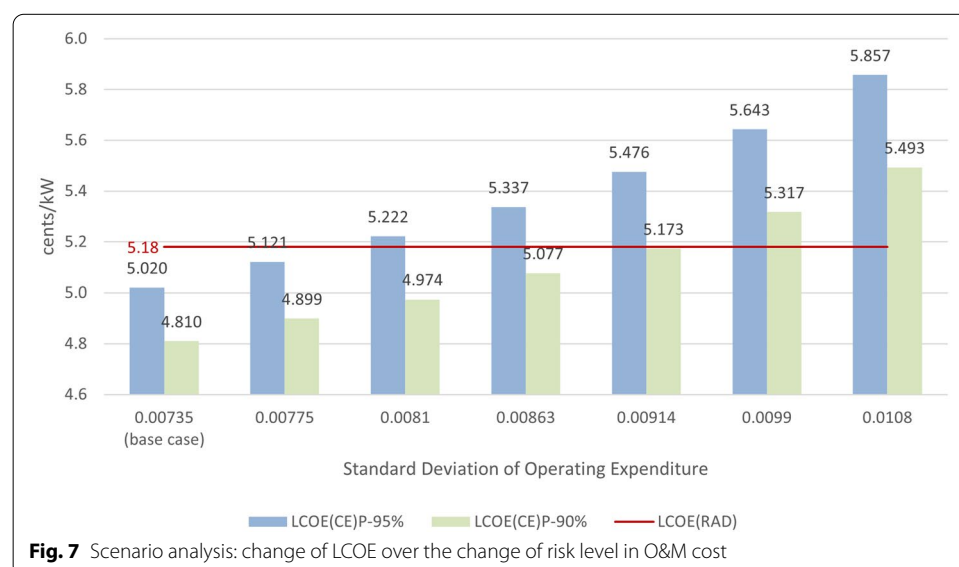
Fig. 8 Scenario analysis: change of LCOE over the change of risk level in capacity factor

Table 2 The change of LCOE over the simultaneous change of risk in three factors

Scenario	Standard deviation of capital expenditure			LCOE$_{CE}$ (P-95%) ¢/KW	LCOE$_{CE}$ (P-90%) ¢/KW
	Capex	O&M	Cap		
1	0.00749	0.00735	0.00742	5.020	4.810
2	0.00793	0.00775	0.00749	5.195	4.952
3	0.00851	0.00810	0.00760	5.374	5.102
4	0.00925	0.00863	0.00768	5.582	5.267
5	0.00997	0.00914	0.00793	5.806	5.442
6	0.01076	0.00990	0.00809	6.104	5.665
7	0.01175	0.01080	0.00837	6.404	5.923

Finally, we test how LCOE$_{CE}$ changes by increasing the risk of the three factors simultaneously. When the standard deviation of capital expenditure, O&M, and capacity factor are 0.01175, 0.0108, and 0.00837, respectively, both LCOE$_{CE}$ (P-95%) and LCOE$_{CE}$ (P-90%) far exceed the LCOE$_{RAD}$. As is illustrated in Fig. 9, the slope of LCOE$_{CE}$ lines is steeper than those of the previous graphs. We infer that the combination of individual risk enlarges the total project risk, increasing the LCOE$_{CE}$ faster. However, LCOE$_{RAD}$ remains at the same level due to the constant level of mean value in all three factors (Table 2).

Discussion

From the scenario analysis, we can see LCOE$_{RAD}$ does not change, although the uncertainty of the individual input variable increases. The LCOE$_{RAD}$ is estimated to be larger than the LCOE$_{CE}$ (P-95%) by 0.16 ¢/KW (3.1%) in the base case (scenario 1 from Fig. 9). It could have led underinvestment if a policymaker relied on the LCOE$_{RAD}$. On the other way, a policymaker could have overinvested under the scenario 7 from Fig. 9 if the person relies on the LCOE$_{RAD}$. This analysis shows the limit of LCOE$_{RAD}$, which is based on

Fig. 9 Scenario analysis: change of LCOE over the simultaneous change in capital expenditure, O&M cost, and capacity factor

the deterministic approach. Alternatively, $LCOE_{CE}$ can reflect a different level of risk at a specific input variable.

A more serious problem of $LCOE_{RAD}$ lies in discounting costs with WACC. The LCOE numerator comprises various costs, which is purely negative cash flow. In the case of negative cash flow, a higher WACC for risky projects generates lower present costs in absolute value, which result suggests a favorable option and leads to wrong decision. Thus, using a higher WACC for riskier project may mislead the evaluator.

Most frequently, a WACC is used as a risk-adjusted discount rate for calculating the $LCOE_{RAD}$. But theoretically the WACC is not a proper measure for adjusting the risk of cost $(C_t + O_t + V_t)$ as well as the generated energy (E_t) in LCOE. The WACC is influenced by degree of financial leverage, cost of debt as well as risk-free rate because it is designed to discount free cash flow to a firm (FCFF), which is after-tax and cash-based operating income. However, the risk level of cost $(C_t + O_t + V_t)$ as well as the generated energy (E_t) are not directly affected by either cost of debt or degree of financial leverage. This critique can be shown clear with a simple example. If a public authority develops a project using cheaper capital source such as sovereign bond, the WACC will become lower than that of private developer. It is highly probable, even though not always, the lower WACC causes lower $LCOE_{RAD}$, which result means a project can save LCOE only by changing private developer with public authority in ceteris paribus condition. If it is possible, we could easily enhance social welfare by changing all the private development project into public, which is, of course, not true.

If $LCOE_{RAD}$ is used without caution, it may lead policymakers in the wrong direction in terms of social resource allocation. In the base case from "LCOE estimation". LCOE estimation, where $LCOE_{RAD}$ is higher than $LCOE_{CE}$, policymakers might invest in geothermal technology less than is socially optimal. Alternatively, where $LCOE_{CE}$ should be evaluated higher than $LCOE_{RAD}$ due to a specific risk expected from a target project from "Scenario Analysis", policymakers might invest in geothermal technology more than a social optimum. This possibility will be larger when the target project has either a

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higher or lower level of idiosyncratic risk than the industry average, especially if the geothermal technology has a higher deviation in project-specific risk.

Numerous studies have estimated the LCOE based on the probabilistic approach, using a Monte Carlo simulation. However, the majority estimated the most probable value of the LCOE, which is conceptually the weighted average with an assigned probability. They also applied WACC to reflect project risk. Therefore, these studies are not free from the limit of $LCOE_{RAD,}$ although they use a probabilistic approach. Some studies suggest that the confidence interval for the LCOE is an underestimated distribution. However, they may provide poorer results because the risk is double counted: not only discounted by WACC, but also expressed by a range of confidence levels, reflecting the combined risk of input variables that should have been already included in the WACC.

As Gordon (1986) maintained, the certainty equivalent (CE) approach has several advantages over the risk-adjusted discount rate (RADR) (Sick 1986). First, the CE model allows for a separation of the risk adjustment from the time value discounting process, which can resolve various complex issues. Second, the beta used in the risk-adjusted discount rate method is an aggregate risk measure, which is the average of all cash flows in the firm measured from security-market data. It is not possible to find data for security that represents a pure type of project or a specific item of risk. Third, the multiplicative models using risk-adjusted discount rates are less tractable for changes in specific risk levels.

Conclusion

LCOE estimation is critical in supporting both policymakers and investors in key investment decisions or the determination of the most viable energy mix. However, the traditional method of calculating the LCOE cannot reflect the individual status of risk per variable because it depends on a deterministic method using a WACC. The WACC does not apply a specific level of risk in a target project since it is approximated from comparable projects or industry averages. A serious potential pitfall lies in discounting series of project costs with WACC, which is a risk-embedded discount rate. As a result, making decisions based on the traditional LCOE method may result in a wrong investment due to poor evaluation of individual project risk. We propose the traditional method of LCOE should be used prudently, recognizing it can distort the calculation result more if the target project has a greater discrepancy of risk from the industry average.

We suggest $LCOE_{CE}$ as an alternative LCOE estimation methodology in terms of risk consideration. We showed that this methodology could rationally reflect the risk of the individual input variable through scenario analysis. More importantly, we provide a theoretical background of risk formulation based on the utility theory as well as a probabilistic LCOE estimation methodology.

However, there are several limitations in this paper. First, the certainty equivalent is a theoretical value. Therefore, we introduced a quasi-certainty equivalent and its function with a designated confidence level ($(1 - \alpha)$%). It is not possible to answer what percentage of confidence level is proper to identify the CE value in Eq. (7), which depends on the individual evaluator's risk preference. Second, the dataset used in this study included only the U.S. market and not enough in number. Further research on data is required from different regions that have geothermal resources. The distribution curves used

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are arbitrary to some degree; therefore, more study is required on the appropriate form of the distribution curve. Third, the LCOE$_{CE}$ methodology is cumbersome for practical usage. A realistic set of distribution data on major input variables is necessary and should be processed with a Monte Carlo simulation tool. Additionally, some level of statistical knowledge is required to interpret the result. Finally, we argued that a WACC cannot accurately reflect risk when calculating LCOE based on previous literature, including Beedles (1978), Lewellen (1977), and Damodaran (2006). However, we did not show the relation between discount rate and LCOE value enough. Further study is necessary for this topic.

Abbreviations
EGS: Enhanced geothermal system; LCOE: Levelized cost of energy; WACC: Weighted average cost of capital; U.S. EIA: United States Energy Information Agency; IEA: International Energy Agency; IRENA: International Renewable Energy Agency; LCOE$_{RAD}$: Risk-adjusted discount LCOE; LCOE$_{CE}$: Certainty equivalent LCOE; CAPM: Capital asset pricing model; ∂LCOE$_{CE}$/$\partial\sigma$ (CaPex): LCOE$_{CE}$ changes due to the change of standard deviation in the capital expenditure; ∂LCOE$_{CE}$/$\partial\sigma$ (O&M): Change of LCOE$_{CE}$ due to the change of standard deviation in the O&M cost; ∂LCOE$_{CE}$/$\partial\sigma$ (CaP): Change of LCOE$_{CE}$ due to the change in standard deviation of capacity factor; RADR: Risk-adjusted discount rate.

List of symbols
t: Timing of cost or energy generation of the project's duration of n; C_t: Capital and decommissioning cost in period t; O_t: Fixed operating cost in period t; V_t: Variable operating cost in period t; E_t: Energy generated in period t; R_{RAD}: Risk-adjusted discount rate; $E(CF_1)$: Expected cash flow at year one; R_f: Risk-free rate; $E(R_m)$: Expected market return; β: Systematic risk; $CE(CF_1)$: Certainty equivalent of CF_1; RP: Risk premium; Ω: A sample space of cost (C_t); $\mathbb{R}$: Set of natural numbers; CDF: Cumulative distribution function; O&M: Operations and maintenance; USD/KW: US dollar per kilowatt; ¢/KW: Cents per kilowatt; PERT: Project evaluation and review technique.

Declarations

Competing interests
The authors declare they have no competing interest.

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