

Flexible Design with Real Options for Geothermal Energy

A case study on modular power plant expansion with binary
cycle EGS

MIT Student 2
Massachusetts Institute of Technology
IDS.330: Real Options
May 2021

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Executive Summary

In the state of New Mexico, electricity is generated from a variety of renewable options, including a single commercial geothermal plant to the southwest of the state known as Lightning Dock. This facility operates on a known conventional hydrothermal system associated with a deep normal fault, generating 10MW of electricity after recent capacity upgrades. Geothermal additions to the energy grid fulfill a state mandate for renewable diversification beyond just wind and solar power, so the additional capacity upgrades would have market interest from local utility companies.

This report investigates applying flexibility with real options to the design of a modular geothermal power plant extension at Lightning Dock. The modeled expansion amounts to 5 MW of additional generation from an offset enhanced geothermal system (EGS), targeting hot, dry reservoir rock with small-scale power plant modules. Each module is fully self-contained, comprising a single injector-producer pair connected to a binary cycle generator rated at ~1 MW based on a present-day commercial analog. The initial cost model provides a static assessment of capital expenses, operating and maintenance costs, and income from power sales to determine the net present value (NPV) for a 30-year useful life of the plant expansion. However, deeper consideration of the uncertainties in the subsurface resource, the impact of climate change, and potential disruptions to the electricity market highlight a number of variables that can greatly impact model results depending on the choice of their representative values. To adequately address this, variables are assigned probability functions and randomly sampled many times over in a Monte Carlo simulation to produce an ensemble of NPV estimates.

In addition, three real option decision rules allow the project design to adjust as operating conditions change over time. The first scenario implements well redevelopment in response to degrading subsurface thermal conditions that reduce the productivity of power plant modules. This results in a negative NPV but less downside risk compared to the no-flexibility base case scenario. Adding a decision rule for plant expansion when electricity prices surge effectively captures upside potential, making the ensemble-averaged NPV (ENPV) both positive and attractive. By comparison, adding the option to remove modules during a price downturn lowers ENPV due to the dominant factor of income loss as capacity decreases. An exception is observed when plant reductions are limited to only 10% of existing modules at a time. This preferred model integrates all three flexibilities to achieve the greatest ENPV, upside capture, and downside risk mitigation, with the caveat that module removal in response to downturns must be performed slowly and with care to preserve maximum value for the power plant expansion.

Disclaimer

The work presented here was completed by the author as an academic exercise in partial fulfillment of the requirements for MIT course IDS.330 and is not endorsed by any professional company, organization, or working group. Information included in the models is based on publicly available data. Model inputs were determined from the referenced primary sources or selected as best educated guesses by the author when suitable references could not be identified. Although noted by name due to historical association with Lightning Dock or commercial geothermal products and services, no direct consultation with Cyrq Energy, Turboden, or Climeon on the contents of this report is implied. Conclusions drawn within this report should not be considered a professional recommendation, but simply a hypothetical analysis for the purposes of educational training.

Introduction

Lightning Dock Power Plant

Geothermal power plants capture subsurface heat and convert it to electricity for direct use or as input into the regional power grid. In Animas Valley, New Mexico, the USGS identified a known geothermal resource area (KGRA) called “Lightning Dock” in 1974 that has remained a developing field since that time (Dahal et al., 2012) (Figure 1). The origins of the Lightning Dock thermal anomaly are not fully understood, although hydrothermal fluids are believed to be heated to $\sim 250^{\circ}\text{C}$ by a source at great depth before flowing up the local Animas Valley fault to the shallow subsurface. There, they mix with cooler recharge waters from bordering mountain ranges to form the $150\text{-}170^{\circ}\text{C}$ brine encountered at Lightning Dock (Crowell & Crowell, 2014). The present-day geothermal power plant is owned by Cyrq Energy. Commercial production began in late 2013 at a generating capacity of 4 MW, and a 2018 upgrade by Turboden brought production up to the anticipated 10 MW level (Figure 2) (Bonafin & Dickey, 2019).

Binary Cycle

In order to generate electricity at Lightning Dock, hot water from the producing wells enters a heat exchanger, where it warms a secondary working fluid with a low boiling point before being reinjected into the ground. The secondary fluid (isobutane) converts to steam and moves a turbine before being condensed back to liquid phase and sent back to the

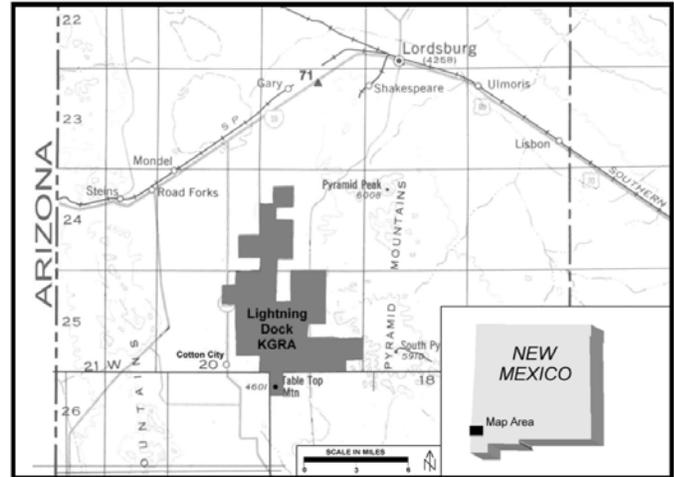


Figure 1: Lightning Dock KGRA location, from (Dahal et al., 2012).



Figure 2: Lightning Dock after Turboden upgrade. Image from www.turboden.com/upload/blocchi/002-24780.jpg
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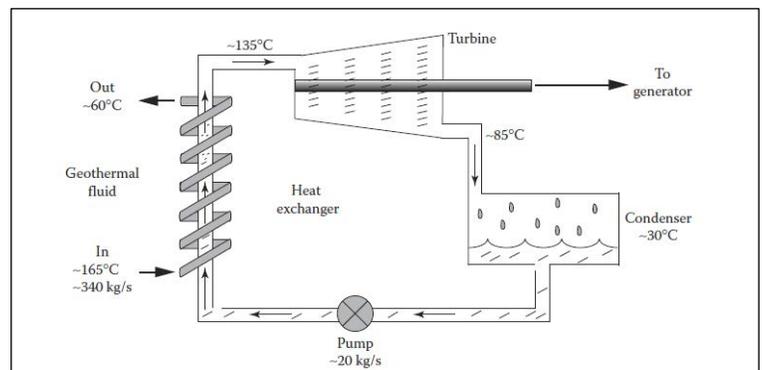


Figure 3: Schematic diagram of a binary cycle power plant, from Figure 10.12 in (Glassley, 2015).

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heat exchanger. This power generation concept, commonly known as a binary cycle or Organic Rankine Cycle (ORC), is efficient for low to medium-temperature fields where recovered fluids are generally less than 180°C (Figure 3) (Glassley, 2015).

Open Loop EGS

Geothermal subsurface loops are composed of injector-producer groupings, most commonly in doublet (1:1) or triplet (1:2) ratios. Wells are separated at depth by a permeable region of fractured rock through which fluid is pumped to capture thermal energy. Heat exchange via direct flow through permeable hot rock makes this an “open loop” arrangement. In conventional geothermal, the natural presence of a heat source, circulating subsurface fluids, and the fractured permeable zone provide a complete system for power plants to access. In Enhanced Geothermal Systems (EGS), one of these three components must be artificially created (Figure 3). For example,

stimulation of the country rock (by hydrofracking) can create the necessary fracture network to support flow between the injection and producing wells at depth. Externally-sourced water pumped down the injection well and into the reservoir can also be used when in situ fluids are missing. As long as a sufficient heat source is present, EGS is technically feasible. At Lightning Dock, the hydrothermal (water-bearing) anomaly is quite local, but the geothermal temperature gradient remains high (80-125°C) for at least several kilometers away from the power plant (Cunniff & Bowers, 2003). To generate electricity away from the Animas Valley Fault, e.g., as an extension to the existing power plant, EGS would be necessary.

Modular Power Plants



Figure 5: Climeon Power Block installation with a single injector well and producer well completing the binary cycle. Image from <https://climeon.com/geothermal-plants>

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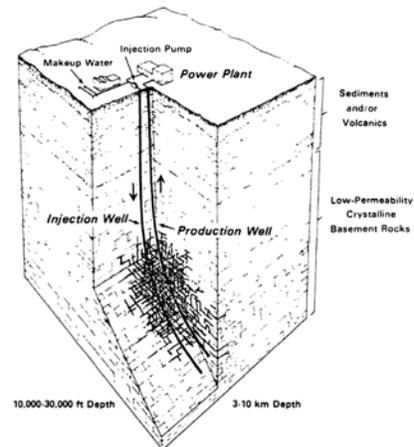


Figure 4: Schematic diagram of an open loop geothermal system, from Figure 3.2 in (Tester and Herzog, 1990). For EGS, the fractures would be artificially stimulated and/or the circulating fluid supplied by the operator.

Recent innovations in power plant technology have led investors like Jeff Bezos, Bill Gates, and Jack Ma to start paying closer attention to geothermal (Shieber, 2019). Taking a modular approach, Climeon has designed a compact binary cycle unit that can provide 150 kW of electricity with inlet fluid temperatures rated up to 120°C and flow rates of up to 35 kg/s (Climeon, 2021). These

units can be combined into a larger deployable Power Block for 1050 kW of generated electricity (Winther, 2018) (Figure 4). Power plants can thus now be designed as a combination of multi-unit assemblages, deployable all at once or over an extended period of time (Figure 5) (Climeon, 2018).

New Mexico Public Utilities

The Energy Transition Act signed in 2019 updated the New Mexico renewable portfolio standard (RPS) to go zero-carbon by 2050, with milestone targets along the way (Lillian, 2019). The RPS dates back to the Renewable Energy Act passed in 2004 and comes with several carve-outs, including a 30% requirement for wind energy, 20% for solar, and 5% for other renewable technologies like geothermal



Figure 6: Incremental deployment of geothermal power plant modules. Image from slide 15 of (Climeon, 2018).

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(DSIRE, 2021). Public Service Company of New Mexico (PNM) is the state’s largest energy provider and services the Lordsburg area in the southwest corner of the state where Lightning Dock is located. Cyrg Energy and PNM currently share a 20-year power purchase agreement (PPA) for electricity generated at Lightning Dock that will remain in effect through 2033. The PPA has going through amendments to update the amount of electricity being provided to PNM as well as the pricing structure per MWh (e.g., *NM PRC Case No. 14-00__-UT*, 2014; Stanfield, 2017), suggesting PPAs are not set in stone and can be revisited as conditions change. Given the RPS requirement for a diversified renewables portfolio and forthcoming shut-downs of existing coal power plants (see Figure 6) as mandated by the Energy Transition Act, there is an opportunity to increase geothermal production to provide electricity for New Mexico consumers.

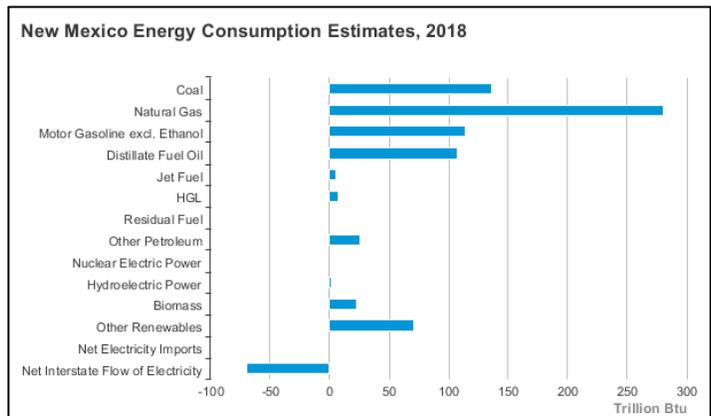


Figure 7: Energy consumption by source for New Mexico. Downloaded from EIA at <https://www.eia.gov/state/?sid=NM>.

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Motivation

Performing flexible design analysis with provides value to engineering projects in a number of ways. First, flexible design recognizes and incorporates uncertainty by replacing single value estimates with realistic distributions for model variables. This enables a model to describe a representative range of possible outcomes when simulated many times over. Flexibility also provides the opportunity to execute

real options, where design updates triggered by changing conditions capture upside potential or mitigate against downside risks. Designs need not be static, and real options can offer a means to greatly increase the expected value of a project (de Neufville & Scholtes, 2011).

Well-established geothermal cost models like GETEM provide a highly parameterized but deterministic view of the cost and investment opportunity given a defined geothermal resource and development concept (Entingh et al., 2006). Other models may apply different assumptions or mathematical treatments for various facets of the system, but they uniformly offer a one-track aspect to how the project unfolds over its lifecycle (Augustine, 2009; Beckers, 2016; Tester et al., 2006; Tester & Herzog, 1990). Explicitly sampling from the range of possible values for model-sensitive variables as well as including real option decision rules in a geothermal cost model could provide new insights into project viability and execution strategy missing from these previous approaches.

The cost model investigated here loosely follows a proposal from (Schochet & Cunniff, 2001) for the development of a near-hydrothermal field EGS (NF-EGS) reservoir at ~0.9-1.2 km depth at Lightning Dock. Stepping out from the hydrothermal zone in proximity to the N-S trending Animas Valley Fault, thermal conditions settle toward a background level with geothermal gradients between ~80-120 °C/km based on boreholes TG 56-14 and TG 12-7 (Cunniff & Bowers, 2003). These conditions make for an interesting case study in planning a facility extension to the Lightning Dock power plant that utilizes binary cycle modules similar to a Climeon Power Block, with a single open-loop EGS injector-producer doublet per module.

Public records on the expected generation power of Lightning Dock provide some guidance on the appropriate size for an expansion. With the Turboden repowering of the existing plant, production increased to 10 MW in December 2018 after several years of missed targets and projections (Think GeoEnergy, 2020). Interestingly, PNM notes on their website that Lightning Dock capacity is actually 15 MW (PNM, 2021), reminiscent of the dissonance between the original PPA for 10 MW and the actual 4 MW capacity of Lightning Dock prior to 2018 (*NM PRC Case No. 14-00__-UT*, 2014). The ±5 MW character of these agreements and upgrades suggests a comparable-sized expansion would be a reasonable target for this flexible design modeling exercise.

Problem Statement: *To build a flexible economic model with real options for the design of a 5 MW power plant expansion, by constructing a discounted cash flow analysis with data and parameter choices characteristic of an open-loop EGS binary cycle aggregate facility and conditions in southwest New Mexico, using an Excel spreadsheet with random sampling against key variable probability density*

functions, decision rule statements, and Monte Carlo simulation capabilities. Scenario testing will explore the benefits and trade-offs associated with exercising several real options, with a focus on ENPV, target curves, and extreme values for comparing the different project strategies.

Economic Model

Net Present Value

A simplified model was developed in Microsoft Excel to represent the primary sources of cost and revenue for a geothermal power plant. Geothermal cost models tend to report Levelized Cost of Electricity (LCOE) for simple comparison with other renewable options, however this measure is standardized to represent the total lifetime costs incurred by a power plant normalized by the total lifetime power generation from start-up to plant decommissioning. It does not account for changes in pricing, which is a key uncertainty associated with flexible plant design. Instead, this analysis focuses on Net Present Value (NPV) calculated on a 2020 cost basis with a discount rate of 9% over a 30-year lifespan, which is typical for geothermal power plants.

Following the general outline for geothermal cost modeling from different sources (Augustine, 2009; Beckers et al., 2013; Tester et al., 2006; Tester & Herzog, 1990), the main components of the NPV model are as follows:

$$NPV = Revenue - CAPEX_{pp} - CAPEX_{dc} - CAPEX_{exp} - CAPEX_{dist} - CAPEX_{stim} - OPEX$$

where:

$$Revenue = degraded\ capacity\ (kWh) * PPA\ pricing\ \left(\frac{\$}{kWh}\right)$$

$$CAPEX_{pp} = surface\ plant\ costs\ \left(\frac{\$}{kWe}\right) * average\ net\ power\ per\ unit\ (kWe)$$

$$CAPEX_{dc} = drilling\ costs\ \left(\frac{\$}{well}\right) * 2\ (wells\ per\ doublet)$$

$$CAPEX_{exp} = f(drilling\ costs)\ where\ f\ is\ a\ linear\ function$$

$$CAPEX_{dist} = D * enthalpy\ drop, where\ D\ is\ a\ constant\ factor\ in\ \frac{\$}{kWe}$$

$$CAPEX_{stim} = S * 2\ (wells\ per\ doublet), where\ S\ is\ a\ constant\ factor\ in\ \frac{\$}{well}$$

$$OPEX = Labor\ \left(\frac{\$}{yr}\right) + Plant\ O\&M\ \left(\frac{\$}{yr}\right) + Field\ O\&M\ \left(\frac{\$}{yr}\right) + Water\ O\&M\ \left(\frac{\$}{yr}\right)$$

Model Parameters

In order to estimate the values of these components, the following parameters were defined for the deterministic model. Note that the values are reflective of the Animas, NM region, the Lightning Dock facility, and/or the author’s knowledge of limits on the components of the system (e.g., Climeon modules).

1. Resource – characteristics of thermal resource

Parameter	Value	Reference/Notes
Surface Temperature	15.8°C	(Dahal et al., 2012)
Geothermal Gradient	100°C	(Crowell & Crowell, 2014)
Production Well Temperature Loss	5°C	Based on (Beckers et al., 2013; Entingh et al., 2006)
Production Temperature at Surface	120°C	Upper limit inlet temperature (Climeon, 2021)
Water Loss Rate	2%	(Freeman et al., 2018)
Production Flow Rate (per doublet)	35 kg/s	Limit on inlet flow rate (Climeon, 2021)

Table 1: Resource parameters for cost model

2. CAPEX (power plant, drilling & completions, exploration, distribution, stimulation)

Parameter	Value	Reference/Notes
Drilling and completions costs	\$1,305,956	From table, 2020 USD adj. (Beckers et al., 2013)
Surface plant costs	\$1000/kWe	Best guess without confirmation from Climeon
Reservoir stimulation costs	\$1.25MM	(Lowry et al., 2017)
Fluid distribution costs	\$50,000/kWth	(Beckers et al., 2013)
Redevelopment factor	85%	Pers. comm. K. Prestidge (Chevron)
Thermal drawdown rate	0.5%	(Entingh et al., 2006)

Table 2: CAPEX parameters for cost model

3. Power Plant – characteristics of binary cycle modules

Parameter	Value	Reference/Notes
Heat capacity	2.28 kJ/kg-K	isobutane (Dincer & Kanoglu, 2010)
Capacity factor	95%	(Entingh et al., 2006)
Degradation factor	0.5%	(Augustine et al., 2019)
Generation efficiency	30%	(Glassley, 2015)

Table 3: Power plant parameters for cost model

4. OPEX – annual operations and maintenance costs

Parameter	Value	Reference/Notes
Labor (per module)	\$386,839	From table, 2020 USD adjusted (Entingh et al., 2006)
Power plant O&M (per module)	\$314,009	Weighted average of labor and CAPEX _{pp} (Beckers et al., 2013)
Field O&M (per module)	\$122,829	Weighted average of labor and CAPEX _{dc} (Beckers et al., 2013)
Water O&M (per module)	\$300/acre-ft	(Entingh et al., 2006)

Table 4: OPEX parameters for cost model

5. Calculated - additional model parameters calculated from the inputs

Parameter	Value
Well depth	1.1 km
Initial reservoir temperature	125°C
Thermal drawdown threshold	13°C
Redevelopment cycle time	24 yrs.
Capacity degradation rate	0.5%
Heat inlet temperature	120°C
Temperature drop	70°C
Enthalpy drop	5.6 MWth

Table 5: Calculated parameters for cost model

6. Adjustable - adjustable inputs for the model

Parameter	Value	Reference/Notes
Discount rate	9%	(Sanyal & Butler, 2005)
Learning rate (drilling)	6%	(Lukawski et al., 2014)
PPA contract rate above wholesale	50%	(NM PRC Case No. 14-00 __-UT, 2014)
Price trigger for flexibility	20%	[used for flexible options]
Expansion amount	25%	[used for flexible options]
Reduction amount	25%	[used for flexible options]

Table 6: Adjustable parameters for cost model

Electricity Price

Electricity prices were referenced from the industrial electricity price forecast for the Mountain region (includes New Mexico) provided by the U.S. Energy Information Agency (EIA) in their Short-Term Energy Outlook (STEO) projections out to 2023 (EIA, 2021a). While industrial pricing differs from wholesale, it more closely mimics wholesale prices than residential or commercial rates and was therefore selected as a wholesale proxy for the cost model. The Forecast Tool internal

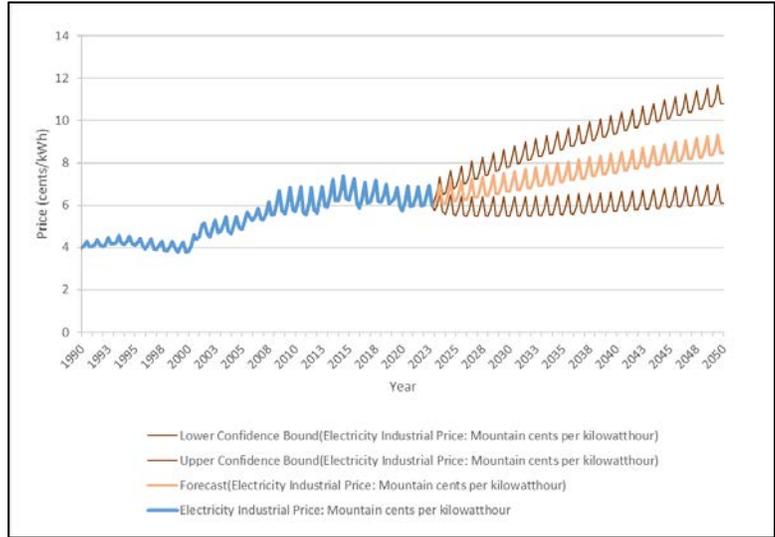


Figure 8: Price of electricity forecast based on EIA Short-Term Energy Outlook. A seasonal signal is visible due to the quarterly sampling of the data.

to Excel was then used to push the projection out to 2050 with confidence intervals (Figure 8). For the static cost model, electricity prices are directly sampled from the forecast and multiplied by the *PPA contract rate above wholesale* listed in Table 6 for any year when capacity is manually increased. Price is held flat compared to the previous year when no capacity change occurs. This simulates the signing of power purchase agreements with a local utility.

Spreadsheet

RESOURCE	VALUE	UNITS	REFERENCE
Surface Temperature (2020)	15.8	degrees C	Dahal, 2012
Average Geothermal Gradient	100	degrees C / km	Crowell, 2014; can be hi
Average Well Depth (near vertical, MD)	1.1	km	
Initial Average Reservoir Temperature	125	degrees C	
Production Well Temperature Loss	5	degrees C	Beckers, 2013; GETEM
Production Temperature (at well head)	120	degrees C	
Water Loss Rate	2%	% of injected water	SAM
Production Flow Rate per Well Pair	35	kg/s	GETEM, NREL

Table 7: First section of spreadsheet for geothermal power plant cost model.

CAPEX (per module)	VALUE	UNITS	REFERENCE			
Drilling & Completions Costs	\$ 1,305,956.16	USD (1 well)	Beckers 2013			
Wells per module		2 well count per unit				
Surface Plant Costs	\$ 1,000.00	\$/kWe	Beckers 2013			
Reservoir Stimulation per injection well	\$ 1,250,000.00	USD	Lowry, 2017			
Fluid Distribution Costs	\$ 279,300.00	USD	Beckers 2013			
Redevelopment Factor	0.85		pers. conversation, Pre			
Thermal Drawdown Threshold	13.0	degrees C	GETEM			
Thermal Drawdown Rate	0.5%		GETEM			
Redevelop Every	24	years				
Exploration Success Rate	100.0%					
Total Capital Costs (exploration)	\$ 2,133,542.54	USD	Beckers 2016			
Total Capital Costs (drilling)	\$ 2,611,912.33	USD	Beckers 2016			
Total Capital Costs (non-drilling)	\$ 3,121,310.00	USD	Beckers 2016			
POWER PLANT (modules)	VALUE	UNITS	REFERENCE			
Plant Type	Binary ORC					
Plant Useful Life	30	years	Augustine, 2009			
Heat Inlet Temperature	120	degrees C				
Cool Inlet Temperature	50	degrees C				
Heat Capacity	2.28	kJ/kg-K	Dincer, 2010			
Temperature Drop	70.0	degrees C (or K)				
Enthalpy Drop	5.6	MWth				
Capacity Factor	95%		Glassly 2015, GETEM			
Degradation Factor	0.5%		NREL, 2002			
Generation Efficiency (2nd Law Efficiency)	0.3		Beckers 2019, Glassly			
Avg Net Power Output per Unit	1.59	MWe				
OPEX	VALUE	UNITS	REFERENCE			
Labor (per module)	\$ 386,838.52	USD	GETEM			
Power Plant Ops & Maintenance (per module)	\$ 314,009.04	USD	Beckers 2013			
Field Ops & Maintenance (per module)	\$ 122,828.75	USD	Beckers 2013			
Water Ops & Maintenance	\$ 5,481.02	USD	GETEM			
Total Annual O&M costs (per module)	\$ 442,318.81	USD				
FACTORS/INDICES	VALUE	UNITS	REFERENCE			
Price Index from for Q4 2004 to 2020 USD	143%		UCCI (IHS)			
Price Index from for Q4 2009 to 2020 USD	104%		UCCI (IHS)			
Price Index from for Q4 2012 to 2020 USD	107%		UCCI (IHS)			
Employment Cost Index (Utilities) compared to 2004	145%		BLS			
Discount rate	9%		Sanyal 2007			
Learning rate	6%		Lukawski 2014			
Contract rate above wholesale	50%		PNM, 2014			
Calendar Year	2020	2021	2022	2023	2024	2025
Nominal Year	0	1	2	3	4	5
Calculated Price	0.086	0.000	0.000	0.000	0.000	0.000
Price (\$/kWh)	0.086	0.090	0.090	0.090	0.090	0.090
Capacity Level Increase [Input]	1	4	0	0	0	0
Unit Count	1	5	5	5	5	5
Total Capacity Increase (kWh)	13946008	55784030	0	0	0	0
Total Undegraded Capacity (kWh)	0	13946008	69730038	69730038	69730038	69730038
Thermal Decline (deg C)	120	119	119	118	118	117
Thermal Decline Degradation (kWh)	0	119537	1192384	1784108	2372873	2958695
Power Plant Degradation Factor	1.000	1.000	0.995	0.990	0.985	0.980
Total Overall Capacity (kWh)	0	13826470	68194966	67268170	66351851	65445899
Revenue	\$0.00	\$1,240,234.39	\$6,117,088.46	\$6,033,954.81	\$5,951,761.00	\$5,870,497.10
CAPEX (Drilling)	\$2,611,912.33	\$9,049,475.21	\$0.00	\$0.00	\$0.00	\$0.00
CAPEX (Redevelopment)	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00	\$0.00
CAPEX (Other)	\$5,254,852.54	\$12,485,240.00	\$0.00	\$0.00	\$0.00	\$0.00
OPEX	\$0.00	\$442,318.81	\$2,211,594.06	\$2,211,594.06	\$2,211,594.06	\$2,211,594.06
Cashflow	\$0.00	(\$20,736,799.63)	\$3,905,494.40	\$3,822,360.76	\$3,740,166.95	\$3,658,903.04
DCF	\$0.00	(\$19,024,586.81)	\$3,287,176.50	\$2,951,563.83	\$2,649,628.56	\$2,378,035.93
Present value of cashflow	\$11,687,244					
Up-front investment	\$7,866,765					
Net present value	\$3,820,478.99					

Table 8: Second part of spreadsheet for geothermal power plant cost model. The yearly breakdown of cost and revenue has been cropped at year 5 for visualization purposes but continues out to year 30 in the actual spreadsheet.

The spreadsheet described in Table 7 and continued in Table 8 illustrates the entire deterministic model for the Lightning Dock expansion project. Note that the predicted NPV is \$3.8MM based on the construction schedule discussed later in this report (Table 12).

Rate Calculations

The cost model considers four (4) rates when performing the NPV calculation.

1. **Discount rate** – Defines the time value of money. The value used for discount rate (Table 6) is held constant throughout the modeled timespan and applied to the Cashflow row in Table 8 to determine the Discounted Cash Flow (DCF) using the following relationship:

$$DCF = \frac{CF}{(1+r)^n}$$

where r is discount rate, n is number of years (de Neufville & Scholtes, 2011).

2. **Learning rate** – Applied only to drilling & completions costs. This represents the cost savings from accumulated experience and knowledge as wells are repeatedly drilled in the Lightning Dock expansion area. Drilling costs are implemented in Table 8 to progressively decrease based on the following relationship:

$$U_i = U_1 i^B$$

where U_i and U_1 are costs to drill the i^{th} and first wells, i is well count, B is slope of the learning rate curve, i.e., the learning rate listed in Table 6 (de Neufville & Scholtes, 2011).

3. **Thermal drawdown rate** – Defines the thermal decline of the accessible geothermal reservoir over time. Temperatures tracked in Table 8 are determined by applying the rate listed in Table 6 based on the following relationship:

$$T_n = T_0 * (1 - d)^n$$

where T_n and T_0 are temperatures at time 0 and n , d is thermal drawdown rate, n is number of years. (Entingh et al., 2006)

4. **Capacity degradation rate** – Sets the progressive decrease in power plant capacity factor over the life of the plant. Degradation is calculated in Table 8 using the capacity and degradation factors defined in Table 5 and the following relationship:

$$C_n = C_0 * (1 - a)^n$$

where C_n and C_0 are power plant capacity factors at year 0 and n , a is degradation factor, n is number of years.

Uncertainties

The model described thus far takes a deterministic approach; parameter values are fixed to their most-likely or average values when performing the NPV calculation. A probabilistic approach like Monte Carlo simulation replaces these static values with distributions and repeatedly samples from those distributions to capture an ensemble of results, which can give a more realistic assessment of system performance. However, all variables in the model have underlying uncertainties, and defining distributions for every variable would add significant complexity to the model with diminishing returns. In order to balance model simplicity with representativeness of the physical system, a review of broader uncertainties was conducted. The impact of these uncertainties was then compiled in a tornado diagram to judge model sensitivity to specific parameters, effectively high-grading which variables should be modeled with distributions in the final cost model.

The following issues constitute major uncertainties that could impact the performance and overall success of the geothermal project being modeled.

Electricity Prices (1): Carbon Tax

One proposed solution to advancing the energy transition to more renewable and sustainable energy solutions in the United States is the imposition of a carbon tax on fossil fuels. The SIPA Center on Global Energy Policy at Columbia University recently studied three (3) analytical scenarios based on federal agency

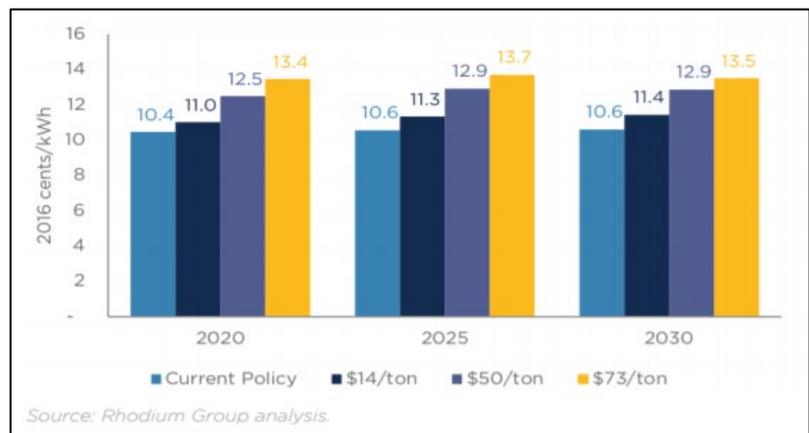


Figure 9: National average retail electricity price changes with benchmark levels of carbon taxation, from Fig 30 in (Larson et al., 2018).

© Columbia University. All rights reserved. This content is excluded from our Creative Commons license. For more information, see <https://ocw.mit.edu/help/faq-fair-use/> benchmark taxation rates of \$14/ton, \$50/ton, and \$73/ton CO₂e with annual percentage rate increases of 3, 2, and 1.5%, respectively (Larson et al., 2018) (Figure 9). Their analysis provides projections for the impact on electricity pricing out to 2030, with relatively steady-state implications that depend on the specified carbon tax rate. In all taxation cases, electricity prices increase over the present-day, no-tax scenario, likewise boosting the value of a zero-emissions geothermal power plant relative to fossil fuel-based electricity generators. The selected value range for sensitivity testing was a 0-28% increase in wholesale price, which matches Figure 9.

Electricity Prices (2): Energy Transition/Future Electrification

The National Renewable Energy Lab (NREL) published a new report earlier this year outlining the potential impact of heightened public trends away from non-electric sources of consumed energy, otherwise known as widespread electrification (Murphy et al., 2021). Some key findings include: (i) end-use natural gas consumption decreases, but so do natural gas prices, which can lead to an increase in natural gas-fueled power plants (assuming no curtailments due to fossil fuel policies), (ii) deployment of renewables will intensify overall, and (iii) local resources, potentially including new renewable electricity generation facilities, will be relied on to mitigate the need for long-distance electricity transmission (Murphy et al., 2021).

The issue of electrification is complex and will involve a delicate interplay between the natural gas market and renewables. Other dependencies include infrastructure upgrades and development to handle growing capacity, as well as local effects (e.g., permitting, water or electrical transmission, community support) that act as enablers or hurdles to building a new renewable-fueled power plant or expanding on existing power facilities with hybrid energy options. One way to simplify a model representation of widespread electrification is to incorporate swings in electricity prices similar to the scenarios shown in Figure 10 with the caveat that other related factors (e.g., federal and state-level incentive programs or infrastructure improvements) could also influence the bottom line for a geothermal power plant. Based on these NREL projections, wholesale electricity pricing in 2050 could vary from 0.65 to 1.25 times the prices recorded in 2018. Using the High Future Electrification (HFE) Base Case as a reference, prices are 25% greater by 2050 for the HFE Constant Renewable Technology Costs case and prices drop by 35% for the HFE Low Renewable Technology Costs case (Figure 10). Therefore, +25% and -35% can define a range of price factors when sensitivity testing.

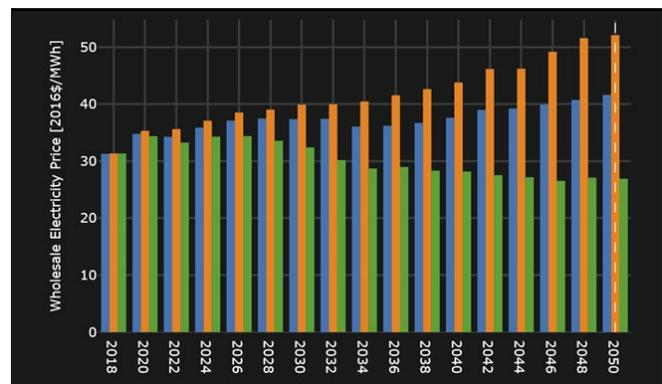


Figure 10: Wholesale electricity price forecast for high future electrification base case scenario (blue), constant renewable technology cost scenario (orange), and low renewable technology cost scenario (green) (Murphy et al., 2021), plots from: <https://cambium.nrel.gov/?project=fc00a185-f280-47d5-a610-2f892c296e51> Source: public domain. Used with permission.

Climate Change: Surface Temperature

NCA Region	RCP4.5 Mid-Century (2036–2065)	RCP8.5 Mid-Century (2036–2065)	RCP4.5 Late-Century (2071–2100)	RCP8.5 Late-Century (2071–2100)
Northeast	3.98°F	5.09°F	5.27°F	9.11°F
Southeast	3.40°F	4.30°F	4.43°F	7.72°F
Midwest	4.21°F	5.29°F	5.57°F	9.49°F
Great Plains North	4.05°F	5.10°F	5.44°F	9.37°F
Great Plains South	3.62°F	4.61°F	4.78°F	8.44°F
Southwest	3.72°F	4.80°F	4.93°F	8.65°F
Northwest	3.66°F	4.67°F	4.99°F	8.51°F

Table 9: Projected average temperatures relative to the 1976–2005 average baseline under lower emissions (RCP4.5) and higher emissions (RCP8.5) scenarios, from Table 6.4 in (Vose et al., 2017)

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targets may mask more extreme local temperature changes in certain parts of the world. New Mexico, a state defined by semi-arid conditions, is at risk of encountering warming far in excess of the 1.5°C goal by 2050 (Table 9, Figure 11). The North Carolina Institute for Climate Studies (NCICS) reports the annual average temperatures have already increased 1.1°C since the 1970s, and the observed number of days with maximum temperatures of 100°F or higher is climbing, as is the number of nights with minimum temperatures of 70°F or higher (Frankson et al., 2019).

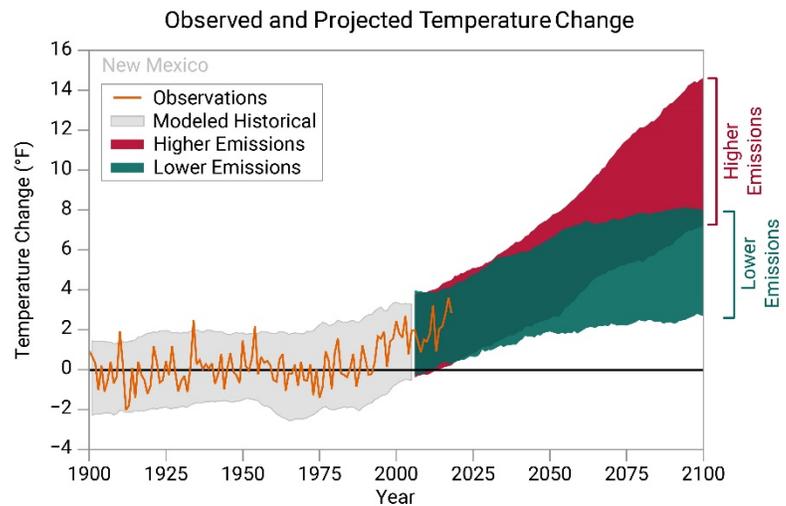


Figure 11: Projected average temperature changes for New Mexico, from Figure 1 in (Frankson et al., 2019). Source: public domain. Used with permission.

Binary cycle power plants require a temperature differential (more concretely, an enthalpy change) to drive generation of electricity. In air-cooled power plants, as most binary cycle plants tend to be, hot summer days can reduce plant efficiencies. To this extent, tracking variations in weather conditions at a seasonal and even monthly basis could reveal significant variability in power plant generation potential. But even on an average annual basis, as temperatures climb in New Mexico, the electricity generation capacity will correspondingly decline.

In the 4th National Climate Assessment report, the U.S. Global Change Research Program (USGCRP) noted the Southwest region of the United States, including New Mexico, is projected to experience up to a 2.7°C increase in average temperature in the period between 2036–2065 compared to the near-present (1976–2005) (Wuebbles et al., 2017). The cool inlet temperature of the power plant will

vary with changes in ambient conditions, so an adjustment of 0 to +2.7°C by 2050 can be applied to this variable for sensitivity testing.

Drilling & Completions

Studies on Enhanced Geothermal Systems (EGS) consistently show drilling-related costs are the primary contributor to overall expenses. By one estimate, drilling accounts for 60-75% of the total cost of an EGS project (Figure 12) (Lukawski et al., 2016).

According to annual benchmark standards published by NREL, probable future advances in geothermal technology include more efficient rate of penetration and bit life, new casing methods that reduce drilling time, and overall reductions in drilling material consumption as wells are completed faster. All aspects of rock stimulation also need to show improved economics to drive down costs (NREL, 2020). In the 2019 Geothermal Vision Study for the U.S. Department of Energy, future projections were based on a number of key assumptions about changes in geothermal technology (Augustine et al., 2019):

- Incorporating data analytics into the pre-exploration phase, resulting in a higher success rate in exploration wells (90% vs. 75%).
- Use of microdrilling exploration wells instead of drilling slim or full-size boreholes. Estimates are ~33.5% savings compared to full-size holes, 29% cost reduction over slim holes.
- Adoption of learnings and techniques from unconventional oil & gas operations like directional drilling, multi-zonal isolation, and stimulation methods. This is predicted to generate higher flow rates (110 kg/s for binary cycle) and productivity (4.6 kg/s/bar for open loop systems).

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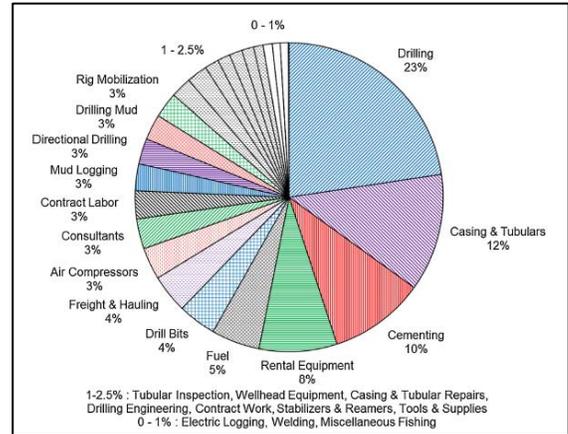


Figure 12: Cost breakdown for commercial EGS wells, from Fig 2 in (Lukawski et al., 2016).

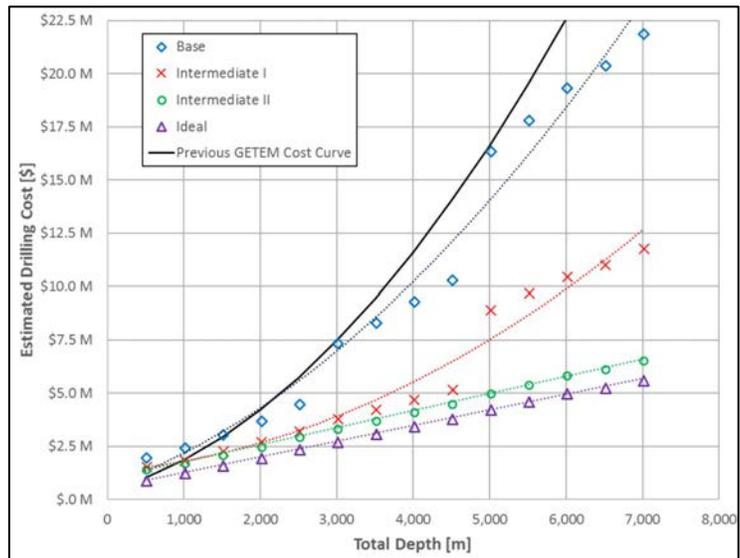


Figure 13: Drilling cost curves in USD per meters depth for technology improvement scenarios, from Fig 8 in (Augustine et al., 2019).

Source: public domain. Used with permission.

- Advanced methods for drilling and completions (D&C) to reduce the drilling cost curve. The GeoVision report provides the existing GETEM (baseline) curve, two intermediate improvement curves, and a final ideal curve for reduced D&C costs (Augustine et al., 2019).

Based on the cost curve data shown in Figure 13 and the well depth estimate from Table 5, the range of testable costs in 2020 USD is ~\$1.0MM-\$2.8MM.

Thermal Drawdown

Like wells used for water or oil & gas operations, geothermal wells generate a drawdown effect from production activities impacting fluid recovery (hydrothermal), pressure (flash design), and enthalpy (binary design). Models vary in the decline rate applied to the latter, sometimes called thermal drawdown rate. As thermal drawdown increases, the temperature of produced fluids decreases, as does the enthalpy drop and amount of electricity generated by the binary cycle process. Recent EGS studies suggest 0.5-0.6%/year is an appropriate drawdown rate for EGS applications (Augustine et al., 2019), although more pessimistic assessments range from 1.5%/yr. (Beckers, 2016), to 3.33%/yr. (Augustine, 2009) and 4%/yr. (Tester & Herzog, 1990). Endcap values of 0.5% and 4% were used for sensitivity analysis.

Geothermal Gradient

The Lightning Dock discovery ties directly to observations of anomalously high temperature gradients in agricultural wells drilled in the area (Crowell & Crowell, 2014). While well data from the KGRA are generally not available to the author for review, Table 10 (Cunniff & Bowers, 2005) illustrates the range of gradients detected in the area. Note that the Gradient column is a linear fit to bottom hole temperature alone, potentially oversimplifying complex temperature relationships with depth. Thermal models show local gradients in excess of 300°C/km near the field center and temperature inversions on the flanks of the main anomaly (Figure 14) (Cunniff & Bowers, 2003). Away from the fault-centered hydrothermal plume, the thermal field settles into a more traditional pseudo-linear depth trend. Wells TG12-7 and TG56-14, located 1 km and 4 km away from the central borehole TFD55-7 (arrow notation in Figure 14), have reported gradients of 80-120°C/km. This range is used for testing model sensitivity to thermal gradient variations.

Well Name	Depth (m)	BHT (°C)	Gradient (°C/km)	Reported (°C/km)
TG12-7	305	69	177	120
TG56-14	381	36	55	80
TG36-7	305	90	246	-
TG57-x	278	108	335	-
TG52-7	771	137	158	-

Table 10: Examples of Lightning Dock KGRA geothermal gradients from well bottom hole temperatures (BHT). Gradient is calculated assuming a surface temperature of 15°C. Reported temperatures use temperature log trends near TD and are more reliable. Table modified from (Cunniff and Bowers, 2005). Source: public domain. Used with permission.

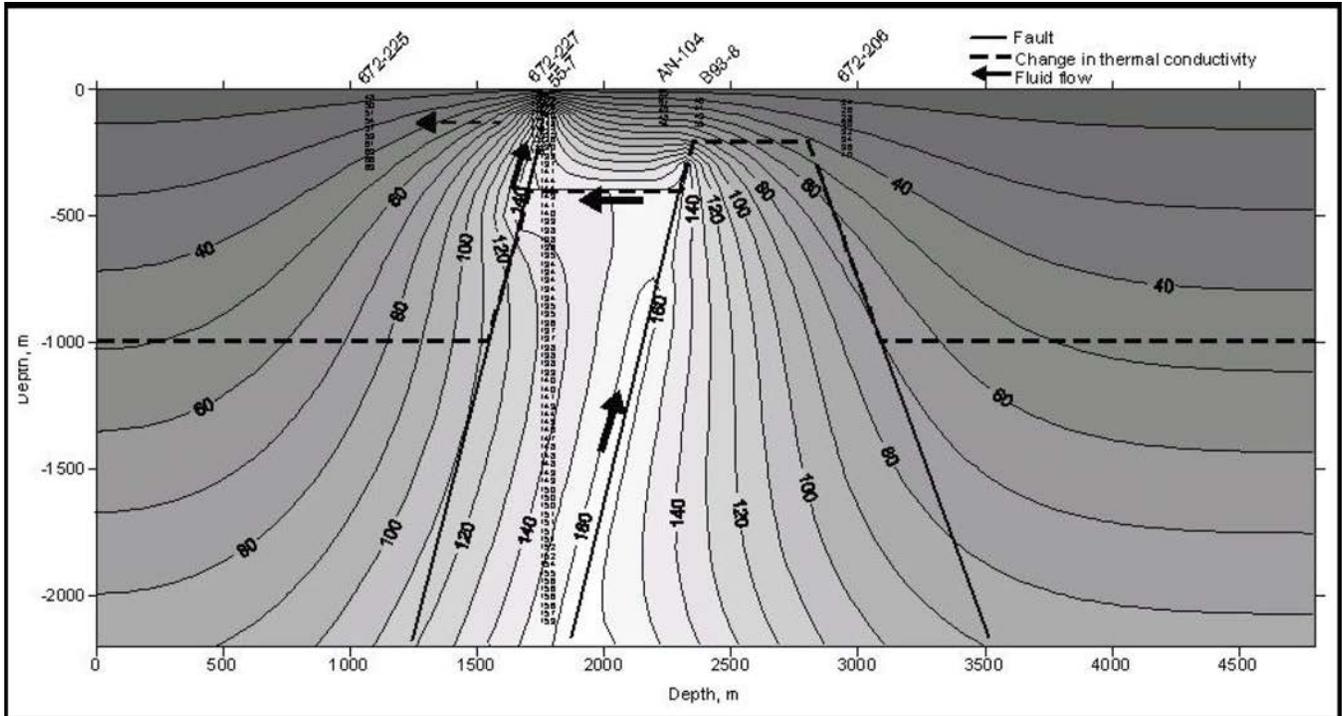


Figure 14: Thermal model of Lightning Dock showing the locations of several wells and the extraordinary thermal anomaly where active hydrothermal circulation takes place. Off-center wells determine background trends. Image from Figure 23 of (Cunniff and Bowers, 2003).

Source: public domain. Used with permission.

Sensitivity Analysis

The tornado diagram in Figure 15 provides a simple visualization of variable importances on NPV. Model sensitivity is assessed by recalculating NPV after adjusting a single variable at a time to match the extremal values outlined in the previous discussion. The model baseline matches that shown in Table 8. Based on this analysis, and the raw results listed in Table 11, the model is most sensitive to electricity

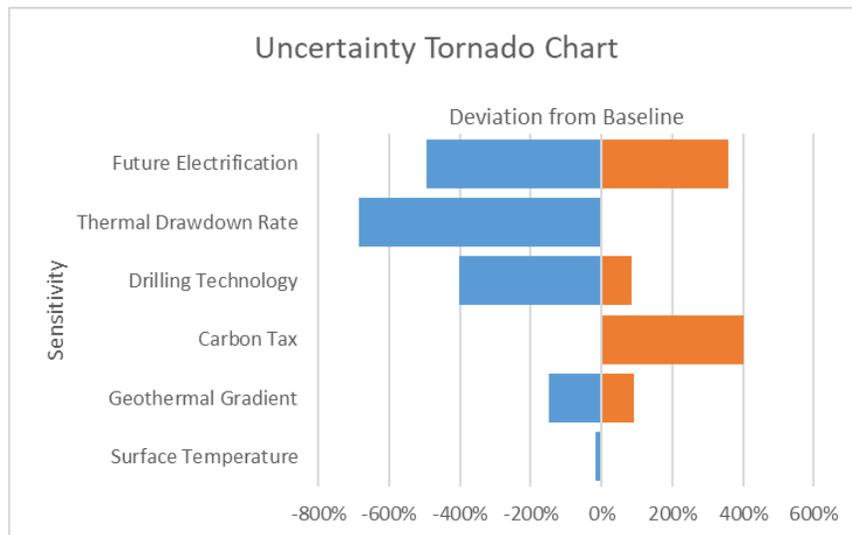


Figure 15: Tornado diagram showing the sensitivity of different uncertainties on NPV for the proposed Lightning Dock expansion. X-axis measures percentage deviation from the deterministic NPV that uses average values and no change to EIA price forecast.

	Low Relative	High Relative	Low (\$MM)	High (\$MM)	Range (\$MM)
Future Electrification	-481%	344%	(\$14.6)	\$17.0	\$31.5
Thermal Drawdown Rate	-666%	0%	(\$21.6)	\$3.8	\$25.4
Drilling & Completions	-392%	80%	(\$11.2)	\$6.9	\$18.1
Carbon Tax	0%	385%	\$3.8	\$18.5	\$14.7
Geothermal Gradient	-148%	87%	(\$1.8)	\$7.1	\$9.0
Surface Temperature	-20%	0%	\$3.1	\$3.8	\$0.8
Base Case (\$MM)	\$3.82				

Table 11: Results of sensitivity testing for different uncertainties associated with the Lightning Dock expansion. Currency values are in \$MM USD, where MM is million.

price changes from future electrification, thermal drawdown rate, drilling technology, carbon tax effects on pricing, and geothermal gradient, in that order. Increasing surface temperatures from climate change do impact the model results, but by two orders of magnitude less than the other variables. In the simplified High Future Electrification and Carbon Tax scenarios implemented within the model spreadsheet, electricity prices were scaled by the price factors described earlier in this report. Prices are tied to when a PPA is negotiated with the local utility company, which the model connects with years when capacity increases. The modeled construction timeline follows the optimal staged approach described later in this report (Table 12), so the price scaling factors impact year 1 prices, which then carry over into all subsequent years. Raw results will vary with different construction plans, but the impact of price-related variables is demonstrated to clearly be significant based on this sensitivity analysis.

As a quick aside: no additional effects from competitive markets or enhanced need for increased capacity were included. To that end, it could be said that the impact of the energy transition and energy pricing on geothermal viability might be even more significant than modeled. It would also be a mistake to consider Future Electrification fully independent from Carbon Tax scenarios since environmental drivers are at the heart of decisions, policies, and future trends for both. Even so, the model appears to be less sensitive to a carbon tax than widespread electrification on a national level.

Flexible Design

Probability Functions

Having established which variables impact the cost model the most, probability functions can be defined for use as part of a stochastic strategy that fully leverages the uncertainty in those variables.

Drilling and Completions Costs

Drilling costs for geothermal wells, especially EGS wells, remains an area of intense study and debate due to the inherent differences (higher temperatures, harder rock, different hole sizes) between geothermal drilling and conventional oil & gas drilling. This discrepancy was noted in the 2006 MIT study on EGS potential, leading the authors to advocate for a dedicated cost index (Tester et al., 2006). Nevertheless, the literature remains full of broadly-varying cost estimates, particularly covering the 1.0-1.5 km depths being considered in this project; costs range from a quite low ~\$500/m (Lukawski et al., 2016) to very high \$2,800/m (Lowry et al., 2017). In order to capture a reasonable spread while recognizing uncertainty exists in even the underlying distribution shape, geothermal drilling costs are modeled as a triangular distribution (Figure 16). The midpoint value of \$1195/m is based on a 1.1 km depth (Table 1) and the cost relationship used in the deterministic model (Beckers et al., 2013). The extremes of \$1000/km and \$2800/km roughly approximate the values shown for depths of 1.0-1.5 km in Figure 13 (Augustine et al., 2019).

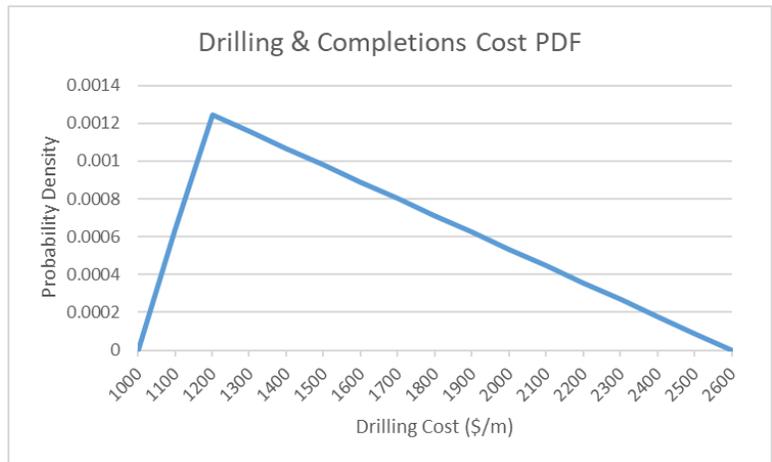


Figure 16: Probability density function for drilling and completions costs

Wholesale Electricity Price

The short-term electricity price forecast from the EIA (EIA, 2021a) offers a good baseline trend for industrial prices, which are treated as a proxy for wholesale prices in this model. In order to capture the potentially sudden nature of energy transition events, i.e., as initiated by new policies or taxes, this price curve is disrupted on a randomly-selected year between 2020-2050 with a step change in price. The magnitude of the step change is determined from a uniform distribution using the range of 2050 high electrification prices relative to the base case in the Electrification Futures Study (Murphy et al., 2021) (Figure 17).

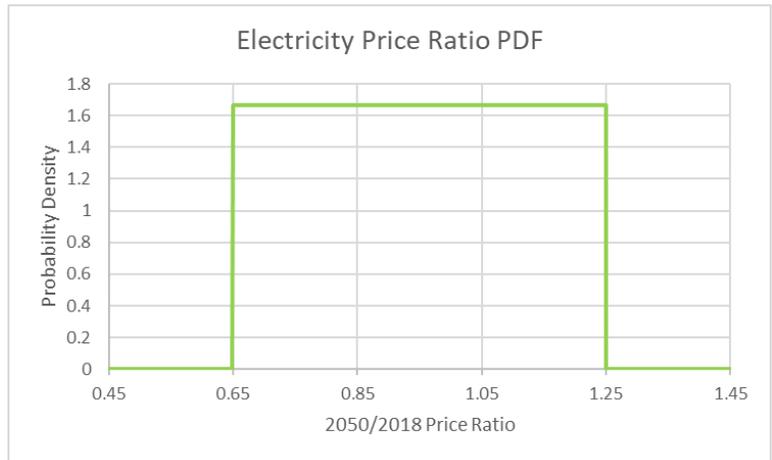


Figure 17: Probability density function for electricity price ratio.

An example of how this randomly-timed, randomly-sampled step change affects the price curve is shown in Figure 18. Volatility can also be added to the forecast. Using the 95% confidence bounds to determine standard deviation on any given year, each point in the forecast can be treated as a normal distribution and randomly sampled to produce different price model realizations. This is illustrated in Figure 19.

Thermal Drawdown Rate

As noted earlier, the reservoir thermal drawdown rate can vary substantially in the literature, with significant impact on the model results based on the tornado plot. The

latest versions of the GETEM and SAM cost models (Freeman et al., 2018; Mines, 2016) are consistent in their use of 0.5% for default scenarios, and the 4.0% extreme dates back to literature from the 1990s (Tester & Herzog, 1990). The probability density function for thermal drawdown is therefore modeled using a beta function such that the P50 value aligns with 0.5% annual drawdown rate, and 4.0% represents the P97.5 case (Figure 20). Note that the beta function has been slightly altered to follow a linear trend from P95 to P100 to ensure rare extremely high rates in the distribution function do not asymptotically approach >10% per year. The highest rate in the distribution is 5.6%.

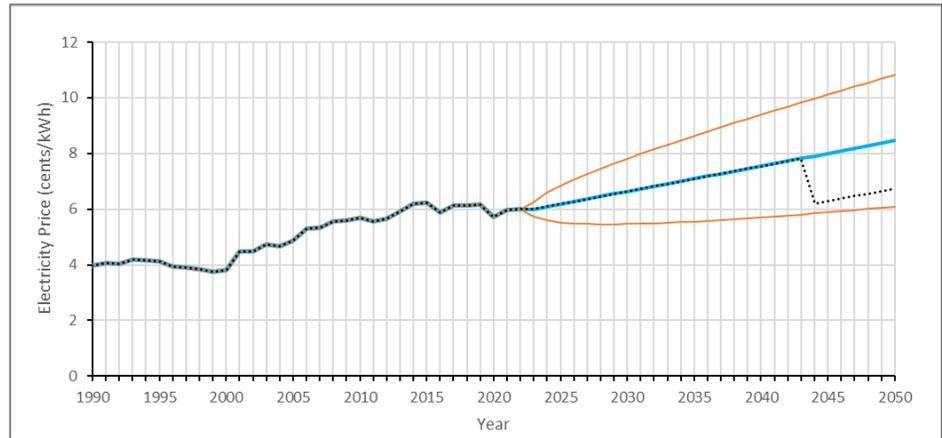


Figure 19: Price forecast to 2050 with randomly-generated step change in pricing. In this example, a change occurs in 2044 that represents a sudden drop in prices.

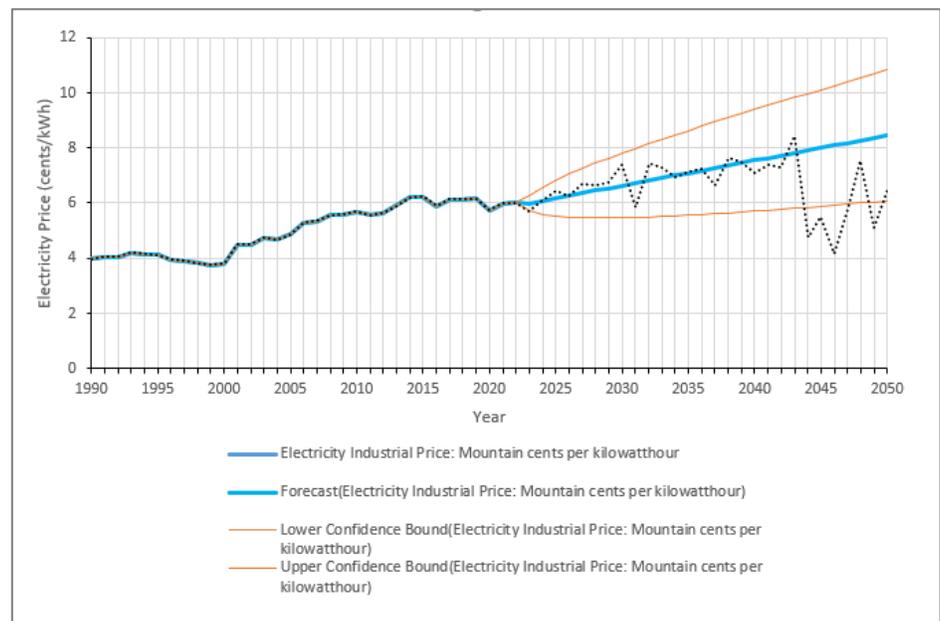


Figure 18: Price forecast to 2050 with randomly-generated step change in pricing in 2044 as well as annual volatility using the original forecast confidence intervals.

Geothermal Gradient

Spatial variation in geothermal gradient is difficult to characterize with only a sparse sampling of the Lightning Dock KGRA by predominantly shallow boreholes. Thermal models will naturally skew toward simplified approximations in the absence of observational data (Figure 14), so model-derived distributions of gradient can be somewhat unreliable. Instead, uncertainty in gradient is represented by a uniform probability distribution with end points determined by measured gradients from wells TG12-7 and TG56-14 (Figure 21).

Monte Carlo Simulation

Once probability functions for the key uncertain variables are defined, a model can be run many times over to generate a suite

of solutions. Each solution represents the model response to a different combination of variable values. With many cost model results generated from randomly-sampled realizations, a Monte Carlo ensemble of NPV solutions can be created. These solutions can be combined into a histogram, reported as a cumulative distribution function (target curve), and averaged together to define the Expected Value of NPV (ENPV). Other interesting metrics include standard deviation of NPV, extreme cases like P05 and P95 results, and a direct comparison to the deterministic NPV (NPV_{Det}).

Base Case

The Base Case scenario directly mimics the Deterministic model. All parameters in Table 1-Table 6 still apply, except for the four variables with uncertainty characterized by distributions described in the previous section: drilling costs (Figure 16), electricity price ratio (Figure 17), thermal drawdown rate (Figure 20), and geothermal gradient (Figure 21). A Monte Carlo simulation is executed with 2000 realizations. In each realization, the pdfs are randomly sampled to determine new values for the uncertain

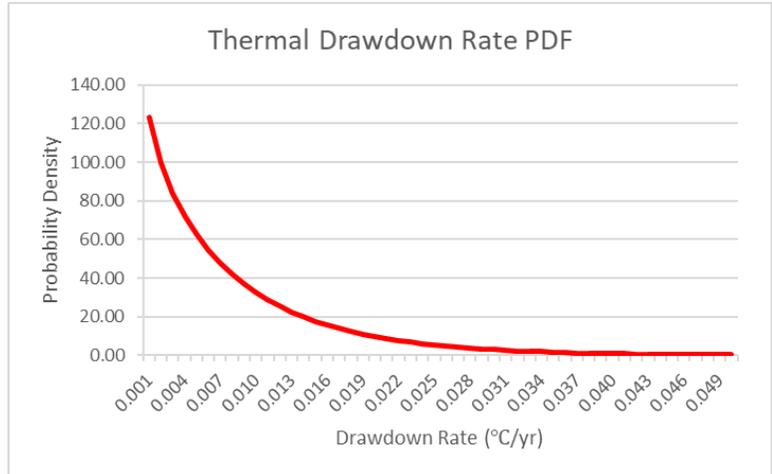


Figure 20: Probability distribution function for thermal drawdown rate.

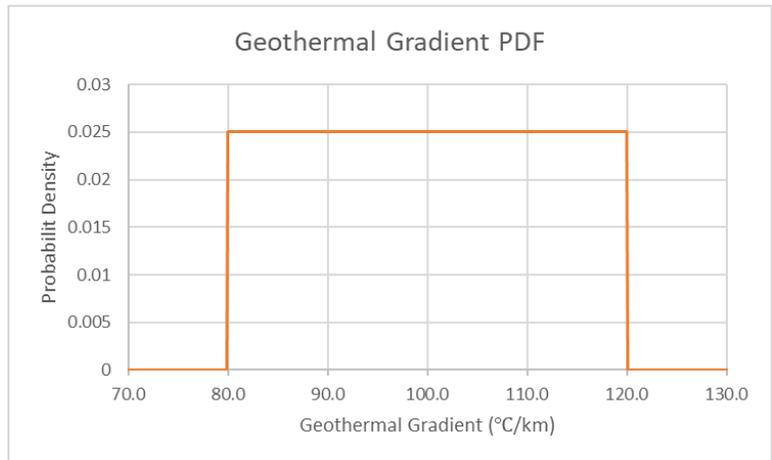


Figure 21: Probability density function for geothermal gradient

variables before the NPV calculation completes. The results of this simulation are then aggregated for evaluation and comparison with other scenarios.

Rule-Based Scenario Testing

Decision rules define conditional statements that govern how a model behaves based on past observations. The following scenarios extend the Base Case model with one or more decision rules to examine the impact of flexible design on ENPV, target curves, and other performance forecast measures.

Redevelop Only Case

Thermal drawdown results in temperature decline of produced fluids, which directly influences electricity generation efficiency. If the latter drops below a certain level, redrilling or restimulation of the reservoir are required to ensure generation rates remain within a reasonable (or profitable) range. The GETEM cost model (Entingh et al., 2006) tracks thermal decline and discounts power plant performance until the temperature drop reaches a certain threshold defined by:

$$\Delta T_{max} = (T_f - T_i)_{max} = 0.21 * T_i - 12.2$$

In binary plants, thermal decline follows a harmonic decline curve: $T_f = T_i / (1 + Dt)$, where D is the decline factor and t represents time in years. Rearranging this relationship and substituting in for T_f from the GETEM formula above results in the following equation:

$$t = \frac{1}{D} * \left(\left(\frac{T_i}{T_f} \right) - 1 \right) = \frac{1}{D} * \left(\left(\frac{T_i}{1.21 * T_i - 12.2} \right) - 1 \right)$$

This equation determines the time before the maximum temperature decline is reached.

To counteract the negative impact of this decline, a full field re-drill campaign is triggered in geothermal cost models like GETEM (Entingh et al., 2006). This may occur several times over a plant's lifespan depending on the drawdown rate, although GETEM freezes redrills in the final 5 years to ensure no redevelopment cost is incurred just prior to end of life for the facility (Entingh et al., 2006). This methodology is applied here using the following decision rule.

Decision Rule:

1. Determine *Thermal Drawdown Threshold* from *Initial Average Reservoir Temperature* using the GETEM relationship for ΔT_{max} .
2. Use *Thermal Drawdown Rate* to calculate the number of years until the *Thermal Drawdown Threshold* is reached. Store this value in *Redevelop Every*.

3. In the annual cashflow analysis, IF power plant modules were installed a multiple of the *Redevelop Every* years ago AND the year is not within 5 years of *Plant Useful Life*, THEN:
 - a. Store the number of modules in *Capacity Level Increase [Manual]* from *Redevelop Every* years ago in *Units Redeveloped*.
 - b. Add *Capacity Level Increase [Manual]* for the current year to *Units Redeveloped*. Multiply this by *Wells per Module* and add to *Wells Drilled or Redrilled* from the previous year to determine the current year's *Wells Drilled or Redrilled*.
 - c. Determine *CAPEX (Redevelopment)* as *Units Redeveloped * Total Capital Costs (drilling) * Redevelopment Factor*. Scale this value by the learning rate discount of the form i^B , where i is *Wells Drilled or Redrilled* from the previous year and B is the *Learning rate exponent*. Note that *Total Capital Costs (drilling)* is a per-module value, not per well.
 - d. Reset *Heat Inlet Temperature* to *Production Temperature at Well Head*.

Redevelop and Grow Case

Redevelopment of the geothermal field is primarily a mitigation strategy against loss of accessible thermal resources as drawdown impacts the subsurface regions around the wells. Capturing upside potential is equally important. The Redevelop and Grow case recognizes that up-swings in wholesale electricity prices may signal a comprehensive shift in long-term energy pricing due to influences like carbon taxation or societal shifts toward more electricity usage. To take advantage of the opportunity, this case considers a price change threshold as the trigger for installing additional geothermal power plant modules and renegotiating the PPA with the local utility company. The scenario assumes a flat percentage increase in capacity (*Price trigger for flexibility*) and universal success in establishing new power agreements at a set mark-up percentage above wholesale (*Contract rate over wholesale*). The field redevelopment decision rule outlined for the Redevelop Only case remains intact, and another decision rule for design flexibility in modular growth is as follows:

Decision Rule:

1. Set the *Auto Renegotiated Price* to the *Price Forecast* for the current year multiplied by the *Contract rate above wholesale*.
2. In the annual cashflow analysis, look up the forecasted wholesale electricity price for the current year ($p2$). Compare this value to the base price ($p1$) determined the last time *Capacity Level*

Increase was non-zero, i.e. when the last PPA was negotiated. Note that $p1$ captures the price before the *Contract rate above wholesale* mark-up. Calculate *Price Deviance* as $\left(\frac{p2-p1}{p1}\right)$.

3. IF *Price Deviance* exceeds the *Price trigger for flexibility* and the current year is not within 5 years of *Plant Useful Life*, THEN:
 - a. Multiply the past year's *Unit Count* by the *Expansion amount*. Round this number up to the nearest integer. This is the *Capacity Level Change [Auto]*.
 - b. Add *Capacity Level Increase [Manual]* + *Capacity Level Change [Auto]* + *Units Redeveloped*. Multiply this by *Wells per Module* and add to *Wells Drilled or Redrilled* from the previous year to determine the current year's *Wells Drilled or Redrilled*.
 - c. Add drilling costs to that year's CAPEX in two parts: new wells and redeveloped wells:
 - i. For *CAPEX Redevelopment*, determine the costs as described in the *Redevelop Only* decision rule.
 - ii. For *CAPEX Drilling*, multiply the sum total of *Capacity Level Increase [Manual]* and *Capacity Level Change [Auto]* by *Total Capital Costs (drilling)* and apply the learning rate discount as defined in the *Redevelop Only* decision rule. Note that *Total Capital Costs (drilling)* is a per-module value, not per well.

Full Flexibility Case

Price swings can go the opposite direction as well. The Electrification Futures Study (Murphy et al., 2021) identified some scenarios where electricity prices drop between 2020 and 2050, so having a means of addressing a future with tighter margins would be a useful flexibility. In the Full Flexibility Case, field redevelopment with thermal degradation and capacity increases in response to price surges remain in effect. In addition, a sudden drop in electricity prices serves as a trigger for the power plant operator to remove or decommission a number of binary cycle modules. Since modules operate independently with their own injector-producer couplet and stand-alone operations, they can be individually decommissioned with no impact on other installed modules in the aggregate facility. Additional cost savings might be realized if the modules were leased and the internal equipment returned to the vendor when no longer in use, although for the sake of simplicity, this option has not been included in the cost model. The decision rule for price-based decommissioning of active modules is as follows:

Decision Rule:

1. Calculate *Price Deviance* as in the *Redevelop* and *Grow* decision rule.

2. IF *Price Deviance* is negative, exceeds the *Price trigger for flexibility* in magnitude, and the current year is not within 5 years of *Plant Useful Life*, THEN:
 - a. Multiply the past year’s *Unit Count* by the *Reduction amount*. Round this number down to the nearest integer and multiply by -1. This is the *Capacity Level Change [Auto]*.
 - b. Store the sum of the previous year’s *Unit Count* and the current year’s *Capacity Level Change [Auto]* as the current year’s *Unit Count*. OPEX is calculated using this value, so any reduction in number of modules will reduce OPEX accordingly.
 - c. Do not reduce *Wells Drilled or Redrilled* using a negative value for *Capacity Level Change [Auto]*. This variable tracks learning over time and shutting down a module does not negate the experience of drilling that module’s wells.

Results and Discussion

Construction Schedule

The number of modules installed each year was varied by hand using the Deterministic model to identify an NPV-optimal construction schedule for the modular geothermal units (Table 1). Of the trials attempted, the lowest (worst) NPV is achieved when all modules are brought online for use in the first year. Instead, installing one (1) module initially, then adding four (4) more after one year is predicted to result in over 2x the NPV compared to the all-at-once strategy. This is likely due to the impact of the discount rate and an adjustment to the power purchase agreement triggered whenever new capacity is added.

Trial	Year 0	Year 1	Year 2	NPV _{Det}
1	5	0	0	\$1.19MM
2	2	2	1	\$3.59MM
3	2	3	0	\$3.76MM
4	1	2	2	\$3.29MM
5	1	3	1	\$3.61MM
6	1	4	0	\$3.82MM

Table 12: Results of adjusting the deterministic model to identify the optimal power plant build-out schedule. NPV_{Det} is deterministic model NPV in USD. 1 MM = 1 million.

Monte Carlo Results

Base Case

The Base Case scenario incorporates uncertainties in geothermal gradient, drilling and completions costs, thermal drawdown rate, and step-change price adjustments to provide a more realistic range of forecasts than the deterministic cost model. No flexible decision rules were included in this scenario. Results from 2000 Monte Carlo

realizations are shown in Table 13. The same construction schedule highlighted in Table 12 was applied to this and all other Monte Carlo models for comparability to the deterministic case. Base Case Expected Value of NPV (ENPV) captures the average result for all realizations. At -\$4.0MM, ENPV is over 200%

Base Case Statistics	N=2000
ENPV	-\$4.0MM
STD(NPV)	\$8.7MM
P05 NPV	-\$19.8MM
P50 NPV	-\$2.3MM
P95 NPV	\$6.6MM
% Difference from NPV _{Det}	-207%

Table 13: Base Case Monte Carlo results

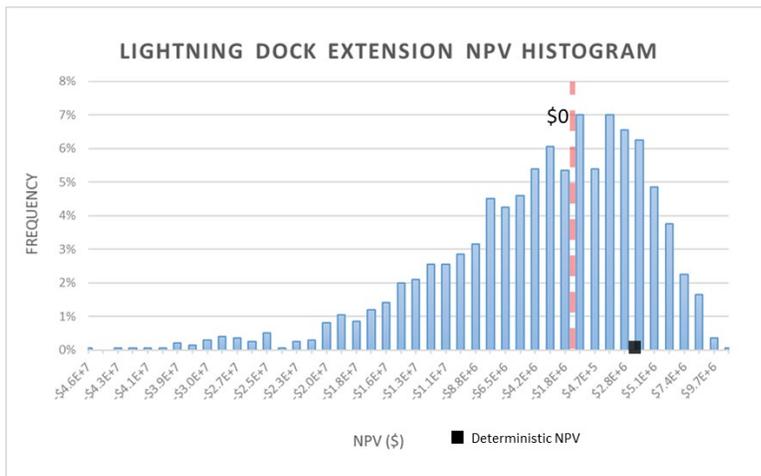


Figure 22: Base Case histogram showing distribution of 2000 realization results. NPV is reported in 2020 USD.

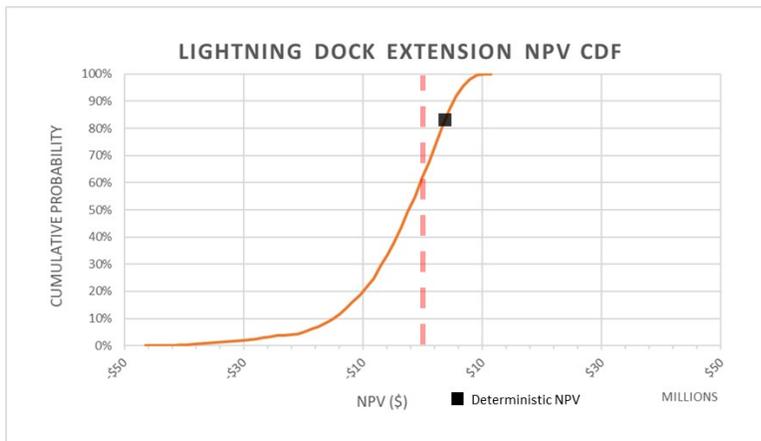


Figure 23: Base Case target curve (CDF). NPV is reported in 2020 USD.

less than NPV_{Det}. The histogram in Figure 22 illustrates the extended tail of downside cases that drives this result. Cumulatively, ~60% of the realizations end in a net loss for the project (Figure 23). And at 2x greater than ENPV, standard deviation of NPV indicates this solution is not robust. For the deterministic case, the Flaw of Averages is in effect; by applying only the average values for uncertain variables that have a skewed probability distribution (e.g., thermal draw-down rate), the possibility of poor results is hidden from view. The Monte Carlo results display both a negative ENPV and a high likelihood of project financial loss. Without additional scenarios or clear strategies for mitigating risk, this project would and should be rejected by a responsible portfolio manager.

Redevelop Only Case

The Redevelop Only scenario extends the Base Case with a decision rule to redrill both the injector and producer wells for each module at a time interval tied to the thermal drawdown rate. With each redevelopment, the reservoir temperature used in the capacity calculations resets to the original reservoir temperature in the model, improving the electricity generation actuals and the associated revenue. Table 14 lists the results after 2000 realizations of the Monte Carlo simulation. ENPV is an improvement (+\$2MM) over the Base Case but still predicts

Redevelop Only Statistics	N=2000
ENPV	-\$1.8MM
STD(NPV)	\$6.5MM
P05 NPV	-\$14.3MM
P50 NPV	-\$0.7MM
P95 NPV	\$6.5MM
% Difference from NPV _{Det}	-150%

Table 14: Redevelop Only Monte Carlo results.

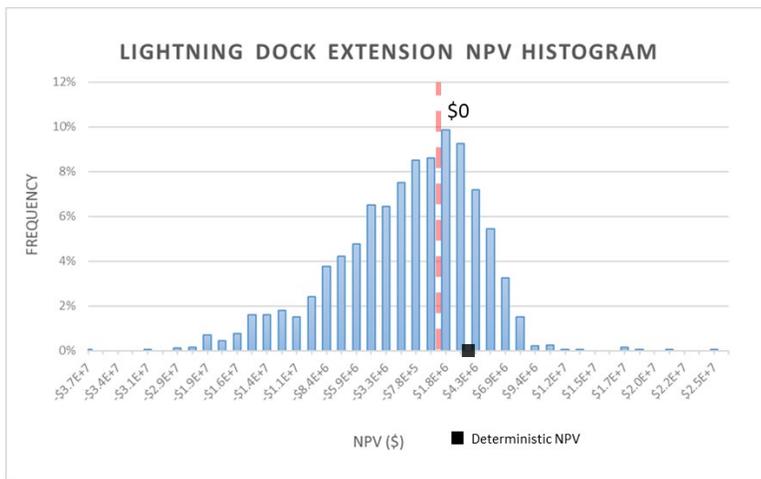


Figure 24: Redevelop Only case histogram showing distribution of 2000 realization results. NPV is reported in 2020 USD.

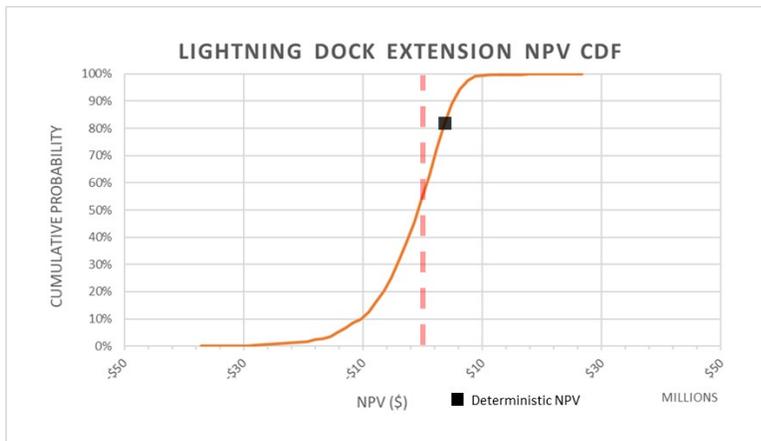


Figure 25: Redevelop Only target curve (CDF). NPV is reported in 2020 USD.

a significant project loss of -\$1.8MM. This case exhibits a slightly more compact distribution of results (Figure 24) compared to the strongly-skewed Base Case (Figure 22). But the standard deviation of NPV still remains high at \$6.5MM because the downside tail persists. About the same percentage of cases result in a net loss for the project as for the Base Case (Figure 25).

The redevelopment flexibility does not address upside potential. Instead, it focuses on maintaining power generation efficiency as physical conditions degrade over time. Unsurprisingly, the Monte Carlo estimate for P95 NPV is \$6.5MM, quite similar to the Base Case (Table 2, Table 3).

As a brief caveat: the idea of periodic redevelopment for a geothermal field is not novel. In fact, it's a built-in feature of the

GETEM model (Entingh et al., 2006), among others. Nevertheless, the analysis above illustrates why this real option should be included in geothermal planning and cost analysis strategies to help mitigate against the risk of high thermal drawdown rates, as long as drilling costs are low enough to make it attractive.

Redevelop and Grow Case

The third flexible design under consideration, Redevelop and Grow, takes the Redevelop Only model and extends it with a decision rule tied to wholesale electricity pricing. If a price increase of 20% or more is detected compared to pricing when the last PPA was negotiated, that is, when the last capacity increase was installed, then the capacity is automatically increased by 25% and a new PPA price applied. Under this scenario, ENPV leaps to \$9.7MM as power plant growth captures market potential (Table 15). In addition, there is increased mitigation of downside risk compared to the Redevelop Only case (Figure 26). Fewer than 17% of Monte Carlo realizations result in a project loss (Figure 27). ENPV outperforms NPV_{Det} by about \$6MM and the target curve shows a P95 NPV of \$27.0MM. Standard deviation of NPV increases

Redevelop Grow Statistics	N=2000
ENPV	\$9.7MM
STD(NPV)	\$10.3MM
P05 NPV	-\$6.6MM
P50 NPV	\$9.4MM
P95 NPV	\$27.0MM
% Difference from NPV _{Det}	162%

Table 15: Redevelop and Grow Monte Carlo results.

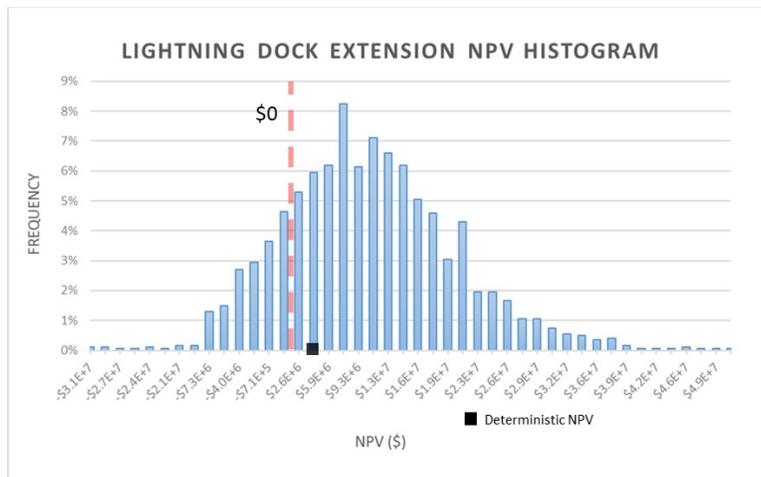


Figure 26: Redevelop and Grow case histogram showing distribution of 2000 realization results. NPV is reported in 2020 USD.

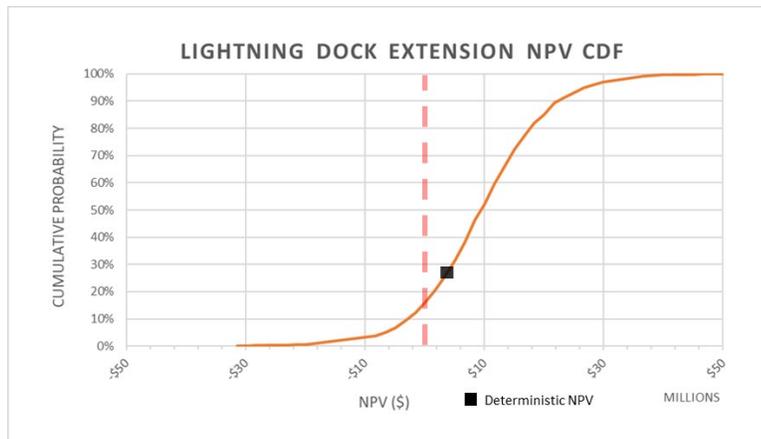


Figure 27: Redevelop and Grow case target curve (CDF). NPV is reported in 2020 USD.

compared to the Redevelop Only case, suggesting this model is less robust. But unlike either of the prior models, the greater spread here skews toward the upside and is a desirable feature. It stands to reason then that robustness measured by standard deviation of NPV is not as useful a measure of design benefit as the other metrics in Table 15.

It is also worth noting that the distribution of model results sharply cuts off around -\$7MM NPV in Figure 26. One interpretation relies on the balance between new capital costs incurred and wholesale electricity price trends. Specifically, the downside results for Redevelop Only realizations are driven by additional OPEX from drilling and completions, and very negative NPV realizations likely reflect

high thermal drawdown rates that require very frequent re-drills. Meanwhile, the wholesale electricity price forecast monotonically increases with some probability of a positive or negative step change related to sudden policy changes or global events. In high-frequency redrill model realizations, revenue increases from PPA adjustments act as a stopgap on the impact of cumulative drilling costs. Using a different price forecasting technique with negative year-on-year trends in wholesale electricity prices – as some scenarios in the Electrification Futures Study predict (Murphy et al., 2021) – could lead to downside model results without such a sharp cut-off.

Full Flexibility Case

The final case extends the Redevelop and Grow logic with one additional decision rule to allow decommissioning of power plant modules when wholesale power prices suddenly drop by 20% or more. This drop could signal a longer-term change in electricity trends, which a proactive

Full Flexibility Statistics	N=2000
ENPV	\$8.2MM
STD(NPV)	\$10.3MM
P05 NPV	-\$8.8MM
P50 NPV	\$8.1MM
P95 NPV	\$25.2MM
% Difference from NPV _{Det}	121%

Table 16: Full Flexibility Monte Carlo results.

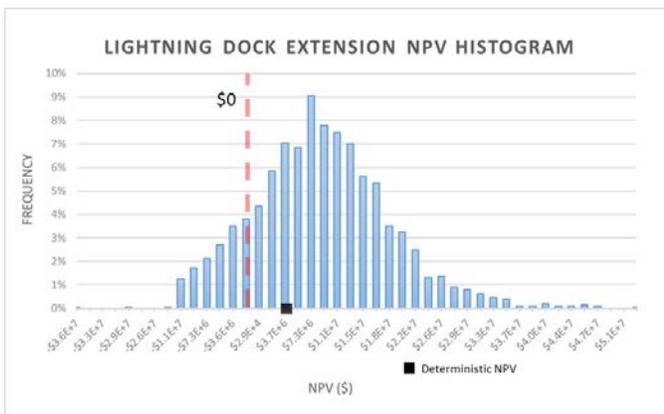


Figure 28: Full Flexibility case histogram showing distribution of 2000 realization results. NPV is reported in 2020 USD.

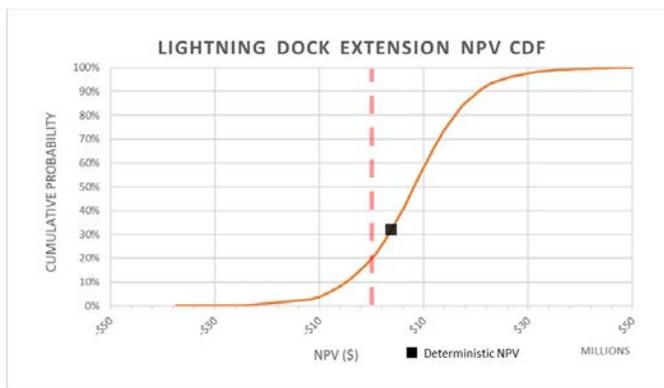


Figure 29: Full Flexibility case target curve (CDF). NPV is reported in 2020 USD.

operator may want to get ahead of by shutting down some modules to save on OPEX. In modeling this decision rule, the same capacity change percentage is used as with the Redevelop and Grow case, i.e., 25% of installed modules are removed from production when a significant price drop is detected. Using the same 2000-run Monte Carlo methodology, the predicted ENPV is \$1.5MM lower than the ENPV for the Redevelop and Grow model. Similar differences are seen in P05, P50, and P95 NPV values (Table 16). The results histogram and associated target curve are shown in Figure 28 and Figure 29.

It is interesting to note that the modeled electricity forecast includes enough volatility to generate cases with both +20% and -20% price changes (Figure 19), potentially (and perhaps unrealistically) triggering both a capacity

expansion and reduction within the same 30-year lifespan of a simulated facility. Nevertheless, the model results indicate this case is fully dominated by the Redevelop and Grow case. One simple explanation is that if modules are taken offline, the model is more sensitive to the reduction in total amount of electricity produced than any benefit realized by not operating those modules. There may be cost savings in less OPEX, but income reductions exert a stronger influence on overall NPV.

Sensitivity Testing

The Full Flexibility case relies on the *Reduction amount (RA)* parameter to determine how many modules are decommissioned when a significant electricity price drop is detected. In order to investigate how the model reacts to changes in this parameter, alternate Monte Carlo simulations with 2000 runs each were executed using *RA* values of 10% and 50%. Figure 30 shows the resulting target curves relative to the other scenarios described in this report. Increasing *RA* from 25% to 50% accentuates the poorer performance of this model compared to the Redevelop and Grow case. As *RA* values are increased, the target curve shifts further to the left, making the scenario less desirable. Interestingly, decreasing *RA* results from 25% to 10% results in a crossover of the target curves such that Full Flexibility is the dominant case. Recall that Full Flexibility implements the Redevelop and Grow decision rules, so setting *RA* to 0% reproduces the Redevelop and Grow case. Thus, there appears to be a small window of values for *Reduction amount* over which the Full Flexibility would be the preferred design. If an operator decommissions 25% or more of the modules at once, the loss of income from the decrease in power generation carries greater financial impact. A more conservative decommissioning approach that shuts down only 10% of existing modules at a time enables reduced operating expenses and maintenance to surpass the loss in income, providing greater overall ENPV and reduced downside risk relative to all other modeled cases (Table 17). This is the preferred model for developing the Lightning Dock expansion.

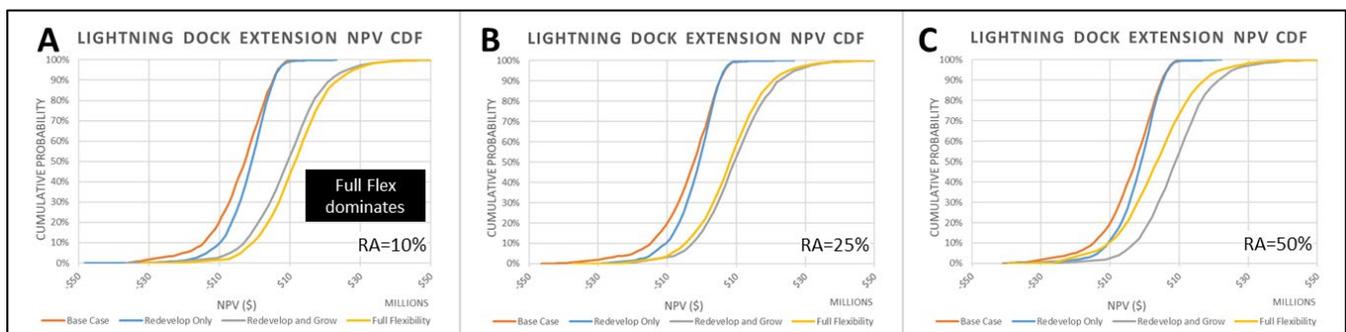


Figure 30: Sensitivity testing of the Reduction amount parameter on the Full Flexibility case relative to all other models. A. Reduction amount = 10%, B. Reduction amount = 25%, C. Reduction amount = 50%. Note the changing relationship between Redevelop and Grow case and Full Flexibility case as Reduction amount is increased above 10%.

Full Flexibility Statistics	N=2000
ENPV	\$11.5MM
STD(NPV)	\$9.8MM
P05 NPV	-\$3.9MM
P50 NPV	\$11.4MM
P95 NPV	\$27.9MM
% Difference from NPV _{Det}	212%

Table 17: Summary statistics of the preferred model for Lightning Dock expansion. Results use the Full Flexibility decision rules with a reduced amount parameter set to 10%.

Conclusions

In this case study, an economic model for a 5 MW modular expansion of the Lightning Dock power plant was developed in Excel. The subsurface thermal resource, binary cycle electricity generation system characteristics, power plant efficiency, and associated capital and operating expenses were assigned values for a deterministic case assessment. Probability distribution functions were defined for drilling costs, changes in wholesale electricity price, thermal drawdown rate, and geothermal gradient. Target curves and expected value estimates were derived using random sampling and Monte Carlo simulation. Decision rules coded in Excel allowed for variation in simulation results as real options around field redevelopment, capacity increases, and module decommissioning were considered. The model results support the following conclusions:

1. The deterministic model overpredicts NPV due to its use of average values rather than probability distributions for uncertain variables (Flaw of Averages). NPV is positive and nearly as large in magnitude as the loss predicted by the probabilistic Base Case.
2. The Base Case model with no flexibility results in net losses in over 60% of the simulated runs. A business plan based on this model would not have enough financial standing to be implemented.
3. Including well redevelopment to mitigate thermal drawdown (Redevelop Only case) serves to limit the downside but does not make the project viable on its own. Approximately 56% of simulated runs result in a net loss, but the magnitude of extreme losses is less those seen for the Base Case.
4. Significant improvements to downside risk and upside capture are realized by flexibly increasing capacity and renegotiating power purchase agreements based on a trigger for wholesale price surges (Redevelop and Grow case). The model forecasts a net profit on average and only sees losses <20% of the time.
5. Including flexibility to decommission modules when electricity prices plummet (Full Flexibility Case) generally results in poorer model performance compared to the Redevelop and Grow case. The target curve is fully dominated when the percentage of modules decommissioned at one time is 25% or greater.

6. There is a sweet spot for the Full Flexibility case observed when the module reduction percentage is set to 10%. Under these conditions, the loss in income due to generating less electricity is overcome by the savings in OPEX from decommissioning modules in a price downturn.

The preferred strategy follows a conservative variation on the Full Flexibility case, which incorporates three decision rules: 1) Redevelop existing injection and production wells as thermal drawdown limits the efficiency of the power plant modules; 2) increase capacity and renegotiate power purchase agreements if sudden increases in the price of electricity take place; and 3) slowly decrease the number of modules operating when electricity prices take a turn for the worse. This project design has an expected NPV of ~\$12MM, making it a feasible design for expanding the Lightning Dock power plant.

Reflection

Academic scientists, government agencies, and energy companies regularly use cost models to predict the viability of commercial electricity generation from renewable resources. Early publications outlining the process of cost modeling for geothermal date back several decades (e.g., Armstead & Tester, 1987; Tester & Herzog, 1990) and laid the groundwork for several modeling tools still in use today (Freeman et al., 2018; Mines, 2016). Only recently have models like SAM begun to incorporate some level of uncertainty, but no broadly-used model (to the author’s knowledge) combines a user-defined geothermal resource, subsurface development concept, and surface facility type with real options for a more comprehensive evaluation.

Real options offer a simple and elegant method for moving beyond sensitivity analysis of key uncertainties into evaluating how uncertainty mitigation can lead to better project plans. Defining real options requires broader thinking about system interactions, stepping away from the strict bounds associated with the cost model being constructed to consider assumptions underlying the model. For example, it may seem safe to assume the geothermal gradient is well-established within a KGRA like Lightning Dock, but a cost model loses all credibility when the first offset well encounters something different. Furthermore, models that rely on other models for input suffer from multiple layers of assumptions. Electricity forecasts from agencies like the U.S. Energy Information Agency (EIA) appear foolproof enough to many, but a review of past Annual Energy Outlook projections (see EIA, 2021b) shows just how frequently those forecasts miss

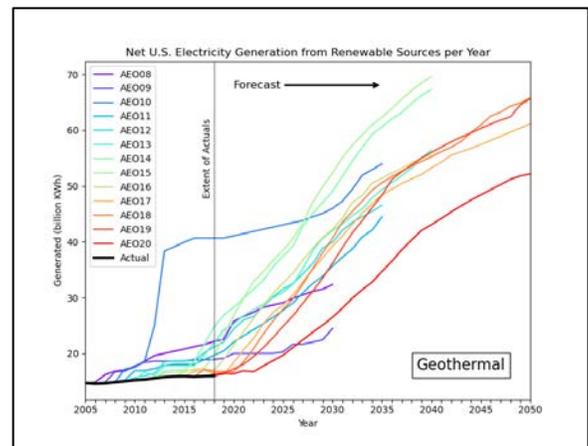


Figure 31: Electricity generation from geothermal production by year (black line). Each colored line represents a forecast from the EIA AEO report associated with the labeled year (see legend).

the mark (Figure 31). Treating forecasts as deterministic ground truth would not only be factually incorrect, it also misses an opportunity for a more thorough examination of the solution space.

Approaching the Lightning Dock expansion project with flexibility in mind flipped the script on how such a project should be modeled. Instead of directly using average values or raw forecasts like the Short-Term Outlook (EIA, 2021a), this methodology encouraged a thoughtful exploration and ranking of uncertainties, followed by a characterization of uncertainty with probability functions. The process of defining these functions was meaningful work since it prompted further research into possible outcomes, from which a project strategy could be devised. These strategies led to the decision rule criteria outlined earlier in this report, which in turn resulted in different model cases to explore as part of a comprehensive exercise in flexible design.

It is not hard to imagine unfortunate (or fortunate) events that would impact the financial success of a power plant expansion rated for a 30-year useful lifespan. Not only are real options relatively simple to define (e.g., IF statements in Excel), they also allow aspects of these events to be included directly in the model for insights into potential impact and the expected outcome of mitigation responses. In this study, the deterministic and Base Case models describe a project with little chance of getting off the ground based on their negative ENPV results. But by using this powerful methodology, flexible cases like Redevelop and Grow and Full Flexibility were devised that characterized unforeseen profit potential. That's a truly useful methodology indeed.

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