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A Python-based Stochastic Library for Assessing Geothermal Power Potential in the Municipality of Nombre de Jesús, El Salvador

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ABSTRACT

We present a Python-based stochastic library for assessing geothermal power potential using the volumetric method in a liquid-dominated reservoir. The specific aims of this study are to use the volumetric method, heat in place, to estimate electrical energy production ability from a geothermal liquid-dominated reservoir, and to build a Python-based stochastic library with useful methods for running such simulations. Although licensed software is available, we selected the open-source programming language Python for this task. The Geothermal Power Potential Evaluation stochastic library (GPPeval) is structured as three essential objects including a geothermal power plant module, a Monte Carlo simulation module, and a tools module. In this study, we use hot spring data from the municipality of Nombre de Jesus, El Salvador, to demonstrate how the GPPeval can be used to assess geothermal power potential. Frequency distribution results from the stochastic simulation shows that this area could initially support a 9.16 MWe power plant for 25 years, with a possible expansion to 17.1 MWe. Further investigations into the geothermal power potential will be conducted to validate the new data.

1. INTRODUCTION

The geothermal resource assessment is an estimation of the amount of thermal energy ("heat in place") that can be transformed from a geothermal reservoir for economic use in a variety of applications. However, such data are often limited or difficult to obtain during initial geothermal exploration, and a basic assessment method is needed (Saibi, 2018). In the 1970s, researchers at the United States Geological Survey (USGS) developed a method to quantify geothermal resource estimate uncertainties associated with a given hydrothermal area. This simple technique, called the USGS volumetric "heat in place" method, (Cataldi et al., 1978; Garg & Combs, 2015; Muffler & Cataldi, 1978), is therefore also employed in the present study.

The primary purpose of this study are to use the volumetric method to estimate electrical energy production ability from a geothermal liquid-dominated reservoir, and to develop a Python-based stochastic library, called the Geothermal Power Potential Evaluation (GPPeval), with suitable methods for running the simulations. The calculation of geothermal energy stored in a given volume is based on a range of reservoir parameters, carried out using a stochastic Monte Carlo simulation, and applies a probabilistic method for evaluating reserves or resources and the associated estimation uncertainties. Given the geological complexity and heterogeneity of most geothermal reservoirs, this method is more appropriate than the usual deterministic approach that assumes a single value for each parameter to represent the entire reservoir. Instead of assigning a fixed value to a reservoir parameter, numbers within a range of the distribution model are randomly selected and drawn for each calculation cycle over a thousand iterations (Sarmiento & Steingrímsson, 2011; Wakeyama & Ehara, 2009).

Licensed software is available for carrying out this simulation, however the algorithm was programmed using the open-source programming language Python (Python Software Foundation, 2016). Python is a platform-independent, full-feature, object-oriented programming language that has grown in popularity over the last decade due to its versatility and explicit syntax. Furthermore, Python is widely used throughout the geophysics community (Krieger & Peacock, 2014). The stochastic library developed in this study is distributed as it is without charge. The Numpy and Scipy modules allow handling of large numerical data sets, and the built-in file handling and flexibility of string manipulations allow for confident processing of files in arbitrary formats, e.g., CSV. In addition to the standard modules within Python, GPPeval utilizes the Matplotlib module for graphical visualization, the Beautifultable module for easily printing tabular data in a visually appealing ASCII format to a terminal, and the Mcerp module for performing non-order specific error propagation[1] or uncertainty analysis (Lee, 2014).

The GPPeval is structured as three essential objects including a geothermal power plant module, a Monte Carlo simulation module, and a tools module. The geothermal power plant abstraction or object contains the necessary properties and methods employed in the Monte Carlo simulation. The Monte Carlo abstraction or object has the essential properties and methods for running the Monte Carlo simulation and obtaining the geothermal power potential. The tools abstraction or object has the necessary properties and methods for showing the simulation results. Hot spring data from the municipality of Nombre de Jesus, El Salvador (Campos, 1988) was used to demonstrate how the GPPeval can be used to assess geothermal power potential.

[1] The "Non-order specific error propagation" means that Mcerp does not make any assumptions or approximations in how uncertainty in the input variables is converted into uncertainty in the output functions. This Python library, being a random sampling based approach, takes the result as it is. It is possible to perform various statistical analyses on the data to find out information about the resultant distribution (Lee, 2014).

2. THERMAL ENERGY CALCULATIONS

A typical geothermal reservoir and the required model parameters are shown in Figure 1. Two distinct purposes are identified in this task:

1. To address the question of geothermal energy, the study area should have specific attributes including a geothermal aquifer or reservoir, cap rock, bedrock, either a fractured-rock environment or permeable rock, convection-driven movement of hot fluid, and a heat source such as an intrusive magma chamber, fossilized dike, or relevant regional activity (DiPippo, 2012).

2. To assess reservoir power generation, the geothermal area should have defined parameters such as the reservoir area (A), thickness (h), and temperature (Tr), the abandon temperature (Ta), average rock porosity (ϕ), rock specific heat (Cr) and density (ρr), fluid specific heat (Cf) and density (ρf), a heat recovery factor (RF), electrical conversion efficiency (ηe), plant net capacity factor (PF), and lifespan (t).

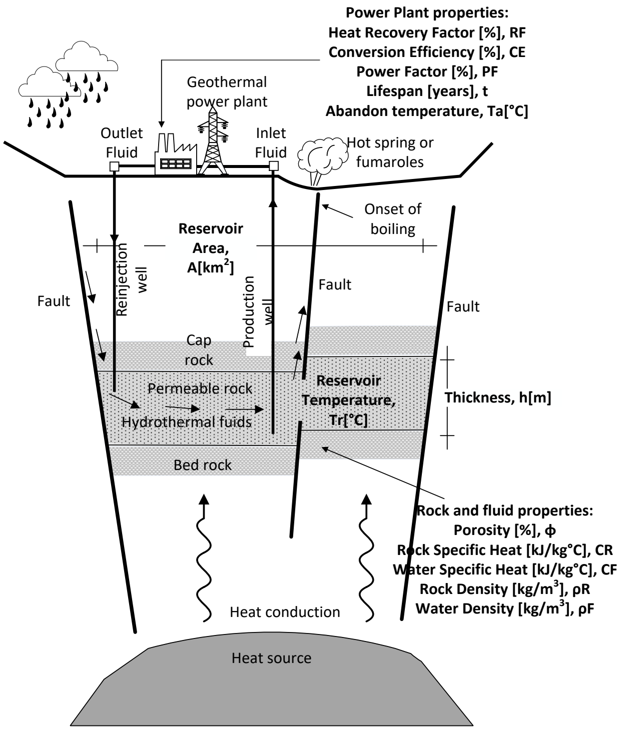

Figure 1. A typical hydrothermal geothermal reservoir with parameters required for assessing the geothermal power potential (DiPippo, 2012).

The volumetric method refers to the calculation of thermal energy in a rock and fluid that can be extracted based on a specified reservoir volume, temperature, and reference or final temperature. This approach is based on methods applied by the USGS to assess geothermal resources of the United States (Muffler & Guffanti, 1978). The final or reference temperature using those methods is based on an ambient temperature of 15 ºC (or a condensing temperature of 40 ºC) that was commonly used in previous USGS applications. However, the use of an arbitrary low reference temperature (i.e., ambient or condensing temperature) often results in an overestimate of the available thermal energy. The abandon temperature, or temperature below which a geothermal reservoir is not producible, should therefore be used as the reference temperature to obtain realistic estimates of the available thermal energy. Abandon temperature values depend on the power cycle. Thus, for a flash-type power plant, the lower limit of the abandon temperature is given by the saturation temperature, which corresponds to the separator pressure, and the so-called pinch point temperature for a binary power plant. Under appropriate space heating conditions, the abandon temperature is usually 30–40 °C, while a typical high-temperature geothermal resource has an average reservoir temperature of 250 ºC. Assuming that a single flash cycle has a separator pressure of 5 bar (saturation temperature of 151.831 ºC), the abandon temperature would be equal to 151.831 ºC. Similarly, a conventional low-enthalpy fluid with an average temperature of 150 ºC is used to heat a secondary working fluid (isobutane) with an assumed pressure of 20 bar and saturation temperature of 100.36 ºC. Therefore, considering a temperature difference of 5 ºC at the pinch point, the abandon temperature is 105.36 ºC (Garg & Combs, 2015; National Institute of Standards and Technology NIST, 2017). The equation used in thermal energy calculations for a liquid-dominated reservoir is as follows:

$$Q_T = Q_r + Q_w \tag{1}$$

where

$$Q_r = A \cdot h \cdot [\rho_r \cdot C_r \cdot (1 - \phi) \cdot (T_r - T_a)] \tag{2}$$

$$Q_w = A \cdot h \cdot [\rho_w \cdot C_w \cdot \phi \cdot (T_r - T_a)] \tag{3}$$

with parameters defined in Table 1.

Table 1. Thermodynamic parameters of the reservoir required for calculating total thermal energy.

Symbol	Description	Units
Q_T	Total thermal energy	kJ
Q_r	Heat in rock	kJ
Q_w	Heat in fluid	kJ
A	Area of the reservoir	km^2
h	The average thickness of the reservoir	m
ρr	Rock density	kg/m^3
ρw	Fluid density	kg/m^3
C_r	Rock specific heat at reservoir conditions	kJ/kg-°C
C_w	Fluid specific heat at reservoir conditions	kJ/kg-°C
ϕ	Porosity	%
T_r	The average temperature of the reservoir	°C
T_a	Final or abandon temperature	°C

3. POWER PLANT SIZING

Solutions to Equation 1 provide only the total thermal energy in the reservoir, while the size of the power plant that could be supported by the resource is calculated by combining the previous into Equation 4 as follows:

$$P = C\left[A \cdot h \cdot (T_r - T_a) \cdot [\rho_r C_r(1-\phi) + \rho_w C_w \phi] \cdot \frac{RF \cdot C_e}{PF \cdot t}\right] \tag{4}$$

Parameters are listed in Table 2.

Table 2. Power plant sizing parameters.

Symbol	Description	Units
P	Geothermal power potential	We
RF	Recovery factor	%
C_e	Conversion efficiency	%
PF	Plant net capacity factor or plant factor	%
t	Lifespan (economic life)	years
C	Unite conversion factor	31.6880878

3.1. Power plant parameters

The recovery factor refers to the fraction of heat stored in the reservoir that could be extracted to the surface (Zaher, 2011; Sanyal & Sarmiento, 2005). This term depends on the reservoir fraction that is considered permeable and the efficiency by which heat can be withdrawn from such permeable channels. The conversion efficiency accounts for the conversion of recoverable thermal energy into electricity. The economic life of the project is the period required for the full investment to be recovered within its target internal rate of return, which is usually 25 to 30 years. The plant factor refers to the plant availability throughout the year, taking into consideration the period when the plant is scheduled for maintenance, or whether the plant is operated as a base-load or peaking plant. A good performance for many geothermal plants around the world is about 90 to 97 % (DiPippo, 2015; Zarrouk & Moon, 2014).

4. GUIDELINES FOR DETERMINATION OF THE RESERVOIR PARAMETERS

Recent developments in the geothermal industry require the establishment of guidelines on how reserve estimation is to be approached and reported in corporate annual reporting or financial statements. Sanyal and Sarmiento (2005) proposed three categories for reserve classification: proven, probable and possible, all of which are more appropriately estimated using volumetric methods. The need for an industry standard is now imminent to create consistency in declarations of estimated reserves for a given project. Sanyal and Sarmiento (2005) used results from Monte Carlo simulations to determine the proven, probable, and possible or inferred reserves based on the resulting percentiles obtained from the cumulative frequency distribution. The percentile value indicates the probability that the reserve quantities to be recovered will equal or exceed estimates. The following terms are defined in this study such that the proven reserves will have a 90 % probability, and 5 % for the proven + probable + possible reserves or the maximum reserves. Histograms of geothermal reserves calculated by Monte Carlo simulations are often highly skewed; hence, the proven + probable is better represented by the most likely value instead of the 50^{th} percentile (Aravena et al., 2016; SPE, 2001).

4.1. Resource and reserves

A resource is the energy that can be economically and legally extracted at some specified time in the future (less than 100 years). Reserves are defined as quantities of thermal energy that are anticipated to be recovered from known reservoirs from a given start date. A reserve is a part of the resource, which can be presently economically and legally extracted, and is known and characterized by drilling or geochemical, geophysical, and geological evidence (Muffler & Cataldi, 1978).

4.2. Proven

Proven reserves are quantities of heat that can be estimated within reasonable certainty, based on geoscientific and engineering data, to be commercially recoverable from known reservoirs under current economic conditions, operating methods, and government regulation. The definition by Clotworthy et al. (2006) gives a more specific description, stating that a proven reserve is the portion of the resource sampled by wells that demonstrate reservoir conditions and significant fluid deliverability from the reservoir.

4.3. Probable

Probable reserves are unproven reserves that are most likely recoverable, but less reliably defined than proven reserves, with sufficient reservoir temperature indicators from either nearby wells or geothermometers along natural surface discharges that characterize the resource temperature and chemistry.

4.4. Possible or inferred

Possible reserves have a slightly smaller recovery chance than probable reserves, but have a sound basis from surface exploration (e.g., springs, fumaroles, resistivity anomalies) to declare that a reservoir may exist. Clotworthy et al. (2006) adopted inferred resources from what could cover possible reserves.

5. UNCERTAINTY DISTRIBUTION

The accuracy of methods used in geothermal reserve estimation depends on the type, amount, and quality of geoscientific and engineering data, which are also dependent on the stage of development and maturity of a given field. Accuracy generally increases once the geothermal field is drilled and more wells and production data become available (Sarmiento & Steingrímsson, 2011). Volumetric estimation is most commonly applied during the early stages of field development to justify drilling and commitment for a specified power plant size. This method is therefore better applied during the early stage than numerical modeling, which requires a significant number of wells and production history to be considered reliable. Assessment of geothermal reserves can be performed during the maturity of the field for use in annual company reporting and to enhance corporate assets for valuation. Some degree of caution and conservatism must be used, however, because of the limited data and uncertainty on the assumptions of reservoir parameters. This approach, which accounts for the risk factor in decision-making, can be quantified with reasonable approximation using a Monte Carlo simulation. Unlike a deterministic approach, where a single value is used representing the best guess, a probabilistic method of calculation is considered to account for the uncertainty on several variables in a geothermal reserve estimation. A Monte Carlo simulation calculates the frequency distribution of the random variables, which are dependent on the number of times a value is extracted from the uncertainty models of the input parameters following frequency distribution previously defined, e.g., Normal, Triangular, Log-Normal, Uniform (Sarmiento & Steingrímsson, 2011; Wakeyama & Ehara, 2009). A range of possible reserve estimates can be obtained depending on the assumptions included in the calculation. In general, the proven, probable, and possible or inferred reserves refer to the minimum, most likely or intermediate, and maximum estimates, respectively. The reservoir area and thickness are usually assigned by triangular distribution because these parameters are obtained directly from drilling and well measurements. A reasonable approximation of the resource area can be made based on temperature contours and electrical resistivity measurements, while permeability, porosity, and temperature values are directly measured from the well. Other parameters such as fluid densities and specific heat are dependent on the reservoir and abandon temperatures.

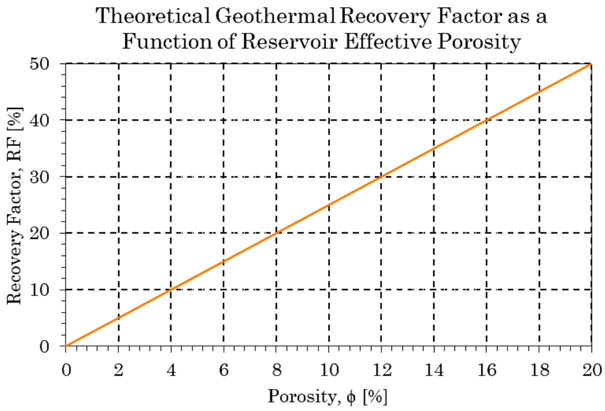

Figure 2. A possible variation of geothermal recovery factor as a function of effective porosity for reservoirs producing by a mechanism of intergranular flow. RF is taken to be 50 % for an ideally permeable reservoir in which total porosity is equal to the effective porosity. In the ideal situation, porosity can be assumed to be 20 % (Nathenson, 1975).

The recovery factor depends on the permeability structure (e.g., fracture vs. matrix, permeability anisotropy, faulting), production and injection well depths and patterns, and the thermal (i.e., heat and fluid recharge from depth) and hydraulic boundary conditions (i.e., recharge/discharge along the ground surface and assumed lateral boundaries of the geothermal reservoir). Because many reservoir properties that affect the thermal recovery factor are likely to be poorly known until the reservoir has been producing for several years, specification of the thermal recovery factor for a given reservoir is often a matter of conjecture. Some estimations of the thermal recovery factor based on both theoretical grounds and data from operating hydrothermal fields suggest that the appropriate range for fracture-dominated geothermal reservoirs is 0.08–0.20 and for sediment-hosted reservoirs the suggested range is slightly higher: 0.10–0.25 (Williams, 2014).The porosity in a geothermal reservoir which produces water or a water-steam mixture through intergranular flow[2] could be reasonably assumed that is a direct linear function of the recovery factor, at least as a conservative approximation (Bodvarsson, 1974; Nathenson, 1975). Figure 2 shows the correlation between the recovery factor (RF)

[2] The intergranular flow of water assumes an ideal, porous reservoir where the fluid has a very large contact area with the rock mass and the thermal contact can, therefore, be almost perfect, and the exchange of heat between the rock and the fluid can be practically complete (Muffler & Cataldi, 1978).

and porosity (ϕ) assuming the geothermal recovery factor to be independent of reservoir temperature under an intergranular flow model. This curve is likely to be conservative, with the true relation falling more towards the upper left of Figure 2, also does not take into account loss in enthalpy as the fluid flows to the earth's surface. For an ideally permeable geothermal reservoir, the RF theoretically could be as much as 50 %, and the effective porosity can be assumed to be 20 %. This assumption points up the immediate need of field and model studies of recoverability of the thermal energy from hot-water systems (Muffler & Cataldi, 1978). The conversion efficiency is the amount of geothermal energy that can be converted into electricity. This parameter is limited by the second law of thermodynamics, and it is also a function of the optimum plant design and the efficiency of different components, i.e., the conversion efficiency depends on each geothermal power plant. For example, the First Law thermal efficiency of a real thermal water engine based on a single flash steam cycle at 40 °C is less than ~12 % for temperatures between 150 and 250 °C and liquid-dominated reservoirs (Bodvarsson, 1974; Zarrouk & Moon, 2014). In the case of low-enthalpy applications, the conversion efficiency for several operating Organic Rankine Cycle (ORC) power plants is analyzed by applying an exergy efficiency analysis or so-called second law efficiencies. Most operating ORC power plants have relatively low (< 25 %) second law efficiencies (DiPippo, 2004). However, the California Energy Commission has suggested a conversion efficiency of 0.45 in a resource assessment of several low-temperature geothermal fields. Although the previous factor is theoretically possible, resource characteristics (e.g., change in resource temperature and pressure over time) and economic considerations usually dictate a much lower value (Garg & Combs, 2015; Klein et al., 2004).

Table 3. Guidelines followed in determining the various parameters for reserve estimation.[3]

Parameter	Proven reserve	Probable resource	Possible resource
Area	Defined by drilled wells with at least 500 meters beyond the drainage of the outermost wells bounded by an extrapolated production temperature of >100 ºC for binary and 180 °C for the flash-type cycle. Enclosed by good permeability and demonstrated commercial production from wells. Acidic blocks excluded until demonstrability for utilization is achieved.	Defined by wells with temperature contours that would extrapolate to >100 ºC for binary and 180 °C for the flash-type cycle. Acidic or reinjection blocks earlier delineated could be included. Areas currently inaccessible because of limited rig capacity and restriction imposed within the boundaries of national parks. Areas with wells which could be enhanced by stimulation like acidizing and hydro-fracturing. Areas with surface manifestations where geothermometers indicate temperatures.	Areas include those not yet drilled but enclosed by geophysical measurements like Schlumberger electrical resistivity and magneto-telluric surveys. Defined by areas with thermal surface manifestations, outflow zones, and temperatures based on geothermometers that are suitable for either binary or flash-type power plant.
Thickness	Depth between the 100 ºC for binary or 180 °C for the flash-type cycle and the maximum drillable depth of the rig that has demonstrated commercial production. Maximum depth should warrant economic output of the well.	Defined by demonstrated productivity in nearby areas or adjacent wells. Depth beyond the deepest well drilled in the area +500 meters provided projected temperatures reached at least 100 ºC for binary or 180 °C for the flash-type cycle.	Defined by demonstrated productivity in nearby areas or adjacent wells. Also, electrical measurements like Schlumberger electrical resistivity and magneto-telluric surveys.
Reservoir temperature	Taken from direct measurement in production wells, supplemented by enthalpy and chemical geothermometers.	Extrapolated from temperature gradients and temperature distribution across the field or results of geothermometers using water, steam, and gas from hot springs and fumaroles	Results of geothermometers using water, steam, and gas from hot springs and fumaroles. Resistivity anomaly where high resistivity anomaly is seen conductive blow cap, indicating chlorite-epidote alteration at depth.
Reference temperature		Use the abandon temperature as a reference temperature. Thus, for a flash-type power plant, the abandon temperature is given by the saturation temperature corresponding to the separator pressure, and for a binary power plant, it equals the so-called pinch point temperature.	

6. MONTE CARLO SIMULATIONS USING A PYTHON STOCHASTIC MODULE

The basic premise of a Monte Carlo simulation is to test various outcome possibilities. In reality, only one outcome possibility will play out, but, regarding risk assessment, any of the options could have occurred. A Monte Carlo simulator can help to visualize most or all of the potential outcomes to provide a better idea regarding the risks of a given decision (Harrison, 2018). In terms of programming area, Monte Carlo methods are a broad class of computational algorithms that depend on repeated random sampling to obtain numerical results. The essential concept is to repeat the experiment many times (or use a sufficiently long simulation run) to obtain many quantities of interest using the law of large numbers and other statistical inference methods (Kroese et al., 2014). Many licensed software are presently available for carrying out this task but in this case, the stochastic Monte Carlo simulation algorithm was programmed using Python (Brueck & Tanner, 2001; Python Software Foundation, 2016) and the Monte Carlo Error Propagation library (Lee, 2014). Python was chosen for the following reasons: 1) simplicity as a pseudo-natural code; 2) the algorithms work either locally (stand-alone) or in web-based applications; 3) Python is open source and is therefore free of charge, and any user can utilize, copy, modify, merge, publish, and distribute it; 4) the Python package can be used in most available operating systems (e.g., Linux-like, Microsoft Windows, MacOS); and 5) the developed stochastic library can be distributed as is without charge.

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[3] These guidelines use suggestions based on a possible classification for geothermal resources (Sanyal, 2005; Sarmiento & Steingrímsson, 2011).

6.1. Object-oriented programming and structure of the library

Object-oriented programming is a programming paradigm based on the concept of objects, which may contain data in the form of fields (often known as attributes or properties), and code, in the form of procedures (often known as methods). The use of classes (i.e., the base form of an object) organizes programs around modules and data abstractions. The key to object-oriented programming is thinking about objects as collections of both data and methods that operate on that data (Guttag, 2015). A generalized flowchart of the several independent steps required for running a Monte Carlo simulation is represented in Figure 3.

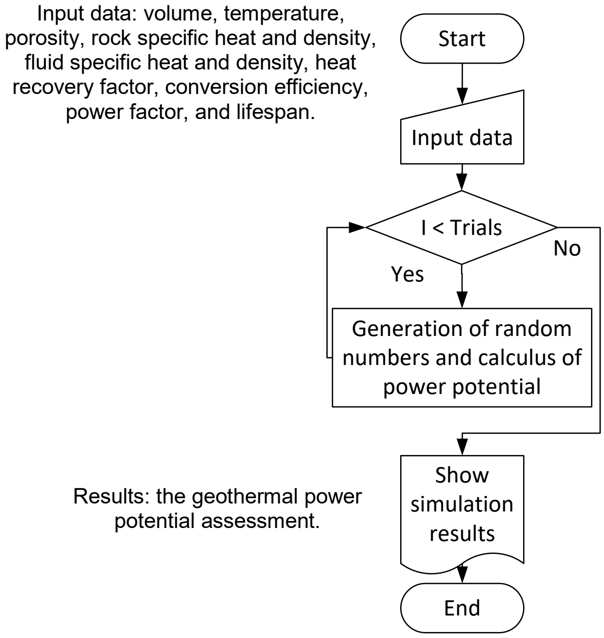


Figure 3. Structural flowchart showing the general simulation steps of a Monte Carlo simulation used by the Python-based stochastic library.

The simulation flowchart (Figure 3) has three general stages. First, the required geothermal reservoir information, such as those described in Section 2, is collected and organized in an input file. The simulation is then run several times, and the amount of trials is customizable to meet the required demands. Controlling the number of trials reduces the root mean square (RMS) of the calculations. Finally, command line text is used to graphically show the results (i.e., frequency bar, cumulative plot).

Reservoir parameters can be prepared by either using an external CSV file or by manually typing the values during the simulation process. An example of a CSV file is shown in Figure 4 which could be edited using either spreadsheet software or a simple ASCII editor. The first two lines are comments and ignored by the reading method. The third line is the first to be imported by the reading method and includes general information related to geothermal reservoir (e.g., name, geographic coordinates, and reservoir surface area). Lines four through fifteen are the remnant parameters required for the simulation.

```
1.      #Input file for the Assessment of Power Energy Generation,,,,,,,,,,,
2.      #Item,Name_Place,Lat,Lon,Properties,Symbol,Unit,Min,Most_Likely,Max,Mean,SD,PDF
3.      0,Name of place,14.00061,-88.73744,area,A,km2,5,6,7,0,0,T
4.      1,,,,thickness,h,m,450,500,600,0,0,T
5.      2,,,,Volume,v,km3,0.01,0.5,1.193,0,0,None
6.      3,,,,ReservoirTemperature,Tr,oC,110.0,110.0,125.0,0.0,0.0,T
7.      4,,,,AbandonTemperature,Ta,oC,0.0,106.7,0.0,0.0,0.0,C
8.      5,,,,Porosity,Phi,%,0.028,0.1,0.166,0.0,0.0,T
9.      6,,,,RockSpecificHeat,Cr,kJ/kg-oC,0.775,0.7925,0.81,0.0,0.0,T
10.     7,,,,WaterSpecificHeat ,Cf,kJ/kg-oC,4.2479,4.2838,4.3164,0.0,0.0,T
11.     8,,,,RockDensity,rho_r,kg/m3,2330.0,2485.0,2640.0,0.0,0.0,T
12.     9,,,,WaterDensity,rho_f,kg/m3,915.37,928.12,944.95,0.0,0.0,T
13.     10,,,,RecoveryFactor,Rf,%,0.08,0.14,0.2,0.0,0.0,T
14.     11,,,,ConversionEfficiency,Ce,%,0.1,0.175,0.25,0.0,0.0,T
15.     12,,,,PowerFactor,Pf,%,0.9,0.95,1.0,0.0,0.0,T
16.     13,,,,LifeSpan,t,years,0.0,20.0,0.0,0.0,0.0,C
```

Figure 4. Code line fragment of a typical comma-separated input file with geothermal reservoir information.

7. PYTHON STOCHASTIC MODULES

The Python-based stochastic library, GPPeval, is structured as three essential objects including a geothermal power plant module, a Monte Carlo simulation module, and a tools module, shown schematically in Figure 5. These three objects provide basic functionalities in the utility of classes and functions, as well as command line scripts. Incorporation of this modular structure not only enables possible adaption to local setups and configurations, but also conveniently extends the toolbox (Krieger & Peacock, 2014). The GPPeval must be installed, along with all dependencies (Numpy, Matplotlib, Scipy, Mcerp, and Beautifultable) prior to running any simulation.

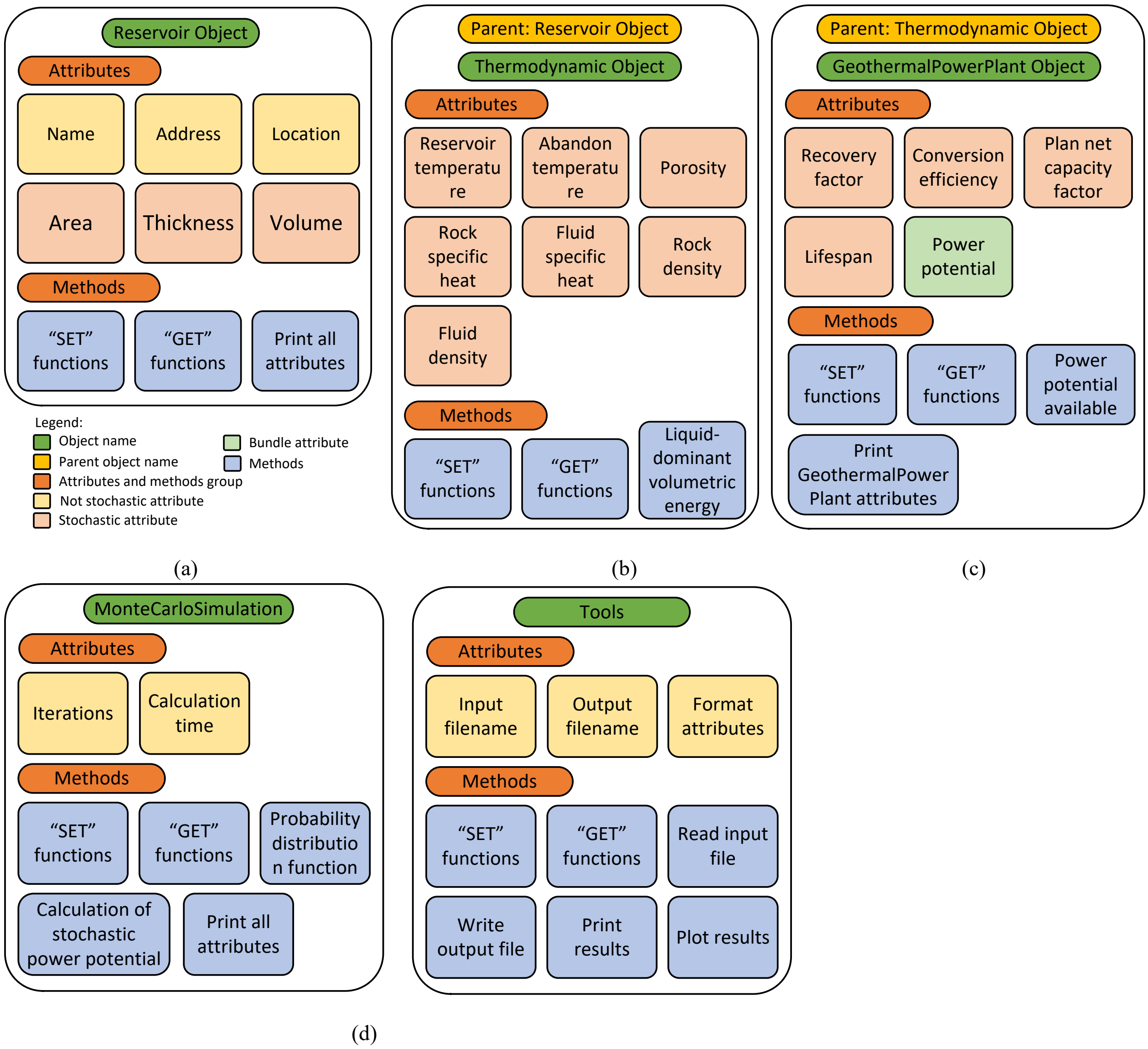


Figure 5. Overview of the objects used in the Python-based stochastic library. (a), (b), and (c), Geothermal power plant module, which inherits properties and methods from parent objects (i.e., thermodynamic and reservoir objects). (d) Monte Carlo and tools modules.

7.1. Reservoir, thermodynamic, and geothermal power plant objects

The reservoir, thermodynamic, and geothermal power plant objects are described below:

The geothermal reservoir abstraction or object has characteristic properties and methods for generally describing a geothermal reservoir (Figure 5a). The object has the following properties: reservoir name; address; geographic coordinates (latitude and longitude); reservoir surface area; reservoir thickness; and reservoir volume[4]. Each object property is classified as a Python data type. For example, name and address are strings, and location is a dictionary that includes latitude and longitude as floating-point numbers. Because reservoir area and thickness are stochastic properties, they are classified as a dictionary consisting of minimum, most likely, maximum, mean, standard deviation, and probability distribution function values, with input in units of km^2 and m, respectively. The geothermal reservoir object also has several methods for setting and obtaining values for every object property.

The thermodynamic abstraction or object has the essential thermodynamic properties and methods for describing the geothermal reservoir (Figure 5b). The object has the following properties: Tr and Ta in units of ºC, ϕ, Cr and Cf in units of kJ/kg, and ρr and ρf in units of kg/m^3. Because all properties of this object are stochastic, they are classified as a Python dictionary with minimum, most likely, maximum, mean, standard deviation, and probability distribution function values. Several methods are available for setting and obtaining values for every object property. Moreover, the volumetric energy (Equation 1 in Section 2) is calculated by the liquid-dominant volumetric energy method.

[4] Reservoir volume is an independent attribute; i.e., it does not have any relationship with both reservoir area and reservoir thickness during the simulation. It must be calculated separately using geoscience methods.

The geothermal power plant abstraction or object has the remnant properties and methods for running the Monte Carlo simulation and obtaining the geothermal power potential (Figure 5c). This object has the following reservoir and geothermal power plant properties: RF, ηe, PF, and t. Because all properties of this object are stochastic, they are classified as a Python dictionary with minimum, most likely, maximum, mean, standard deviation, and probability distribution function values. This object also includes a power potential attribute, which contains all results upon completion of the Monte Carlo simulation. The attributes are the power potential base, frequency distribution, cumulative frequency distribution, trials or iterations, and basic statistics (mean, standard deviation, skew, kurtosis, minimum and maximum value, and percentiles).

7.2. Monte Carlo simulation object

The Monte Carlo abstraction or object has the essential properties and methods for running the Monte Carlo simulation and obtaining the geothermal power potential (Figure 5d). The object has the following properties: number of trials or iterations and the final calculation time. Additionally, it includes a set of the most common probability distribution functions on the geothermal exploration area (i.e., triangular, uniform, normal, lognormal), and a method for calculating the stochastic power potential.

7.3. Tool object

The tool abstraction or object has the essential properties and methods for displaying the simulation results (Figure 5d). The object has the following properties: input and output file name and several attributes for designing the presentation. File reading and the saving of reservoir parameters can be executed by using this object. Additionally, the frequency distribution (FD) and cumulative frequency distribution (CFD) are available as a histogram, which includes information including title, 5th, 10th, and 95th percentiles, and the most likely value. Moreover, the print method is available for displaying the statistical analysis on the command line interface. The printed parameters are the most likely power potential and its occurrence probability, the calculated power potential, number of iterations, mean, median, standard deviation, histogram skew and kurtosis, minimum and maximum values, and percentiles.

8. GEOTHERMAL POWER POTENTIAL ASSESSMENT CASE STUDY: EL SALVADOR

El Salvador is a small country located in Central America between 13.15°N to 14.46°N and 90.13°W to 87.7°W, surrounded by the Pacific Ocean, Guatemala, and Honduras. Because it is located close to the Ring of Fire, there exists a vast geothermal resource potential. The government of El Salvador has made plans to improve electricity generation in the period between 2014 and 2024 using renewable energy, such as geothermal energy (Consejo Nacional de Energía Gobierno de El Salvador, 2014). The government will include two more geothermal power plants, Chinameca and San Vicente (Santos & Rivas, 2009), as well as new studies from low-enthalpy areas, which are the primary purposes of this research.

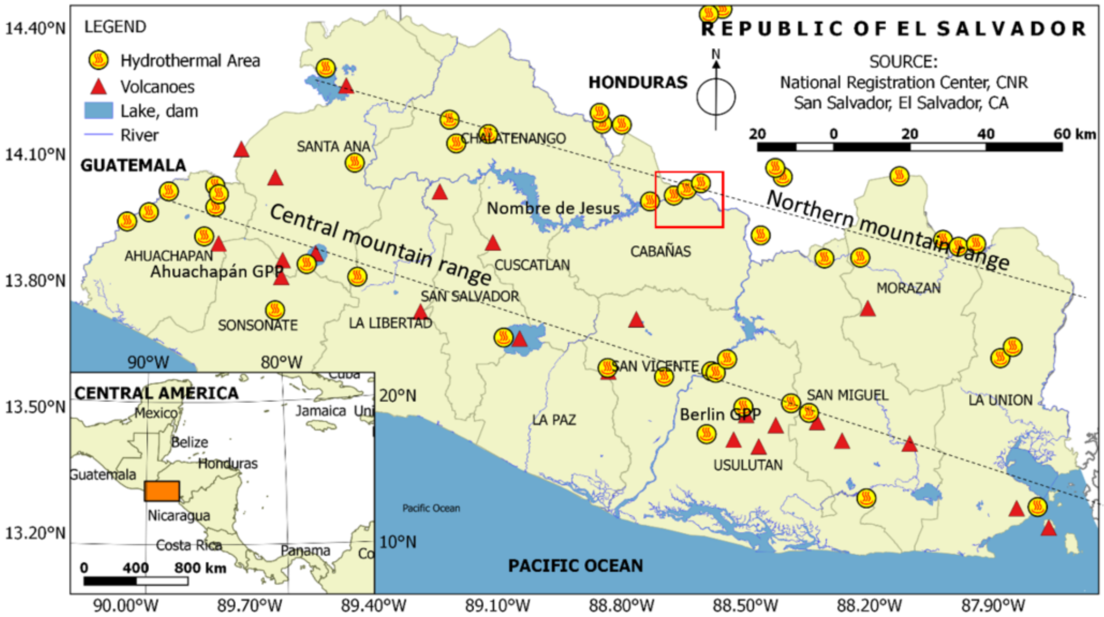


Figure 6. Hydrothermal areas in El Salvador, Central America. Volcanoes are represented as red triangles, lakes, dams, and rivers are in blue, and hydrothermal manifestation areas are represented by yellow-red circles. The red rectangle encloses the hydrothermal manifestations of low-enthalpy fluids in the Municipality of Nombre de Jesus, which are the case study presented here. The study area is located at 14°N and 88.73°W. The figure is a modified map (National Registration Center CNR, 2015) and composed using Geographic Information System software (QGIS Development Team, 2017).

Vast geothermal energy potential can be found throughout the territory, and there are many hydrothermal manifestations of both high and low enthalpy. Many previous studies have been conducted by the government and demonstrated the available geothermal potential. As a result, there are two high-enthalpy hydrothermal fields in operation, Ahuachapán and Berlín. The temperature is higher than 200 °C, and the total power generation is 204.4 MWe, i.e., 95 MWe and 109.4 MWe from Ahuachapán and Berlin power plant respectively (Consejo Nacional de Energía Gobierno de El Salvador, 2010; Gobierno de El Salvador et al., 2012). The low- and high-enthalpy hydrothermal areas of El Salvador are shown in Figure 6 with a red rectangle indicating the working area in the northern zone of El Salvador, which includes the Municipality of Nombre de Jesus, because this region has the highest available potential. The points selected as energy potential sites are as a result of several studies by the government agency called the Hydroelectric Commission of the Lempa River, CEL (Campos, 1988). Two significant areas are identified on the map in Figure 6: the northern and central mountain ranges. The central mountain range is made of young rocks, Quaternary geological structures with ongoing volcanic activity, and high enthalpy points such as Ahuachapán and Usulután. The northern ridge is formed by the oldest, tertiary, or additional geological structures. Hydrothermal manifestations are mostly low enthalpy and are caused by remnants of volcanic or regional activity.

All the hydrothermal manifestations in the Municipality of Nombre de Jesus are considered low-enthalpy fluids. According to government surveys, the inferred resource has an area of 6 km^2 with an average temperature of 160 ºC, as calculated by geothermometers (Campos, 1988). The geologic map also displays a hydrothermal alteration zone on extrusive volcanic rocks or rhyolites due to regional influences. Volcanic activity in this zone is not considered to be recent, so that the heat source might be a fossilized magmatic intrusion such that the temperature is only a remnant of the volcanic effect. An example of a conventional geothermal power potential assessment is presented below to demonstrate the implementation of the GPPeval (Pocasangre & Fujimitsu, 2018). Input file preparation

The input file must be formatted as a CSV file, as shown in Section 6.1. The reservoir parameters are listed in Table 4 (Campos, 1988; Monterrosa & La Geo, 2007). For this example, a low-enthalpy fluid that heats a secondary working fluid (isobutane) with an assumed pressure of 20 bar is used and saturation temperature of 100.36 ºC. Therefore, a temperature difference of 5 ºC at the pinch point, and an abandon temperature of 105.36 ºC and a conversion efficiency of less than 0.25 are considered (DiPippo, 2004).

Table 4. Typical worksheet and input reservoir parameters for assessing the geothermal power potential in Nombre de Jesús (Campos, 1988; Monterrosa & La Geo, 2007).

Reservoir Properties	Min	Most Likely	Max	Distribution
Reservoir Area, A[km^2]	5	6	7	Triangular
Thickness, h[m]	450	500	600	Triangular
Reservoir Temp., Tr[°C]	130	160	163	Triangular
Abandon Temp., Ta[°C]		105.36		Constant
Porosity, ϕ		0.06/0.02		Log-Normal
Rock SH C_r[kJ/kg °C]	0.85	0.85	0.9	Triangular
Water SH, C_f[kJ/kg °C]		5.18		Constant
Rock Density ρ_r[kg/m^3]		2500		Constant
Water Density, ρ_f[kg/m^3]		764.45		Constant
Recovery Factor, RF	0.08		0.2	Uniform
Conversion Efficiency, η_e		0.25		Constant
Power Factor, PF	0.9	0.95	1	Triangular
Lifespan, t[years]		25		Constant

The following example uses the IPython command line interface for running the Monte Carlo simulation and result processing (Golman, 2016; Perez & Granger, 2007). The tool object is used for importing data from the file that has been prepared as a CSV file.

```
user@host:~$ ipython
In [1]: import gppeval # geothermal power potential evaluation library
In [2]: tool = gppeval.Tools()
In [3]: sim = gppeval.MonteCarloSimulation()
In [4]: nj = tool.read_file_csv('reservoir_properties_list.csv')
READ FILE ... OK
In [5]: print nj # show the information that was read before
```

Figure 7. Commands for starting the simulation: 1) import the GPPeval library; 2) create two helping variables, (tool and sim); and 3) create the variable that represents the characteristics of the reservoir.

8.1. Running the Monte Carlo simulation

In this stage, the Monte Carlo simulation object is used.

```
In [6]: nj = sim.calc_energy_potential(nj)
SIMULATION ... DONE
```

Figure 8. Command for running the Monte Carlo simulation.

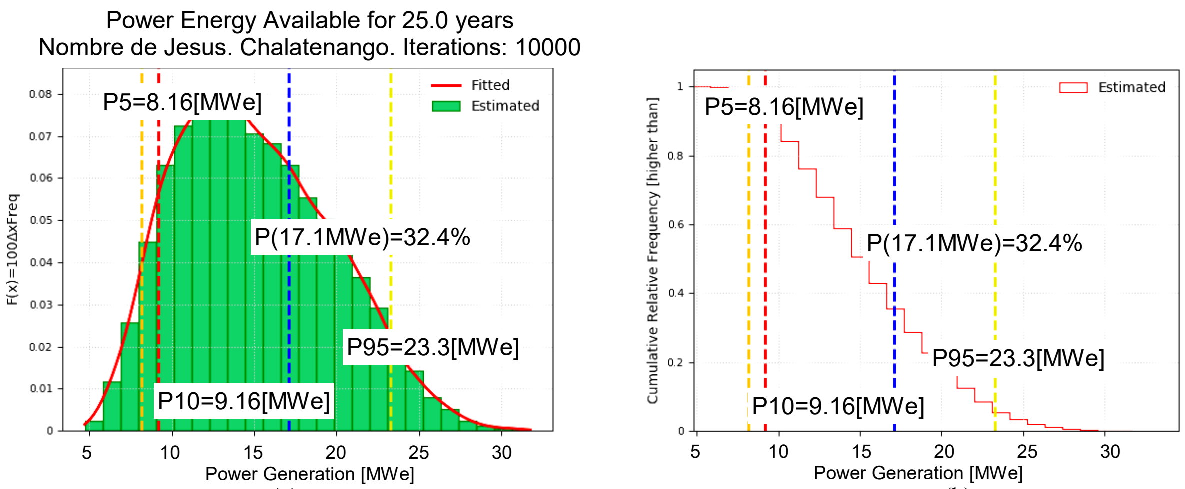
8.2. Displaying simulation results

There are several ways for presenting the results (FD, Figure 10a; CFD,Figure 10b) and command line text.

1. Frequency distribution (FD) as a histogram

```
In [7]: tool.plot_pdf(nj, show=True)
```

Figure 9. Command for plotting the results as a frequency distribution histogram and the empirical density estimation curve.



(a) (b)

Figure 10. (a) Frequency distribution (FD), (b) Cumulative frequency distribution (CFD).

2. Cumulative frequency distribution (CFD)

```
In [8]: tool.plot_pdf(nj, type_graph='higher', show=True)
```

Figure 11. Command for plotting the results as a cumulative frequency distribution.

3. Command line text

This tool, "`tool.print_results(nj)`", shows the statistical results after the Monte Carlo simulation has finished, such as percentiles, mean, median, standard deviation, skew, kurtosis, and values minimum and maximum.

4. Linear figure

```
In [10]: tool.plot_pdf(nj, type_graph='linear', show=True)
```

Figure 12. Command for plotting the results summary as a linear bar.

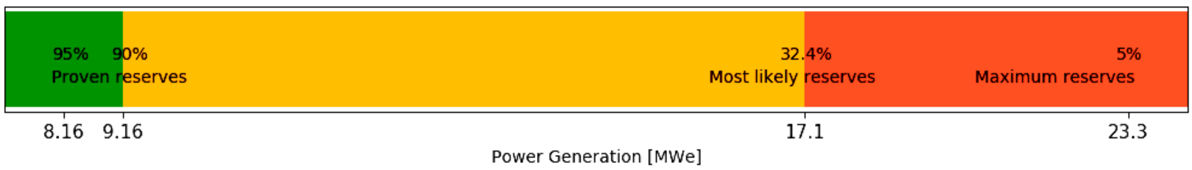


Figure 13. Linear representation of hot spring data from Nombre de Jesus, El Salvador. This simulation was run for 25 years.

In Figure 13, the model reserves are 9.16 MWe with a possible expansion of the geothermal power plant up to 17.1 MWe. Finally, the maximum and less probable geothermal power potentials reach around 23.3 MWe.

8.3. Manual set up of reservoir parameters

Changes to a given reservoir parameter sometimes need to be made to run a simulation and to create several outcome scenarios. For instance, the simulation requires two hypothetical power plants to be operating for 25 and 30 years, respectively. The GPPeval library therefore has several methods for modifying object attributes and for using an external package to create a new scenario from the original one. Figure 14 demonstrates how to edit the original case (lines 1–15) and how to create a new one (lines 16–21).

```
In [13]: nj.set_area(min=5.0, most_likely=6.0, max=7.0, pdf='T')
In [14]: nj.set_thickness(min=450, most_likely=500, max=600, pdf='T')
In [26]: import copy
In [27]: nj_new = copy.deepcopy(nj) # new instance from original instance 'nj'
In [28]: nj_new.set_lifespan(most_likely=30.0)
In [29]: nj_new = sim.calc_energy_potential(nj_new)
SIMULATION ... DONE
In [30]: tool.print_results(nj)
```

Figure 14. Commands for manually setting up the reservoir parameters, e.g., area and thickness, and creating new scenarios.

8.4. Interpretation of Monte Carlo simulation results

Figure 10a, Figure 10b, and Figure 13 show possible inference when the output greater than or equal to 9.16 MWe is 90 % (i.e., proven reserves), and when the capacity greater than or equal to 17.1 MWe is 32.4 % (i.e., proven + probable reserves). Additionally, the probability that the output is greater than or equal to 23.3 MWe is only 5 % (i.e., proven + probable + possible or maximum reserves), after which, the preliminary power potential assessment is 1.53 MWe/km^2 for a maximum of 25 years. These results imply that the field could initially support a 9.16 MWe geothermal power plant for 25 years maximum with a possible expansion to 17.1 MWe, subject to further delineation drilling and availability of field performance data. Finally, the risk that the field could not sustain 9.16 MWe is equal to or less than 10 % can be affirmed. However, this interpretation will be subject to further investigations for obtaining and validating the new data. Alternatively, it has been observed that the reservoir volume (i.e., A and h) has a direct influence over the geothermal potential.

9. CONCLUSION

The primary purposes of this study are to use the volumetric method to estimate the electrical energy production ability from a geothermal liquid-dominated reservoir, and to code a Python-based stochastic library with suitable methods for running the simulation. The calculation of geothermal energy stored in a volume is based on the range of reservoir parameters and carried out using a stochastic Monte Carlo simulation. During early exploration, estimates of essential reservoir parameters are poorly constrained, but application of the USGS “heat in place” evaluation method along with Monte Carlo simulations produces a wide distribution for the probable power potential. The USGS volumetric “heat in place” method, together with Monte Carlo simulations, are a useful tool for assessing the electrical capacity of a geothermal reservoir. Although licensed software is available for carrying out these simulations, an open-source programming language was selected, Python. The resulting stochastic library is called the Geothermal Power Potential Evaluation, GPPeval. The new library utilizes the standard numerical modules, Numpy and Scipy, but also the Matplotlib module for graphical visualization, and the Mcerp module for performing non-order specific error propagation or uncertainty analysis. The GPPeval is structured as three essential objects including a geothermal power plant module, a Monte Carlo simulation module, and a tools module. Finally, to demonstrate how the Python-based stochastic library can be used for assessing the geothermal power potential, an assessment of hot spring data in the municipality of Nombre de Jesus, El Salvador is presented. After running the stochastic simulation, the frequency distribution shows that the field could initially support a 9.16 MWe power plant for 25 years and a possible expansion to 17.1 MWe. However, the geothermal power potential must be investigated further to obtain and validate the new data.

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