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Applying Statistical Methods to Gas Geothermometry to Determine Geothermal Reservoir Temperatures in the Lumut Balai Field

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ABSTRACT

During the exploration stage, reservoir temperatures are usually estimated using geothermometry. Based on experience, abundant surface manifestation data can confuse geologists or geochemists to determine appropriate temperature estimates due to the difference of interpretation and insight. Otherwise, downhole pressure and temperature measurements usually show slightly differences. Application of basic statistical methods can assist in classifying all the data and simplifying the determination of temperature geothermometers quantitatively. The data is classified into several populations based on the similarity of its characteristic. Analyzing all the data using histograms and probability plot (P-plot) diagrams can help to understand the distribution of each population. Outlier data, which is caused by extreme values, are excluded from the populations. The results show that P10 (the most optimistic) values from the histograms compare well with values found from downhole temperature measurements. The estimated reservoir temperatures using geothermometry range between 243–273°C, which is the most optimistic temperature range we can get. This result matches with the range of maximum temperature reservoir from PT data from several production wells, which is 221–266°C. Hence, the geothermometer-based method can give reliable estimates of reservoir temperatures.

1. INTRODUCTION

Geothermal reservoir temperature estimation is an integral part of geothermal exploration. There are two ways of estimating geothermal reservoir temperatures: using direct measurements and using geothermometers (Fournier, 1977). Estimates of reservoir temperatures provide crucial information for making decisions on further field exploration and development strategies.

Geothermometry involves using specific formula which relate the geochemical and isotope composition of the measured fluids to estimates of subsurface temperatures. The most common geothermometers are silica, sodium–potassium, sodium–potassium–calcium, gas, and isotopes. It is normally assumed that the sampled fluids have reached an equilibrium with the surrounding rocks in the geothermal system.

Using geothermometers requires specific considerations, which depend on geochemical characteristics of the fluid and host rocks, to avoid erroneous interpretations. Therefore, understanding the strength and weakness of geothermometers is needed along with an understanding the settings of the geothermal field. To ensure that the results of the geothermometric analysis are valid, the first requirement is that the fluid samples are correctly collected and accurately analyzed.

The formula for some geothermometers are empirical (e.g., Na-K-Ca, D'Amore and Panichi (1980) gas geothermometer), whereas others are based on thermodynamic properties (e.g., Na-K, K-Mg). Controlling factors of empirical geothermometers are not completely known and in some cases the theoretical geothermometers are more reliable. On the other hand, using many geothermometers can be confusing and make it difficult to decide on a representative reservoir temperature.

Temperatures from geothermometer calculation are often slightly different from observed downhole temperatures. To specify the a plausible range of temperatures, geological comprehension is required. However, this will be more difficult if the field has a lot of data from surface manifestation.

However, despite the various techniques used in geothermal exploration, the application of statistics is still uncommon (Agustin, Irawan, Susanto, & Herdianita, 2015). Statistical calculation is often regarded as a complicated procedure, when dealing with data, for some of us who do not have a deep understanding of statistics. Instead of "precise" statistics, there are also "simple" exploratory data analysis methods as introduced by Turkey in 1977, which can be the first choice for analyzing earth science data (Reimann et al., 2008, Suryantini, 2012,. Asfaw, 2016).

Exploratory data analysis (EDA) can help to classify and simplify data into different populations, which are known as normal data distributions. Descriptive statistics combined with histogram and probability plot (P-plot) diagrams can assist to understand normal distributions in each population and help us to calculate the most representative reservoir temperatures. This paper presents our early work on using statistics for temperature determination.

2. REGIONAL GEOLOGICAL CONDITION

The Lumut Balai (LMB) geothermal field is located on the east side of Sumatera's inner-arc or Barisan Mountain Range. Tectonically, LMB is controlled by the Sumatra Fault System (SFS), also known as the Semangko Fault, which is NW-SE trending along more than 1,900 km. The rocks within the Lumut Balai Prospect are predominately Quaternary volcanic rocks overlying a basement of Tertiary sedimentary rocks. Surface manifestations appear in several location as wide altered ground, hot springs, fumaroles, and mud pools.

3. METHODOLOGY

Data was collected from geochemical manifestations in the Lumut Balai field. This study only used gas data collected from 2012 to 2019. Water manifestations data is not used because Lumut Balai is categorized as a high terrain geothermal field, which often reequilibrate in order horizontal transport and causes misinterpretation of reservoir temperature.

Chemical data from each manifestation is used for geothermometer calculation to estimate temperatures. There are several geothermometers that have been examined, namely DAP (D'Amore and Panichi), H_2/Ar, CO_2/N_2, H_2S/Ar, CH_4/CO_2, $CO_2/H2$, and H_2S/H_2.

Estimated temperature values will be vary depending on which geothermometer formula is used. Geothermometer results were transformed into logarithmic values in order to get a normal data distribution. These logarithmic values were subsequently plotted in a probability graph following. In the probability graph, a normal distribution should appear as a straight line. In this study, a 95% level of confidence line is used as a normality boundary accommodating data variations found in a normal distribution. Using this graph, the number of subpopulations in the samples can be counted. Descriptive statistical analysis can also support the interpretation of the normal distributions.

We estimated reservoir temperatures by calculating the 10th percentile (P10) from the histograms and then compared those values with reservoir temperatures indicated from downhole measurement (PT) data.

In this work, we used Microsft Excel to process the data and represent it using histograms and P-plot diagrams. We also used the Minitabs program, which is available for Linux, Mac and Windows operating systems. The program can be downloaded from http://www.minitab.com/en-us/.

4. RESULTS AND DISCUSSION

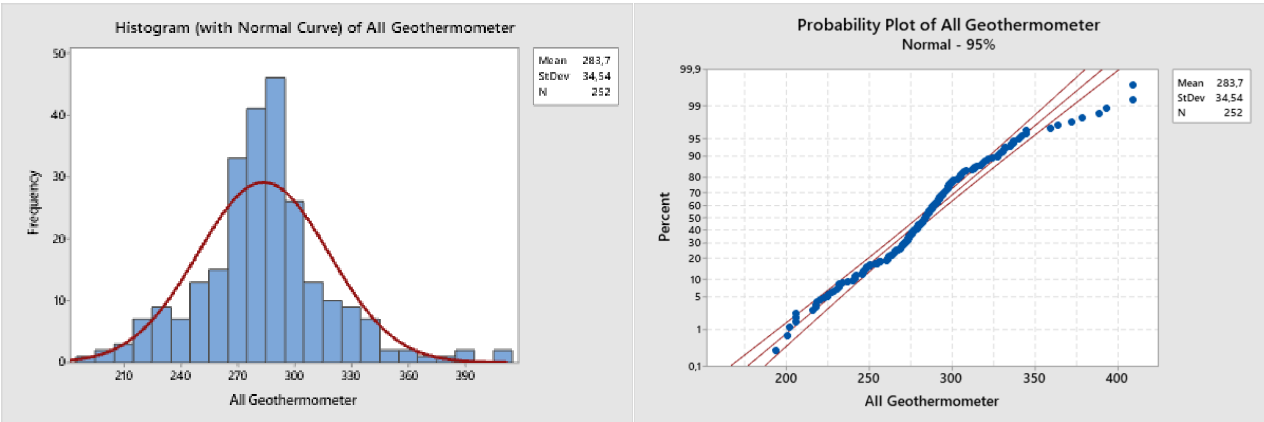


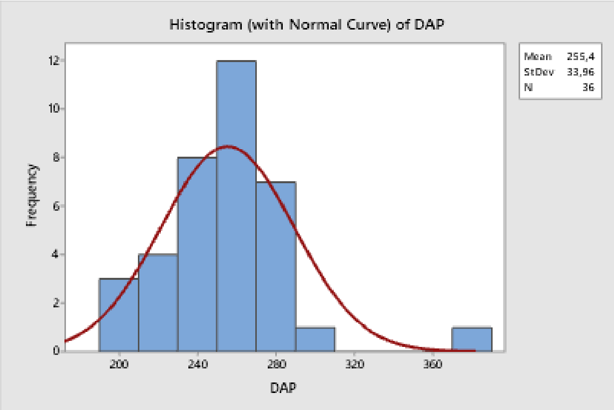
Figure 1: Plots showing the histogram and probability diagram of all geothermometer values. The results consist of more than three sub-populations, which were generated using geothermometer formulas. The outliers are excluded from the populations.

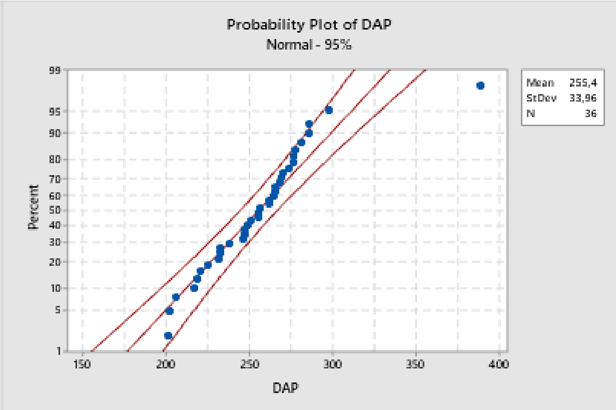
Variable	Total Count	Mean	StDev	Variance	CoefVar	Minimum	Q1	Median
All Geothermometer	252	284	34	1193	12	194	267	284

Variable	Q3	Maximum	Skewness	Kurtosis
All Geothermometer	298	410	0,4	1,7

All the data appear to be relatively normal when viewed as histograms. The data were also viewed using P-plot diagrams to ensure it showed characteristics of a normal distribution. Variance values and smaller coefficient variation in descriptive statistic means that the data has a degree of homogeneity or is normally distributed. The P-plot diagrams show outliers of high temperature estimates.

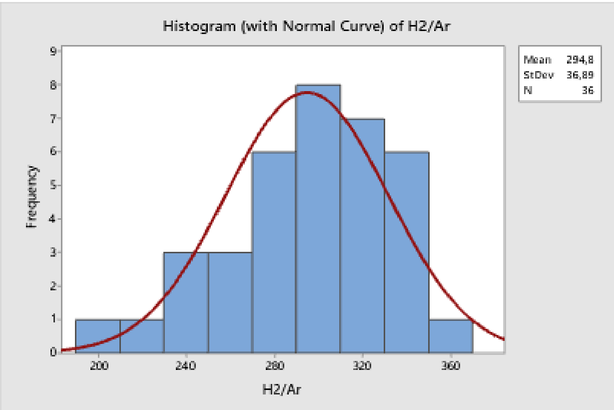
To ensure the data is classified based on the gas geothermometer, which is used with the assumption that using the same formula will produce a relatively normal distribution and also depend on the chemical composition used by each geothermometer. Graphs are shown in the following figure for histograms and P-plots of each gas geothermometer:

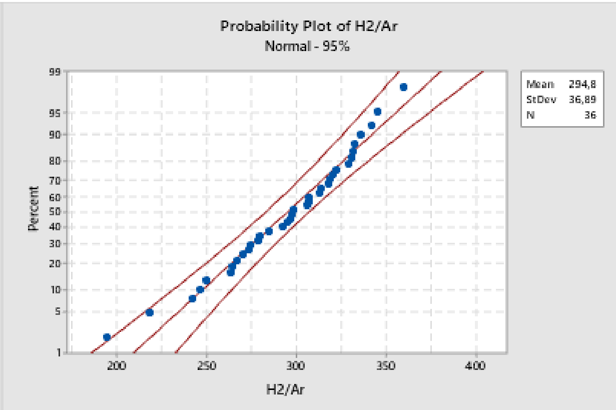

Histogram (with Normal Curve) of DAP
Mean 255,4
StDev 33,96
N 36
Frequency
DAP


Probability Plot of DAP
Normal - 95%
Mean 255,4
StDev 33,96
N 36
Percent
DAP

A.

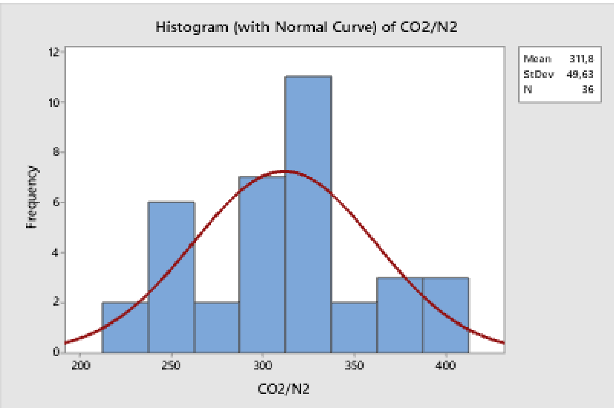
B.

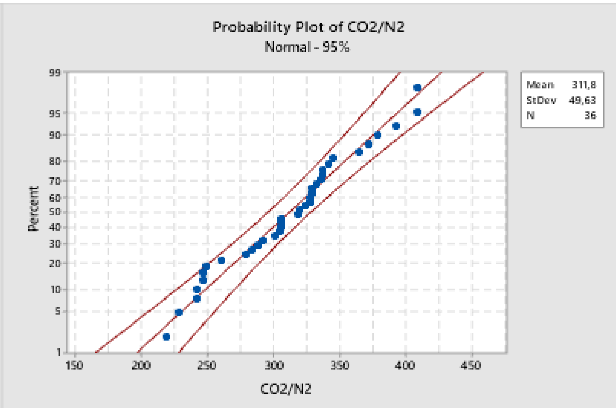

Histogram (with Normal Curve) of H2/Ar
Mean 294,8
StDev 36,89
N 36
Frequency
H2/Ar


Probability Plot of H2/Ar
Normal - 95%
Mean 294,8
StDev 36,89
N 36
Percent
H2/Ar

C.

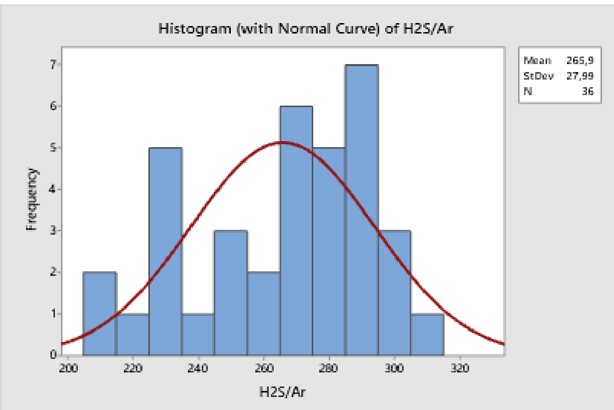
D.

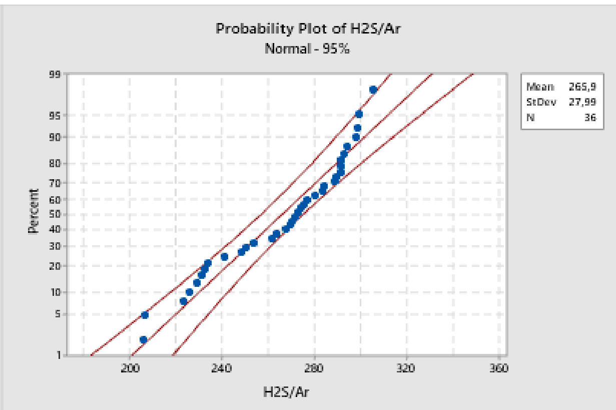

Histogram (with Normal Curve) of CO2/N2
Mean 311,8
StDev 49,63
N 36
Frequency
CO2/N2


Probability Plot of CO2/N2
Normal - 95%
Mean 311,8
StDev 49,63
N 36
Percent
CO2/N2

E.

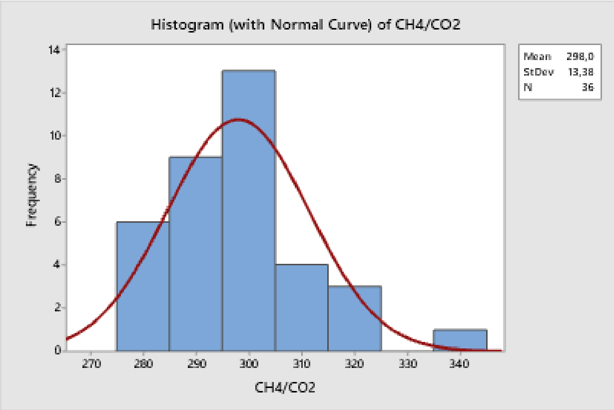
F.


Histogram (with Normal Curve) of H2S/Ar
Mean 265,9
StDev 27,99
N 36
Frequency
H2S/Ar

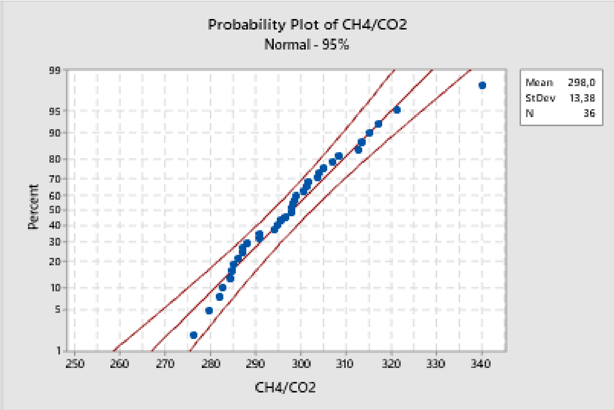

Probability Plot of H2S/Ar
Normal - 95%
Mean 265,9
StDev 27,99
N 36
Percent
H2S/Ar

G.

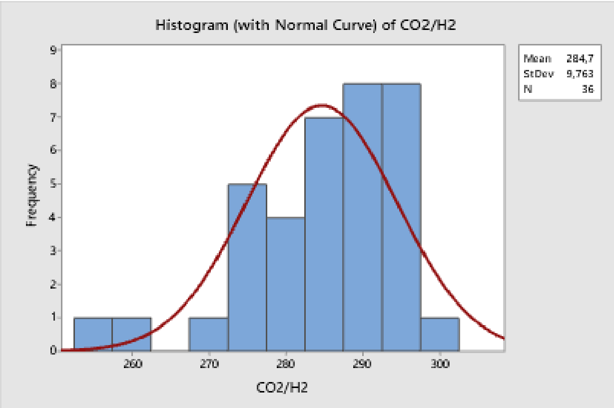
H.



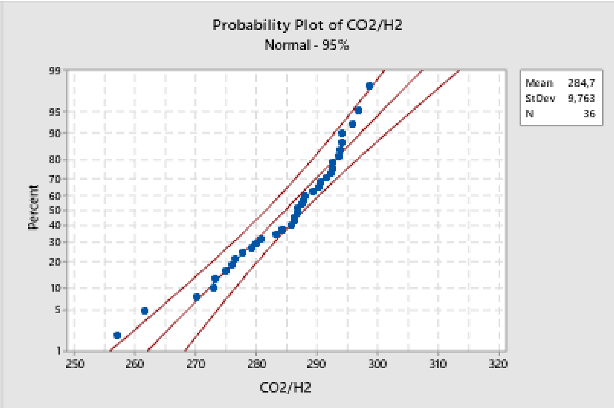
I.



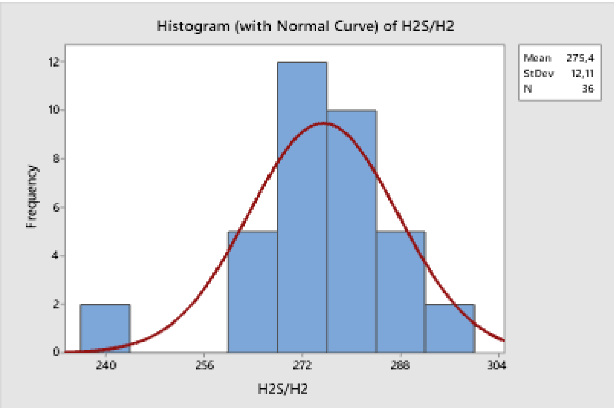
J.



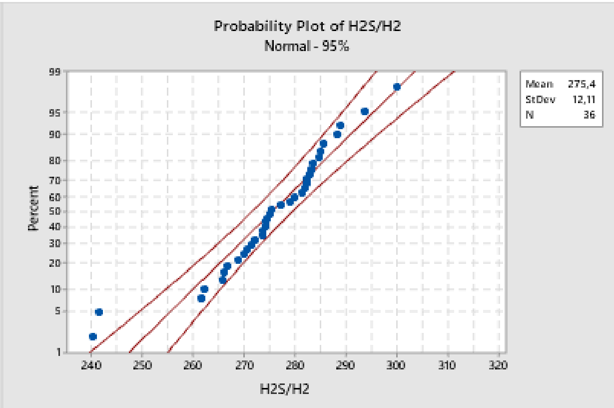
K.



L.



M.



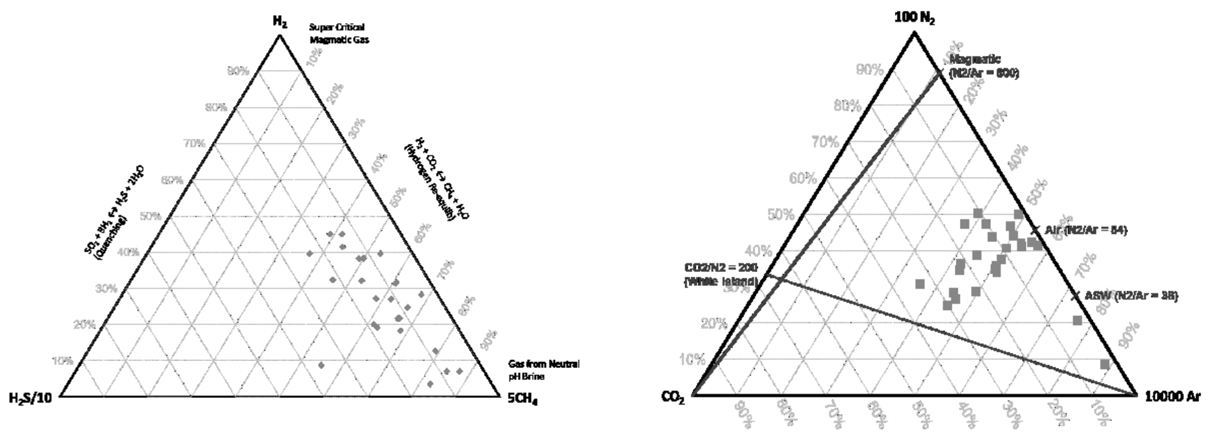
N.

Figure 2: Pictures (A, C, E, G, I, K, M) show histograms of geothermometer values. Some geothermometers resulted in outliers which should be excluded from the population. Pictures (B, D, F, H, J, L, N) show probability plots (P-plots). The P-plots can give additional details about the subpopulation or outliers in the data.

Table 1: Descriptive statistic for each geothermometer, consisting of central tendency and histogram characteristics, such as skewness and kurtosis. The 10th percentiles (P10) are given for the final temperature estimate of each geothermometer.

	Gas Geothermometer							
Variable	**All Data**	**DAP**	**H_2/Ar**	**CO_2/N_2**	**H_2S/Ar**	**CH_4/CO_2**	**CO_2/H_2**	**H_2S/H_2**
N	252	36	36	36	36	36	36	36
Mean	284	255	295	312	266	298	285	275
StDev	35	34	37	50	28	13	10	12
Variance	1193	1153	1361	2463	783	179	95	147
CV	12	13	13	16	11	4	3	4
Minimum	194	201	194	219	206	276	257	240
Q1	267	232	271	280	243	287	278	270
Median	284	256	298	319	272	298	287	275
Q3	299	273	322	337	291	305	293	283
Maximum	410	389	359	409	306	340	299	300
Skewness	0	1	-1	0	-1	1	-1	-1
Kurtosis	2	6	0	0	-1	2	1	2
T P10	**241**	**213**	**261**	**243**	**225**	**281**	**273**	**265**

The range of temperature estimates resulting from the statistical approach is 213–281^oC from the 7 gas geothermometers that were used. While the range for maximum temperatures found using PT analysis in several production wells is 221–266^oC. Tthe best geothermometer should be chosen based on a gas chemical approach as shown in the trilinear diagram of H_2-H_2S-CH_4 (Giggenbach and Glouver, 1992) and N_2-CO_2-Ar (Giggenbach, 1980), see Figure 2.



A. B.

Figure 2: (A) The gas composition shows that some of the gas re-equilibrates to hydrogen to CH_4 so that the plot is attracted to the H_2 and CH_4 apexes. (B) Trilinear diagram of N_2-CO_2-Ar showing that most gas manifestations were plotted at the middle of N_2 to Ar.

The ternary below shows the plot of points on some of the manifestations at the air point (N_2/Ar=84) or the gas has the characteristics of free air. But the majority of the plots show points away from that point so the geothermometers use Ar as the calculations will be more representative of the actual temperatures.

The geothermal field is located in a basin zone which is dominated by organic sediments and it is known that the high values of CH_4 in this field could be due to excess CH_4 from methane gas in the area around the field. As a result, temperatures found using CH_4 geothermometers will result in overestimated values. Therefore, the CH_4/CO_2 geothermometer should be excluded is to avoid misinterpretations.

The geothermometers that are used are H_2/Ar, CO_2/N_2, and CO_2/H_2 which gave temperatures values of 261^oC, 243^oC, and 273^oC. The range values from those geothermometers is, therefore, 243–273 ^oC, which is the most optimistic result and can be compared with the maximum reservoir temperature range of 221–266^oC found using the PT data. We can also compare these values with values found by applying temperature water geothermometers to well discharge fluid data, which gave a range of about 234–265^oC when using the silica geothermometer (Fournier & Potter, 1982).

5. CONCLUSIONS

This study demonstrates that geothermometer values found using a statistical approach which supported at the very least by simple and reasonable method such as exploratory data analysis (EDA) statistical tools. This statistical approach worked well for estimating reservoir temperatures based on geothermometers, with a large amount of data. Moreover, this method can also be combined with geological approaches. We plan to carry out further analysis of various fields will be carried out to validate this method.

However, the descriptive statistical correlations cannot be used to determine the most significant factor way the selection of normality. The small skewness value in the results means that the normal distribution of data with a balanced spread. Then the high number of the coefficient variation (CV) indicates a high variation of the geothermometer in the dataset. This is because of few and fractional data. Moreover, a low CV also determines the normal distribution of the population. To ease the correlation between the components of data distribution from descriptive statistics as a normal distribution, the rule of thumb that suitable in geothermal geochemistry should be determined.

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