Characterization of natural fracture systems: Analysis of uncertainty effects in linear scanline results

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ABSTRACT

The exploitation of hydrocarbon reserves in naturally fractured reservoirs composed of different types of rocks has drawn considerable attention from the fracture characterization research community because of the importance of fractures to the prediction of fluid flow. One of the most common methods for rapidly analyzing fracture features is the scanline technique, which provides an estimate of fracture density and frequency. Despite the confidence provided by the systematic use of this method, errors and uncertainties caused by sampling biases exist. The problems caused by these uncertainties can detrimentally affect the construction of a computational model due to misleading trends.

This study evaluated the uncertainty caused by sampling biases in the scanline data of opening-mode fractures in outcrops of naturally fractured Aptian laminated limestone from the Crato Formation, Araripe Basin, northeastern Brazil. The Monte Carlo method was chosen to introduce random values into the sampled values, which enabled us to verify the importance of errors in the accuracy of the method of representing the fracture network.

In this study, errors and uncertainties were grouped into one parameter, termed the coefficient of uncertainty, which was defined as the ratio between the uncertainties, created by the errors and artifacts introduced artificially, and the original scanline data. The propagation of errors and uncertainties in the scanline data to the coefficients of the corresponding power law were determined.
This evaluation can be applied in the construction of more reliable geomechanical models using analog geological models for naturally fractured reservoirs.

INTRODUCTION

The recovery factor represents an important aspect of a petroleum reservoir that in some cases is a difficult characteristic to determine for an entire reservoir because of limited data provided by a small number of wells. The difficulty arises because of the relationship between the recovery factor and intrinsic geological characteristics, such as permeability, that can vary significantly because of lateral and vertical sedimentary facies changes and diageneric controls. One possible way to account for this difficulty is the study of reservoir analogs. This currently very useful method makes it possible to construct a realistic model using additional data, accessible at the surface, with the common well logs available for subsurface reservoirs. This approach provides the means to reduce the uncertainties related to the geological model features, allowing the construction of sophisticated computational models that are applied for simulations of producing processes (Agar et al., 2010).

In recent decades, the exploitation of hydrocarbon reserves in naturally fractured reservoirs has motivated increasing numbers of investigations because of its importance in fluid flow predictions. For fractured reservoirs that are mainly composed of carbonate and fine-grained rocks, the determination of the number of fracture sets that affect the framework and their importance for fluid flow are the keys to determining the reservoir’s exploitation success (Bourbiaux, 2010; Guerriero et al., 2013). The study of fractured reservoir analogs can provide parameters that can be used in the multiscale integration of reservoir models (thin sections, outcrops), providing a better representation of geological heterogeneities, including fractures (Bourbiaux, 2010; Guerriero et al., 2011). Characterization of porous media with and without the effects of fractures can produce divergent results in numerical modeling (Wilson and Aifants, 1982; Bourbiaux, 2010). Including a multiporosity model that considers the effects of the fracture system is a better way to simulate the single or multiphase flow that occurs in a porous media containing fractures of different hierarchies (Pride and Berryman, 2003). The relationships between the intrinsic factors associated with the rock matrix domain (i.e., porosity and permeability) and the fracture system represent a complex problem in numerical modeling. In the case of a naturally fractured reservoir, in which hydrocarbons flow only through the fracture networks, the...
fracture aperture distribution assumes a key role in the understanding of the flow process.

One of the most common methods for rapidly analyzing a fracture system is the scanline method, which provides an approximate prediction of fracture density and fracture aperture frequency (Marrett, 1996; Marrett et al., 1999; Micarelli et al., 2006; Ortega et al., 2006). This method aims to obtain fracture attributes (spacing, kinematic aperture, and crosscutting relationships) using random scanlines on exposed fractured rocks. This method uses various techniques such as linear surveys, circular windows, and descriptions of fractures in aerial photos. The method makes it possible to quantify fracture attributes via statistical analysis. For example, fracture aperture values can be described by a power law over several scales of observation (Gillespie et al., 1993; Marrett, 1997; Odling et al., 1999; Ortega and Marrett, 2000; Ortega et al., 2006; Guerriero et al., 2010, 2013; Guerriero, 2012). In this study, we focused on the application of the linear scanline technique.

Despite the confidence provided by the systematic use of the linear scanline technique, the existence of uncertainties and errors caused by reading biases and artifacts (because of the difficulty of reading small and large fractures) are well known (Pickering et al., 1995; Ortega et al., 2006). The problems caused by these uncertainties could affect the construction of a geomechanical model of a naturally fractured reservoir due to misleading trends. It is well known that log-log plots of cumulative frequency versus the aperture of fractures show a strong linear trend, suggesting that the data are best described by a power law (Marrett et al., 1999). However, power laws normally show discrepancies between an ideal correlation and the analyzed data. In our case, the differences are probably because of sampling biases in fracture data acquisition (scanline). These biases are recognized as artifacts caused by restrictions of geometry and the dimensions of sampling, which are called truncation and censoring artifacts (Pickering et al., 1995; Ortega et al., 2006). Because the surveying procedures in outcrops include direct observation, with the naked eye and hand lenses, truncation normally occurs because of the difficulty of measuring small fractures (<0.05 mm [<0.002 in.]). Censoring artifacts are usually common because large structures are undersampled because of the limited length of scanlines across the natural exposures. Therefore, helpful and feasible statistical analyses aimed at estimating aperture distributions and related uncertainties are needed to take into account the notable difficulties associated with recording accurate aperture measurements and performing adequately sized scanlines (Guerriero et al., 2011).

This study focused on the evaluation of potential uncertainties caused by errors in aperture statistical analysis. The analyzed data
were obtained from laminated lacustrine limestones from the Lower Cretaceous Crato Formation of the Araripe Basin, northeast Brazil (Neumann, 1999). The excellent exposure in the quarries around the city of Nova Olinda makes the laminated limestone units of the Crato Formation a good example of an analog for naturally fractured carbonate reservoirs, including some reservoirs in offshore basins in Brazil. Initially, a complete analysis of the structural features of the basin, and specifically from the carbonate units, was obtained. Next, a series of linear scanlines was performed in selected outcrops. The scanline data were analyzed to determine the potential uncertainties through the construction of log-log plots concerning the distribution of fracture apertures. Some types of factors that could generate potential uncertainty were studied: (1) subjective uncertainties (such as those generated by the operator during the data collection in the field), (2) naturally prone uncertainties (such as those generated by clusters of fractures or by diagenetic effects on the fracture network), and (3) intrinsic uncertainties (generated by the tools used to perform readings). These types of uncertainties were grouped into one parameter, termed the coefficient of uncertainty (CU) that was defined as the ratio of the uncertainties simulated by the Monte Carlo (MC) method to the original scanline data. A CU was defined for the analysis of uncertainties in the measurements of fracture spacing and aperture.

With this methodology, the propagation of errors and uncertainties from scanline data to the coefficients of the corresponding power law was calculated. Subsequently, we have derived histograms to determine the 95% confidence intervals for each of the power-law coefficients.

STUDY AREA AND GEOLOGICAL SETTING

The study area is located in the Araripe Basin, the largest interior basin of northeast Brazil (Figures 1, 2). In this study, the stratigraphy of the Araripe Basin was adopted according to the proposal of division into five tectono-sedimentary sequences: (1) Paleozoic, represented by the Ordovician-Devonian continental deposits of the Cariri Formation; (2) prerift, represented by the Tithonian continental deposits of the Brejo Santo and Missão Velha Formations; (3) rift, composed of the Neocomian continental deposits of the Abaiara Formation; (4) postrift I, which includes the Aptian-Albian continental deposits of the Barbalha, Crato, and Ipubi Formations and the lacustrine to marine deposits of the Romualdo Formation; and (5) postrift II, which includes the Albian-Cenomanian continental deposits of the Araripina and Exu Formations (Ponte and Appi, 1990; Ponte and Ponte Filho, 1996; Neumann, 1999; Assine, 2007).

The Crato Formation belongs to the postrift tectono-sedimentary sequence and represents the main lacustrine phase of the continental succession of the Araripe Basin (Neumann, 1999). It contains six units of laminated limestones, interbedded with marls, calciferous siltstones, and shales (Neumann et al., 2003). The study was carried out in the thickest limestone unit, the topmost unit C6, which has good exposure in quarries in the northern region of the Araripe Basin (Assine, 1992; Neumann, 1999; Silva and Neumann, 2002) (Figure 2).

Miranda et al. (2012) described three main types of deformation structures in the studied limestone unit C6: (1) shear fractures (synsedimentary normal faults), (2) stylolites, and (3) opening-mode fractures (joints and veins) (Gudmundsson, 1992; Fossen, 2012).

METHODS

Scanline

The first stage of the study was to define the main natural network of fractures present in the limestone unit. Because the Crato Formation was exhumed during the Cenozoic, some structures were generated by reactivation. The study considered therefore only the veins, which represent fractures formed under burial conditions in the limestone unit. After the definition of the main sets of natural fractures used in the study, a series of linear surveys were performed in the outcrops. The surveys captured the attributes of the fracture along the scanlines, perpendicular to the strike of the dominant fracture set, following the rationale described by Marrett (1996), Marrett et al. (1999), Ortega et al. (2006), and Gale et al. (2007).
Figure 1. Simplified geological map of the Araripe Basin. Red polygon shows the study area, in the region of Nova Olinda, Ceará State.
The following features were recorded through the scanline readings: (1) the spacing between fractures, (2) the kinematic aperture, (3) the fracture orientation, (4) the morphology, (5) the crosscutting relationships between fractures, and (6) the composition of the fracture fill (Laubach and Gale, 2006; Ortega et al., 2006; Guerriero et al., 2010) (Figure 3). To measure the fracture apertures, we used a fracture-width comparator with a collection of apertures measuring 0.05 to 5 mm (0.002 to 0.2 in.) (Figure 3) (Ortega et al., 2006). The comparator shows logarithmically graduated lines such that they differ by approximately constant increments when plotted on a logarithmic axis. Because the scanlines do not cross all the fractures perpendicularly, a correction for the measurements obtained for inclined fractures was executed during the data processing, using Terzaghi corrections (Terzaghi, 1965). In the data set obtained by the scanlines, the maximum angle observed between the scanline and fractures was approximately 10°. However, the correction allowed us to maximize the precision of information concerning fracture orientation, aperture, and spacing.

Power Law

One way to apply the power law in studies of fractured systems is to use the cumulative distribution (Childs et al., 1990; Walsh et al., 1991; Pickering et al., 1995; Marrett, 1996):

\[ N = ab^{-k} \]  

(1)
where $b$ is the measure of the fracture aperture, $N$ is the cumulative number of values greater than $b$, $a$ is a constant, and $k$ is the scaling exponent.

In the present study, we used the definition of the power law proposed in equation 1, which was proven to assure the best manipulation of the data, as proposed by Ortega et al. (2006).

**Uncertainties**

The study adopted the classification of uncertainties (caused by errors during acquisition and geological complexity) proposed by Ganoulis (1994), in which the uncertainties were classified in two groups: (1) random uncertainties, or naturals; and (2) epistemic uncertainties. According to this author, the first group is inherent to the process and cannot be reduced by the sophistication of the model or the addition of data. The second group can be reduced depending on the applied method, on the technology adopted, and on the quantity of obtained data. We considered the epistemic uncertainties to be the most important ones in this study because the scanline represents a method for the characterization of fracture populations. In this sense, the epistemic uncertainties can be classified as follows: data uncertainties (related to sampling procedures, measurement errors, or the applied analysis methods) and model uncertainties (inadequate mathematical models or failures of the parameter estimation and operational procedures related to the material or by the individual who made the measurements) (Helton et al., 2004).

**Data Processing**

To artificially introduce uncertainties that represent variations in values of the original data, we used a random number generator following a lognormal probability distribution within a given average and standard deviation based on the $CU$. For the aperture data, the spacing data (the distance between fracture walls) and the obtained cumulative frequency, a set of random numbers was generated following a lognormal probability distribution function. The lognormal function was chosen because it admits only positive values in its domain, and it represents a function commonly applied to represent lengths and apertures of fracture systems (Tonon and Chen, 2007). To find the best fit for the aperture cumulative frequency following a power law, we used the least-squares method (Moritz, 1972).

As a complementary treatment, we applied the MC method to produce random variations in the values and to stimulate the uncertainties based on the original scanline data. This step allowed us to extract the average values from a set of MC simulations over the original scanline data to obtain the best-range estimation for the power law. The coefficient of uncertainty, which constrained the randomness, was considered to be 30% for each fracture aperture and spacing value (Figure 4). This value was chosen based on our general experience with the execution of scanlines and considering the integration of uncertainties from various sources. Additionally, it was possible to find the 95% confidence intervals for the coefficients of the obtained power laws.

In Figure 4, the standard deviations were assigned through the variations in the $CU$ values once the ratio between the standard deviation (represented here by uncertainties) and the scanline data was equivalent to the coefficient of variation ($CV$). The $CV$ is defined as a ratio between the standard deviation and the average of the normal distribution of values (Meyer, 1965; Goldman, 1970).

**Monte Carlo Simulation**

The MC simulation consisted of the generation of independent random values (representing the uncertainties) constrained by a predetermined probability distribution with a given average and standard deviation for each value of the scanline data. In each group of these simulations, adjustments were obtained for the entire scanline data set using the least-squares method to obtain the power-law regression for each scanline data set (Dimov, 2008). Therefore, the average of all of those realizations allowed us to find the power law, defined by the relationship between the aperture values and the cumulative frequency of fractures, which best represents the parameters of the studied fractured system, considering the probable influence of uncertainties in the scanline data.
A total of 1000 artificial random samples were
generated for each aperture and fracture spacing val-
ues of the scanline data set.

The simulations of uncertainties were performed
using the random-number-generator method of
Mersenne Twister (Matsumoto and Nishimura,
1998). For the random numbers, we adopted a seed
equal to 77, which is the number used as the initial
point of the iterative generation of the random
numbers.

RESULTS

Fracturing Analysis

The main fracture types identified in the laminated
limestone unit C6 were shear fractures (normal
faults), opening-mode fractures, and stylolites
(Figure 5). The opening-mode fractures strike in
two main directions, the north-northwest–south-
southwest (set 1), and northeast–southwest (set 2).
These fracture sets were defined in the field by frac-
ture orientation and crosscutting relationships. The
opening-mode fractures were classified as joints and
veins, and the veins were filled (completely or
partially) primarily by calcite. The stylolites present
were identified normal to the bedding, striking
preferentially along the N70E direction. The shear-
mode fractures were classified as synsedimentary
conjugate faults, with moderate dips (approximately
45°) to the west–northwest or northeast, and featuring
millimeter to centimeter displacement. The bedding
dip of the limestone ranges uniformly from 2° to 6°
east–southeast.

In this study, the shear-mode fractures and
stylolites were not included in the scanlines
because of the difficulty of measuring the exact dis-
placement of the faults and because the stylolites
were undersampled in many of the scanlines. Our
study focused only on the opening-mode fractures
(veins).

We measured 195 kinematic apertures of fracture
set 1 from a scanline total of 52 m (171 ft) long (sum
of all scanlines), which has a strike in the N50E
direction (Figure 6). The processing of these data
allowed us to describe the aperture size distribution
using a log-log plot (cumulative frequency vs.
kinematic aperture), in which the apertures ranged
from 0.05 to 2 mm (0.002 to 0.08 in.).
Uncertainty Simulation

The fracture aperture distribution is better observed by a power-law equation represented in a log-log scale than by lognormal or exponential fits (Figure 7). For example, the observed power law in a log-log graph of a fracture distribution enabled the observation that the data form a downward line at the large-size limit of the distribution (i.e., the part of the distribution representing macrofractures, indicating a deviation from the power-law scaling trend). This deviation may be either real or the effect of sampling biases, such as censoring artifacts (Ortega et al., 2006; Hooker et al., 2013) (Figure 8A). In the part of the distribution representing small fracture apertures ($b < 0.05$ mm [0.002 in.]), it is also possible to observe the effect of truncation artifacts (Ortega et al., 2006).

In our first experiment, the processed scanline data set fitted a power law with a slope of approximately $-0.88$. Thereafter, a log-log plot produced after the exclusion of the data corresponding to the identified artifacts (Figure 8B), with the new aperture distribution, fitted a power law with a scaling exponent of approximately $-0.86$. This simple procedure showed that the effects of sampling biases can modify the coefficients of the power law, as well as the scaling exponent.

Based on these results, we attempted to identify the range of possible effects of the uncertainties caused by the sampling biases in the scanline data. We focused on identifying the importance of the data measurement variability to the power-law equation for the distribution of the data. The estimation of these effects is essential for the choice of input parameters in stochastic models of geological systems that use power-law scaling.

The second experiment was based on three simulation cases. First, we considered the introduction of uncertainties only for the fracture spacing values, constrained by a coefficient of uncertainty ($CU_s = 30\%$). No uncertainties were introduced for the aperture values, meaning that $CU_b = 0\%$. Second, we introduced uncertainties only for the fracture aperture values (with $CU_b = 30\%$) and did not introduce uncertainties for spacing values (meaning $CU_s = 0\%$). In the third situation, we simultaneously introduced simulated uncertainties for both fracture spacing and aperture, both with $CU = 30\%$.

Uncertainty Simulation for Fracture Spacings

In the first case of simulation (with $CU_s = 30\%$ and $CU_b = 0\%$ for spacing and aperture values, respectively), the adjustment was provided by the least-squares method for each spacing value obtained by...
the MC simulation, and the distribution was expressed by a power law (Figure 9A). The log-log plot, which expresses the relationship between the cumulative frequency and fracture aperture (Figure 9B), shows two main trends that can be associated with two power laws ($F_1$ and $F_2$). The lines that defined the power laws $F_1$ and $F_2$ represent the maximum and minimum limits yielded by the MC simulations. Between $F_1$ and $F_2$, the coefficient $a$ ranges from 0.250 to 0.181. In these two lines, the scaling exponent is the same ($k = -0.848$) (Figure 9B). It is proposed that these lines probably indicate the confidence interval of the power-law constant $a$. Indeed, the values of the fracture aperture, which are outliers in this interval, should be interpreted as sampling biases specifically related to censoring artifacts (large fractures, $b > 1.1$ mm [0.043 in.]).

Figure 10 shows the behavior of the power-law coefficients and illustrates the symmetry and the outliers for the fracture spacing values after the MC simulations. Because the angular scaling exponent $k$ did not change, the power law showed variation only for the coefficient $a$. This constant has a normal distribution behavior with an average value of 0.2166, a standard deviation of 0.0110, and a $CV_a = 5.1\%$, where $CV_a$ represents the coefficient of variation of $a$. These results indicate that the
Uncertainty Simulation for Fracture Apertures

As aforementioned in case 2, uncertainties were simulated for the fracture aperture values with $CU_b = 30\%$, and for spacing values with $CU_s = 0\%$. The adjustment was made using the least-squares method for each aperture value obtained by the MC simulations, and the distribution was expressed by a power law with a slope of approximately $-0.82$ (Figure 11A). As in the first case, two main trends (meaning two power laws were obtained) were considered the limits of the scaling exponent for the fracture aperture data (Figure 11B). These power laws $F_1b$ and $F_2b$ represent the minimum and maximum slopes determined by the simulations, respectively. As indicated by $F_1b$ and $F_2b$, the confidence interval limits determined through this process allowed the identification of truncation and censoring biases. In this case, truncation is represented by the outliers determined by $b < 0.03$ mm (0.0012 in.), and the censoring biases were defined by values of $b > 0.9$ mm (0.035 in.).

Figure 12 shows the change in the power-law coefficients after the introduction of uncertainties in the fracture aperture values. It is possible to observe that, after the introduction of the simulated values, the $a$ and $k$ coefficients exhibit a normal distribution (Figure 12). The histogram related to the coefficient $a$ has an average value of 0.2213 and a standard
deviation of 0.0103, which produces a $CV_a$ of approximately 5%. The histogram for the scaling exponent $k$ has an average value of $-0.8181$ and a standard deviation of 0.0204, which also produces a coefficient of variation of approximately $-3\%$. The 95% confidence interval for the coefficients $a$ and $k$ is $CI_{ba} = [0.2207; 0.2220]$ and $CI_{bk} = [-0.8194; -0.8168]$, respectively.

Uncertainty Simulation for Fracture Spacings and Apertures
In the third case, the introduction of uncertainties through the MC simulations were performed simultaneously with $CU = 30\%$ for both spacing and aperture values. The processing of the data after the introduction of simulated values was expressed by a power law, which produces the equation $F_{sb} = 0.221b^{-0.820}$ (Figure 13A). In fact, this power law produces the same coefficients observed in Figure 11A ($F_b = 0.221b^{-0.820}$), for which the introduction of simulated values was performed only for aperture values. These results suggest that the values of fracture spacing have less influence on the variation of the power-law coefficients and that the aperture data strongly affect the power-law scaling exponent.

The log-log plot for the relationship between cumulative frequency and fracture aperture
Figure 11. Monte Carlo (MC) simulations of uncertainty in the fracture aperture values. (A) The result of the least-squares regression applied to each aperture data set generated by the simulation (gray lines), and the power-law average (black line); (B) power laws ($F_{1b}$ = dashed line and $F_{2b}$ = continuous line), which were considered the minimum and maximum of the scaling exponent for fracture aperture values, respectively.

(Figure 13B) shows a marked linear behavior concerning the variations in the two power laws ($F_{1b}$ and $F_{2b}$), which were obtained by the simulation of the uncertainties for the aperture and spacing values. The power laws $F_{1b}$ and $F_{2b}$ represent the maximum and minimum slopes, respectively, for these power-law lines. Between the definition of $F_{1b}$ and $F_{2b}$, the coefficient $a$ showed a variation between 0.256 and 0.196, and the maximum and minimum slope ranges from $-0.747$ to $-0.879$.

Figure 12. Histograms showing the normal distribution for the power-law coefficients ($a$, $k$). Analysis of the power-law coefficients after Monte Carlo simulation of the fracture apertures.
These power laws clearly indicate a confidence interval for the power-law coefficients $a$ and $k$. Consequently, the fracture aperture values, which fall within this confidence interval, represent the most reliable data set. Otherwise, the outliers should be interpreted as the data related to sampling biases. In this case, the censoring biases were represented by large fractures with $b > 1 \text{ mm (0.039 in.)}$, and the truncation biases were represented by values of $b < 0.03 \text{ mm (0.0012 in.)}$.

To understand the distribution of the power-law coefficients, a statistical analysis was performed following the simultaneous simulation of random values representing artificial uncertainties. The histogram obtained shows that the coefficient $a$ has an average value of 0.2217, a standard deviation of 0.0152, and a CV $a$ of 6.8%. However, the scaling exponent $k$ has an average value of $-0.8181$, a standard deviation of 0.0204, and a CV $k = -2.5\%$. When the uncertainties were imposed through the simulation only on the fracture spacing values, the coefficient of variation in these data showed a value of CV $a = 5\%$, but when the simulation was performed for aperture and spacing values, the coefficient increased to CV $a = 6.8\%$. The 95% confidence interval for the coefficients $a$ and $k$ was determined as $CI_{bsa} = [0.2207; 0.2226]$ and $CI_{bsk} = [-0.8194; -0.8168]$, respectively.

**Table 1. Summary of Uncertainty Simulations for Fracture Spacing ($s$) and Fracture Aperture ($b$) and Simultaneous Simulation for Fracture Spacing and Aperture ($s$ and $b$)**

<table>
<thead>
<tr>
<th>Analysis</th>
<th>$s$</th>
<th>$b$</th>
<th>CV$_a$ (%)</th>
<th>CV$_k$ (%)</th>
<th>$CI_a$</th>
<th>$CI_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s$</td>
<td>30</td>
<td></td>
<td>5.1</td>
<td></td>
<td>[0.2159; 0.2173]</td>
<td>$-\infty$</td>
</tr>
<tr>
<td>$b$</td>
<td></td>
<td>30</td>
<td>5.1</td>
<td>3.0</td>
<td>[0.2207; 0.2220]</td>
<td>$-0.8168; -0.8194$</td>
</tr>
<tr>
<td>$s$ and $b$</td>
<td>30</td>
<td>30</td>
<td>6.8</td>
<td>2.5</td>
<td>[0.2207; 0.2226]</td>
<td>[0.8168; 0.8194]</td>
</tr>
</tbody>
</table>

*CU = coefficient of uncertainty; CV$_a$ and CV$_k$ = coefficient of variation for the power-law coefficients $a$ and $k$, respectively; $CI_a$ and $CI_k$ are 95% confidence intervals for the coefficients $a$ and $k$, respectively.

**CONCLUSIONS**

The linear scanline technique was efficiently applied to access the fracture attributes of natural fracture systems in laminated lacustrine limestones of the Ararípe Basin in northeastern Brazil, which is an area used as an analog for carbonate reservoirs in the offshore region. Most of the opening-mode fractures documented in studied outcrops are classified as veins filled by calcite. We described two main populations
of opening-mode fractures: (1) set 1, striking northwest–southeast and (2) set 2, striking northeast–southwest.

Fractures of set 1 were used in this investigation to determine the effects of errors and uncertainties in the measurements of fracture attributes collected through the linear scanline surveys. The study of the effects of artifacts on data set processing, related to errors and geological complexity, was performed through the introduction of artificial uncertainties generated using the MC method. The introduction of uncertainties over the real data allowed us to determine the influence of these problems on the resulting power-law coefficients, which express the relationship between the frequency and aperture values of the fracture system.

Using a CU of 30% to constrain the introduction of simulated uncertainty values over the fracture spacing, we observed that the angular coefficient \( k \) for the resulting power-law curve did not change, and only the coefficient \( a \) showed variations because of an adjustment to a more normal distribution pattern. Thus, in this case, the resulting power-law curves \( (F_1 \) and \( F_2 \)) have the same slope. The introduction of simulated uncertainty values only for the fracture aperture values demonstrated that the uncertainties caused variations in both coefficients of the power law \( (a \) and \( k \)). This observation implies that the aperture data are far more important in the determination of the power-law angular coefficients. In a third case in which the simulated uncertainties were introduced for fracture aperture and spacing values, the results also showed that the values of fracture spacing have less effect on the variation of the power-law coefficients.

The results of this study showed that the propagation of uncertainties present a CV value of 6.8% for the coefficient \( a \) of the respective power law. However, with the determination of confidence intervals, with the maximum and minimum limits marked by the simulated power-law curves, it was possible to estimate the better values of the coefficients of the power law (Table 1). In general, the variability of the measurements imposed on the scanline data set makes it possible to propagate and observe a specific variability in the coefficients of the power law. Statistical analysis revealed that the uncertainties can affect the power-law scaling and demonstrated that it is possible to determine a confidence interval based on the defined “reliable” portion of the data set, with the exclusion of the biased values.

As these coefficients are used in the process of modeling of some intrinsic parameters of fractured reservoirs, such as the permeability field, the determination of a confidence interval for the data obtained from analogs and wells is very important to reduce the costs and problems associated with the uncertainties.

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