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Data Analysis and Neuro-Fuzzy Technique for EOR Screening: Application in Angolan Oilfields

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Abstract: In this work, a neuro-fuzzy (NF) simulation study was conducted in order to screen candidate reservoirs for enhanced oil recovery (EOR) projects in Angolan oilfields. First, a knowledge pattern is extracted by combining both the searching potential of fuzzy-logic (FL) and the learning capability of neural network (NN) to make a priori decisions. The extracted knowledge pattern is validated against rock and fluid data trained from successful EOR projects around the world. Then, data from Block K offshore Angolan oilfields are then mined and analysed using box-plot technique for the investigation of the degree of suitability for EOR projects. The trained and validated model is then tested on the Angolan field data (Block K) where EOR application is yet to be fully established. The results from the NF simulation technique applied in this investigation show that polymer, hydrocarbon gas, and combustion are the suitable EOR techniques.

Keywords: enhanced oil recovery (EOR); neuro-fuzzy (NF); artificial intelligence (AI); reservoir screening; neural network (NN)

1. Introduction

The process of selecting potential candidates for enhanced oil recovery (EOR) operation is a complex task involving integration of a set of rock and fluid parameters governing technical and economic performance of a reservoir. It is understood that technical evaluation of EOR techniques is crucial to the success of such projects. However, it is equally important to evaluate the economic viability of an EOR project development including environmental, commercial, political and governmental factors [1–3]. Currently, there is no fully established technique for identifying the potential candidates for EOR operation. Operations are generally based on trial-and error; with reduced chances of success. In order to increase the chances of success and to make an informed decision, parameters obtained from either successful EOR field applications or from existing knowledge of the EOR operation could be effectively utilised. Comparison between these criteria and the reservoir of interest will provide an indication of the possibility of success for future EOR projects [4]. However, matching the parameters from the worldwide successful EOR techniques is a challenge from data mining and screening points of view. This is particularly the case since these parameters may not necessarily be directly dependent on each other. Several methods have been developed and published for screening oil reservoirs such as data analysis by using tables and graphs [5–8] and artificial intelligence (AI) [3,9–13].

AI in oil industry has long been studied and its development has been relatively mature. Fuzzy-neural is an important approach in the area of reservoir characterisation in which knowledge of reservoir performance forecast from well logs can be derived [9]. Chung et al. [10] developed a fuzzy expert system for EOR risk analysis incorporating preliminary screening EOR methods, the field performance estimation and economic analysis. The system reduces the requirements of massive laboratory experiments and field data input. Kamari et al. [3] solved both problems of selecting appropriate EOR method by using an artificial neutral network (ANN) and an economical EOR screening model for prediction of cash flows.

A lot of work has been done on the application of artificial intelligence technique in EOR projects [14–22]. Morel et al. [14] published the screening criteria of the EOR technologies using 347 successful EOR projects worldwide. The study was based on the established analysis through fuzzy-logic (FL) membership functions (triangular, Z-shaped and S-shaped) and results are promising compared to the existing commercial software (EORgui). An neuro-fuzzy (NF) approach to screening reservoir candidates was published [15] by combining the strength of fuzzy technique in searching data with the learning capability of neural network (NN) to deduce knowledge from analogous to linguistic rules. 365 successful EOR data set were used to validate and determine the combination of fluid and rock properties which could best characterise the key parameters that control EOR success.

Kamari et al. [16] presented an AI based on gene expression programming (GEP) for prediction of CO_2—oil minimum miscibility pressure (MMP) at different reservoir temperatures and oil compositions for live oil. In their work, Chen et al. [17], proposed two types of ANN models; back-propagation neural network (BPNN) and radial basic function neural network (RBFNN) for CO_2 solubility prediction in all types of amine solutions. The models were evaluated by comparing the results of experimental data with the predicted results of eight numerical models from the literature. Furthermore, Saeid et al. [18] developed adaptive NF inference system (ANFIS) for the estimation of solubility of hydrogen in heavy oil. To validate the model, both statistical and graphical methods were used in the training and testing data sets for the developed model.

Least square support vector machine (LSSVM) technique has been developed to estimate the interfacial tension (IFT) and MMP in paraffin—CO_2 systems [19], permeability of heterogeneous oil reservoirs [20], and surfactant—polymer flooding performance [21]. The proposed models were validated by statistical and graphical error analysis. Abouzar et al. [22], presented an ANN by using cuckoo optimisation algorithm (COA) and teaching learning based optimisation (TLBO) to predict the pure and impure CO_2 MMP.

As can be seen, most researchers on EOR screening have focused on single data point or use of insufficient number of well data in the models; thereby ignoring the heterogeneity of the fields. This usually leads to non-linearity of the data for the candidate reservoirs for EOR techniques. Hence, a multi-layered genetic fuzzy perceptron approach based on ANFIS [23] is used in this study. It is practical and easy to define constraints for the NF learning procedure, impose the rule of the fuzzy sets intersection point and minimise and stabilise the error between the training and validation data set [15].

It is our motivation to use NF as an AI tool to identify potential reservoir for EOR candidates. The model was performed using an in-house code and is capable of generating an automatic rule-base from successful worldwide database projects, optimising the variables of the fuzzy membership functions and providing interpretation models. The NF algorithm uses a self-organising technique to learn and initialise the membership functions of the input and output variables from a set of training data [24]. This is similar to the work of Zhou and Quek [25] where pseudo outer-product (POP) learning algorithm was used to identify the fuzzy rules instead of competitive learning [26] adopted in this paper. The input variables for the NF model consist of training functions (Figure 1) where the hidden layer nodes are varied in order to obtain the lowest root mean square error (RMSE) and non-dimensional error index (NDEI). Further details about methods are provided in Section 2.3 below. This is the first comprehensive study around the country and we believe the model can be used as an important tool on a technical field and/or reservoir selection.
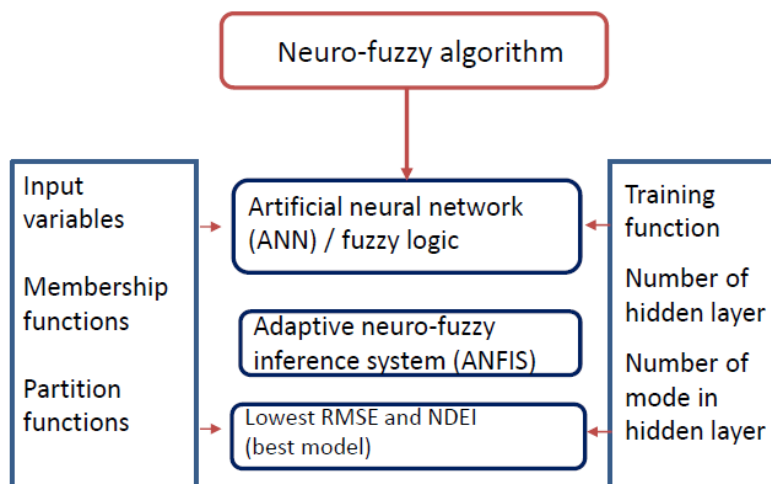
Figure 1. Categorisation of the neuro-fuzzy (NF) technique showing combined artificial neutral network (ANN) and fuzzy-logic (FL) underpinned by adaptive NF inference system (ANFIS).

With the declining production rate within Angolan oil fields, the EOR methods are the most plausible means of increasing the recovery factor of hydrocarbon left in the ground after conventional recovery methods. The application of EOR methods in Angola is very necessary but requires an extensive research, development of a cheap and efficient techniques and more expertise involvement.

The data set used in this study is from 365 multiple successful thermal, miscible gas, chemical and biological EOR projects worldwide. The field data set, consisting of 2994 Angolan oil field data are mined and analysed using box-plot technique for Block K which is made up of four (4) areas, 13 fields, 40 reservoirs and 179 wells. The area grouping is based on production allocation associated with the asset (Figure 2 and Table 1). The results of the NF model can be applied as a preliminary step in technically evaluating the suitability of a particular EOR technique in Angola or elsewhere.


Figure 2. Schematic diagram of Block K (Angola) showing the areas, fields, reservoirs and wells. See Table 1 for detailed breakdown of the distribution of the areas, fields, reservoirs and wells for the Block K.

Table 1. Detailed breakdown of the distribution of the areas, fields, reservoirs and wells of the Block K—Angola (Courtesy: Sonangol EP).

Areas	Fields	Reservoirs	Wells
	X1	7	43
Area 1	X2	4	10
	X3	3	4
Area 2	X4	6	30
	X5	5	13
	X6	3	29
Area 3	X7	1	13
	X8	2	16
	X9	1	1
	X10	1	3
Area 4	X11	3	6
	X12	3	5
	X13	1	6
Total	13	40	179

2. The Methodology and Approach

The methodology employed in this study consists of three main steps: data mining, data analysis, and technical screening of EOR methods by NF algorithm (Figure 3).
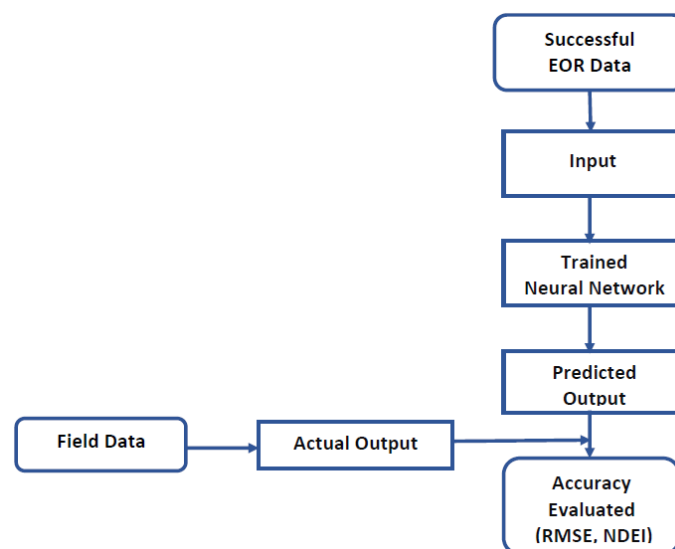
Figure 3. NF architecture.

2.1. Data Mining

The data for EOR screening comprises of two categories. The first category is training or validation data: data derived from laboratories studies, data generated from oil reservoirs simulation, data from successful worldwide projects. Data from successful worldwide projects are the most reliable category by the fact that technical and economical capabilities are proved practically [3]. The second category is the test data from the reservoirs under investigation.

2.2. Data Analysis

In this study, box-plots (Figure 4) were used to represent the distribution of EOR projects against the oil and reservoir properties. These representations illustrate the distribution of oil property and reservoir characteristics for the available EOR data set.
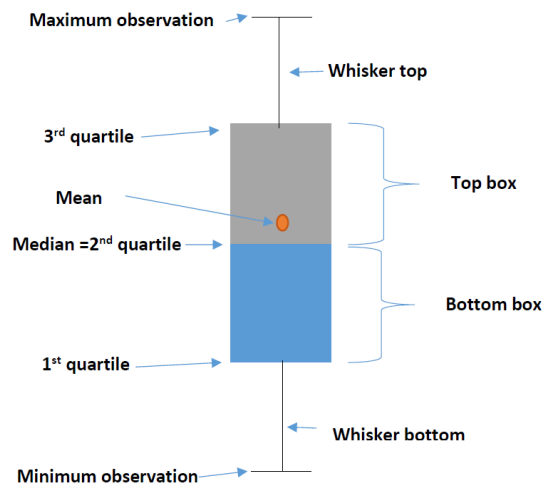
Figure 4. Schematic of box-plot.

The upper limit of the whisker top, represents the maximum value and the lower limit of the whisker bottom represents the minimum value of the data set. All values out of this range (max-min) are considered as outliers. The extreme minimum and maximum values could have negative impact on the EOR criterion; even when the averages are established [7]. The values of both successful EOR data set and from reservoir of the variable under investigation are plotted in a graph. The following expression can be used to effectively analyse the observed variables:

$$[a \cup b] \cap [c \cup d] = f \tag{1}$$

where a and b are the minimum and maximum of the training data set (e.g., successful EOR); c and d are the minimum and maximum of the test data set (e.g., Angolan field), and f is the outcome data set of the investigation. If f is an empty set, then the test variable will be considered unsuitable for the application process under investigation, hence the Equation (1) becomes:

$$[a \cup b] \cap [c \cup d] = \{\} \tag{2}$$

In summary, the box-plots provide a quick and efficient way to analyse the data, providing basic information about minimum, maximum, average and range in which the majority of the projects or data set are concentrated. However, the caveat in the use of box-plot analysis is that, it does not quantify the degree of uncertainty or consider the weight of each parameter, which requires a robust system as NF or laboratory test for full investigation.

2.3. Neuro-Fuzzy Technique

The structure of the model is based on five (5) layered feedforward - backpropagation NN (Figure 5). This structure consists of input, hidden, and output layers. The input layer represents the input variables, whilst the output layer (defuzzification) represents the output decision signals. For the defuzzification, centre of gravity (COG) and min of max (MOM) were employed. In the hidden layers, layer two (2) nodes are functioning as input and output membership functions, and layers three (3) and four (4) nodes act as fuzzy logic rules AND, OR respectively [15,27,28].
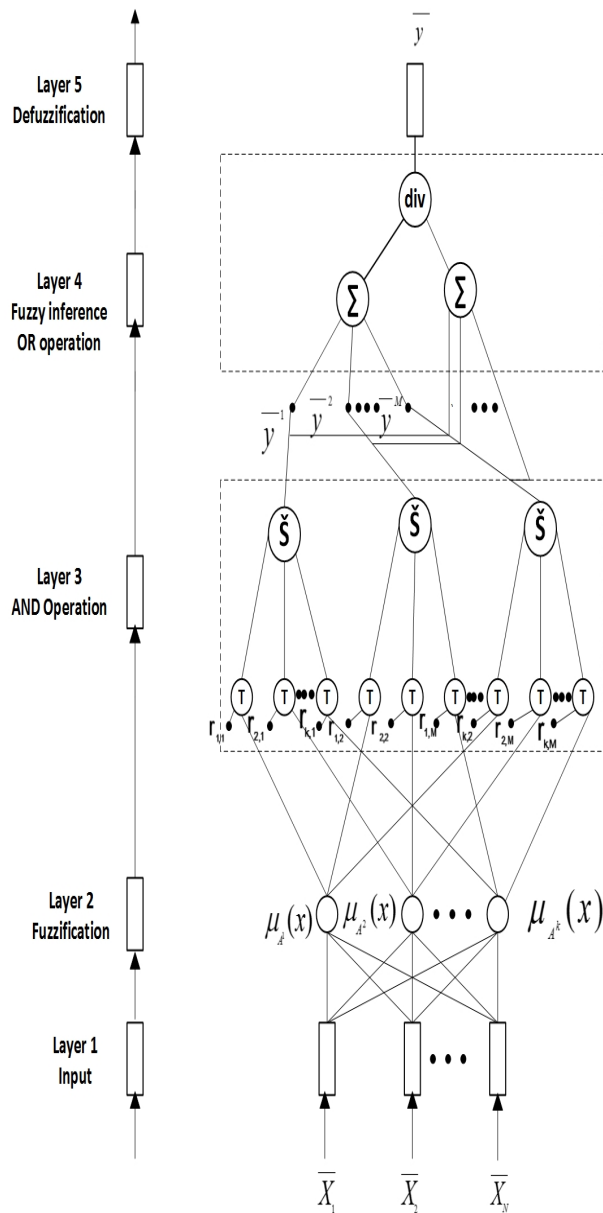
Figure 5. A typical 5 layer NF framework, Adapted from: [15].

The operation is done in many simple individual processors called neurons. On each layer, each neuron is connected to the neurons in the proceeding layer by direct links which have their own special weight [27–29]. Each neuron applies an activation function to its net input to produce its output after receiving signal from the proceeding neurons, and x represents the input signal to a node [27–29].

The description of the membership functions (MFs) applied in this work is highlighted in paper [15,30,31] where triangular, trapezoidal and Gaussian membership functions were all tested and the leftmost and rightmost values were shouldered. The choice was based on specific MFs that adequately matches the available successful EOR data using minimum error. Full details of the development of these NF model applied in this work can be found in [15].

During the learning process, the knowledge extracted from the NF system can be expressed in the form of fuzzy rules by computing weights, number of rules and fuzzy set parameters. These parameters are computed by machine learning process from the EOR data with the input fuzzy sets determined by the fuzzy clustering algorithm. The aforementioned parameters can also be determined by engineers and experts in the field. The back-propagation algorithm developed by [32] is used to tune all

parameters where the error is propagated from the output towards the input units. The mean square error is expressed by the Equation (3) [15,27,28]:

$$E\left(\bar{x}, d\right) = \frac{1}{2}\left[\bar{y}\left(\bar{x}\right) - d\right]^2 \tag{3}$$

$$w\left(t+1\right) = w\left(t\right) - \alpha\frac{\partial E\left[\bar{y}\left(\bar{x}\right), d; t\right]}{\partial w\left(t\right)} \tag{4}$$

where $\bar{y}\left(\bar{x}\right)$ is the desired output and d is the current actual output. α represents a learning rate coefficient, set in simulations to 0.01 after error validation sensitivity. The $\left(\partial E / \partial E_c\right)$ for the input and output of the Layer five (5) and two (2) can be determined, respectively as [15]:

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial E_c}\frac{\partial E_c}{\partial O_5}\frac{\partial O_5}{\partial I_5}\frac{\partial I_5}{\partial w} \tag{5}$$

$$\frac{\partial E}{\partial w} = \frac{\partial E}{\partial E_c}\frac{\partial E_c}{\partial O_5}\frac{\partial O_5}{\partial I_5}\frac{\partial I_5}{\partial O_4}\frac{\partial O_4}{\partial I_4}\frac{\partial I_4}{\partial O_3}\frac{\partial O_3}{\partial I_3}\frac{\partial I_3}{\partial O_2}\frac{\partial O_2}{\partial I_2}\frac{\partial I_2}{\partial w} \tag{6}$$

Hence, the updated value of w can be determined and the root mean square error (RMSE) and non-dimensional error index (NDEI) is used to evaluate the predicted error defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[\bar{y}\left(\bar{x}\right) - d\right]^2} \tag{7}$$

$$\text{NDEI} = \frac{\text{RMSE}}{\sigma\left(d\right)} \tag{8}$$

where $\bar{y}\left(\bar{x}\right)$ is the predicted output, $\sigma(d)$ is the standard deviation of the target series, i is the data point that varies from 1 to N. If the NN is successfully trained, it can now be used to predict the suitability of the test data for the respective EOR technique under investigation.

3. Application of the Techniques in Angolan Oilfields

Angola is producing approximately 1.7 Mbbls/day under primary or secondary recovery mechanisms. The recovery factor from these mechanisms account for about 30% of the original oil in place [29,33] and most of the reservoir fields are maturing with production and pressure declining very rapidly as shown in Figures 6 and 7. Observation of the production and pressure patterns across a single block (Block K) consisting of 13 major fields suggests that there is a significant decline in performance. As an example, the reservoir drawdown; which is the primary force driving the fluids into the wellbore, decreases with time with significant negative impact on the productivity index (PI) of these wells. Figure 8 shows this trend for wells X6Y13W1 and X7Y29W4. PI for well X6Y13W1 is 61.84 *stb/d/psi* from 2005 and down to 10 *stb/d/psi* over a period of five years. Similarly, for well X7Y29W4, PI decreases from 2.91 *stb/d/psi* to 1.29 *stb/d/psi* over a period of ten (10) months in 2011. These observed trends suggest that there is a need for a mechanism for enhancement to be put in place. Hence, improving the performance of these wells is a cost-effective way to reverse the negative production decline trend, extend field life and improve oil recovery.

The term "easy oil" is vanishing in Angola due to the fact that more than 80% of oil production is from offshore fields and the production is moving towards more remote areas like deepwater and ultra-deepwater where the extraction of oil or field development is very costly. Angola can still produce the remaining oil from existing fields by applying new EOR technologies capable of increasing the recovery factor. Not much work has been published in the area of applied EOR technologies; an area which requires more research is the identification of suitable techniques that could allow further extraction of oil beyond primary and secondary recovery.

Historically, only one deep offshore field case of EOR (i.e., polymer injection) in Dalia/Camelia fields has been implemented in Angola [14,34–37]. Considering the large number of fields and start of production activities dated as far back as 1955, Angola can be considered as a potential location for the implementation of EOR techniques. By applying the EOR recovery techniques, millions of barrels of oil will be extracted from the existing fields by increasing the recovery factor up to 60% of the oil in the reservoir [33]. Therefore, screening oil reservoirs can be considered as the first step before an EOR project implementation in Angola. However, before stating with confidence that the selected EOR technique will likely be technically successful, additional evaluations such as core analysis, reservoir simulation and field pilots are required [4].

(a)

(b)

(c)

(d)

(e)

(f)
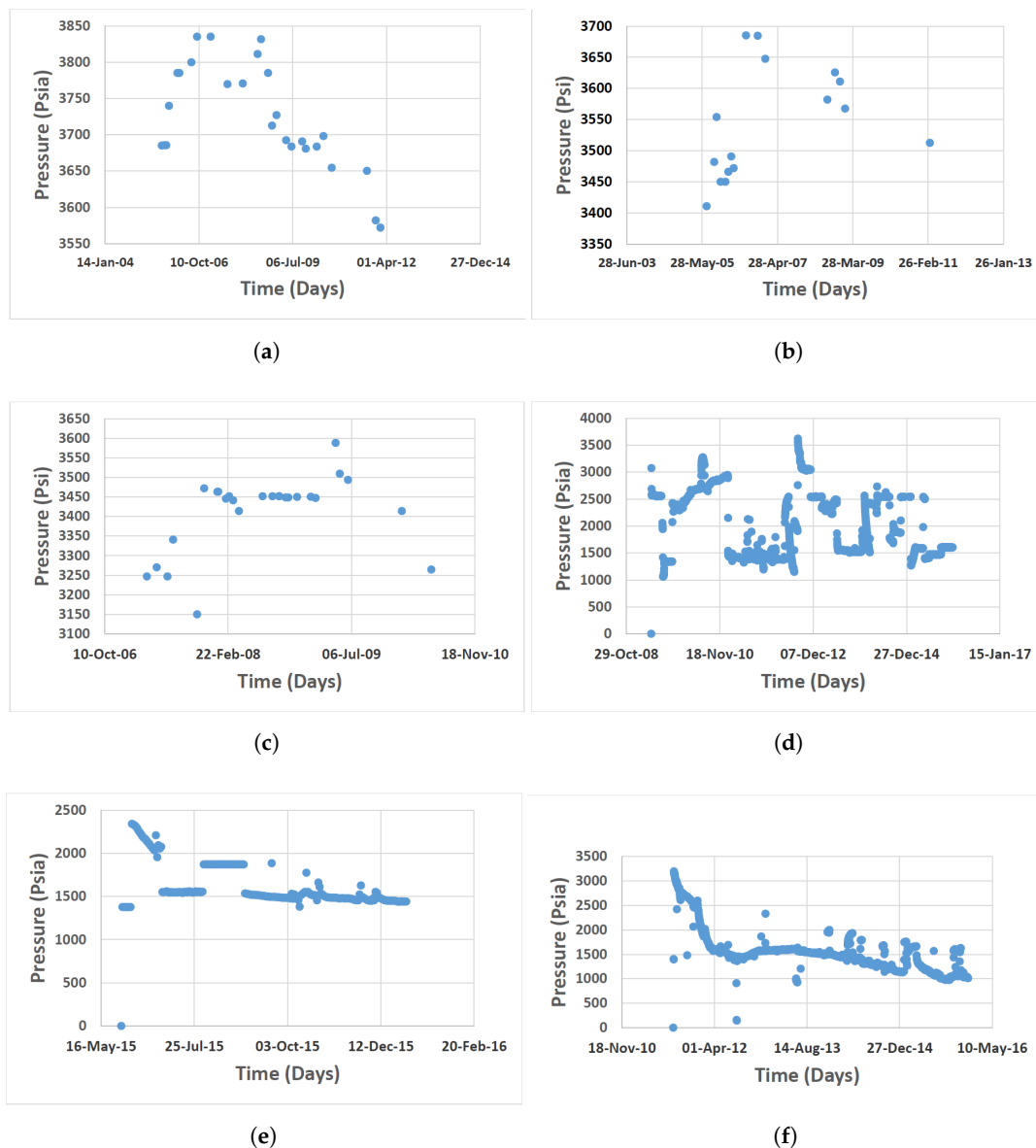
Figure 6. Pressure profile for wells (**a**) X6Y13W1; (**b**) X6Y16W2; (**c**) X5Y9W3; (**d**) X7Y29W4; (**e**) X8Y27W5; and (**f**) X9Y38W6. In all cases X indicates the field, Y the reservoir and W the well and the associated figures signifies the number of the field, reservoir or well in the Block K investigated (Courtesy: Sonangol EP).
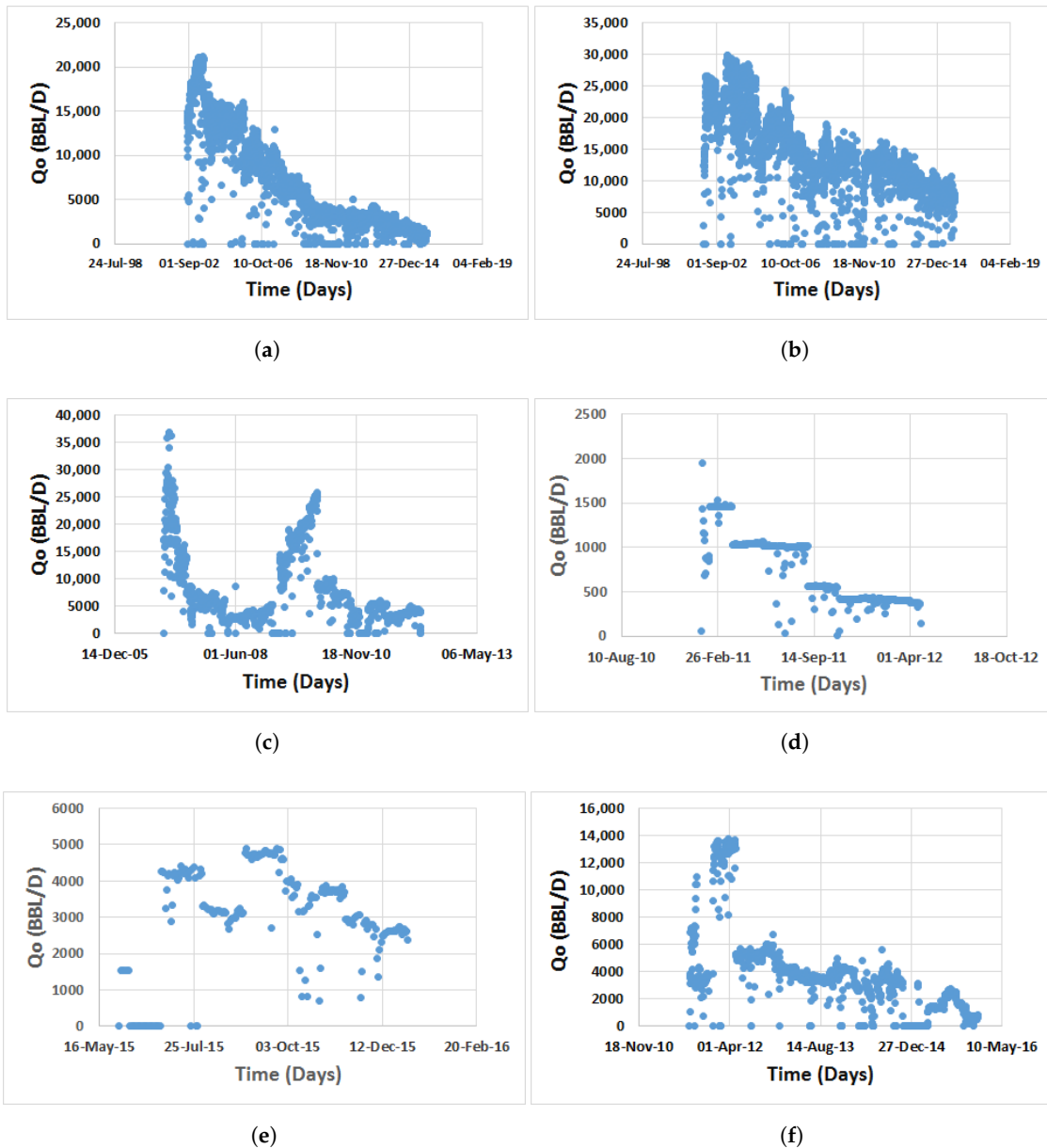
Figure 7. Production profile for wells (**a**) X6Y13W1; (**b**) X6Y16W2; (**c**) X5Y9W3; (**d**) X7Y29W4; (**e**) X8Y27W5; and (**f**) X9Y38W6. In all cases X indicates the field, Y the reservoir and W the well and the associated figures signifies the number of the field, reservoir or well in the Block K investigated (Courtesy: Sonangol EP).

Figure 8. Productivity index for wells (**a**) X6Y13W1; (**b**) X7Y29W4; (**c**) X5Y10W17; (**d**) X5Y11W12; (**e**) X5Y11W24; and (**f**) X7Y24W35. In all cases X indicates the field, Y the reservoir and W the well and the associated figures signifies the number of the field, reservoir or well in the Block K investigated (Courtesy: Sonangol EP).
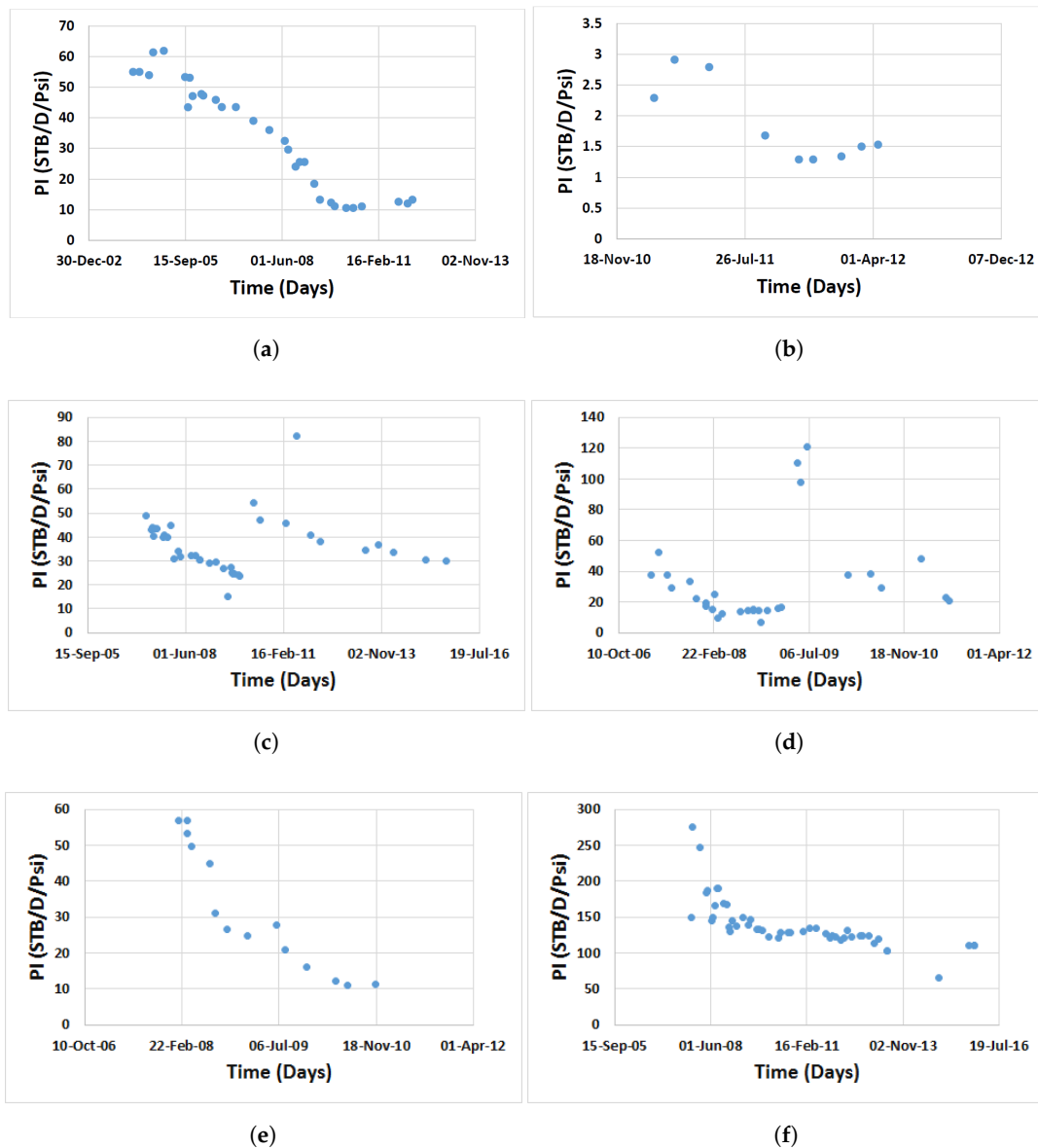
3.1. Data Analysis

The successful EOR data set used in this model is from 365 worldwide successful EOR projects (Figure 9); divided into ten (10) different EOR techniques such as steam, miscible CO_2, miscible hydrocarbon gas, polymer, combustion, surfactants, nitrates, microbial, hot water and miscible acid gas. Some techniques from available data set present a number of successful projects that are considered insufficient for performing advanced statistical test. These techniques which include miscible acid gas, microbial, hot water, surfactant and nitrates will not be investigated in this current study.
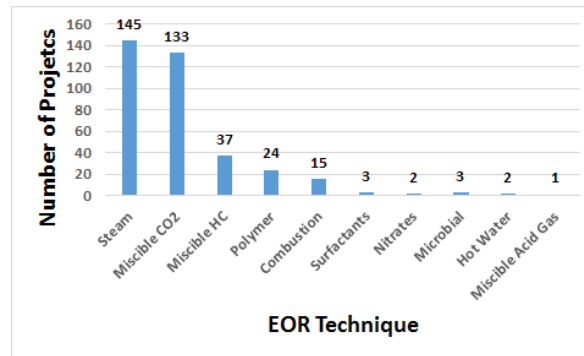
Figure 9. Successful worldwide enhanced oil recovery (EOR) projects. Successful EOR techniques with number of projects less than 15 were not analysed and were excluded in training for training accuracy and efficiency. Data source: [15,38].

Table 2 indicates that oil properties and reservoir characteristics were updated according to the available data set from the worldwide successful EOR projects and is not intended to present threshold limits since the range could be affected also by economic constraints and scientific development.

Angola data set was collected from 13 fields (X_1, X_2, ..., and X_{13}) consisting of reservoir rock and fluid properties including: reservoir depth, oil API gravity, oil viscosity, rock porosity, rock permeability, oil saturation, net pay thickness, reservoir temperature, reservoir pressure, formation water salinity and formation type. These data sets were collected from several reports including well test, geochemistry, fluid sampling, final well, thermodynamic, geological, Drill stem test (DST) and log interpretation reports. No carbonates formation type rock was found in the area under investigation. The area under investigation is an offshore field with water depth greater than 3500 ft and sea bottom temperature approximately 40 °F.

All the mined data are carefully checked for consistency and quality in order to minimise error. The set of data which were not available are highlighted in Table 3. The box plots were used to identify possible inconsistency and discrepancies in the data as the accuracy of the model in predicting the output may be impaired with the presence of outliers [8,39]. Table 4 contains the summary of the minimum, average and maximum values of the variables associated with the area under investigation (Block K). Figure 10 shows a single box-plot for the data-set associated with the successfull EOR and Angolan field for each variable. This is aimed at providing information about the distribution and alignment of both data-sets.

Table 2. Attributes of successful enhanced oil recovery (EOR) projects worldwide. Data source: [15,38].

Type of EOR	Number of Projects	Formation Type	Reservoir Characteristics					Oil Properties	
			Depth (ft)	Porosity %	Permeability (mD)	Oil Saturation (%) *	Oil Viscosity, (cp)	Oil Gravity °API	EOR Prod. (B/D)
Steam	113	sandstone	250–5740	15–39	100–10,000	20–90	18–500,000	8–22	62–86,000
	13	unconsolidated sands	175–3150	25–40	300–15,000	48–90	175–200,000	9–25	500–190,000
	6	carbonates	550–1500	20–65	1–2000	45–85	26–4000	10–29	25–21,200
Miscible CO$_2$	50	sandstone	1600–11,950	10–28	9–2300	26–77	0.3–3.0	27–45	205–15,000
	–	unconsolidated sands	–	–	–	–	–	–	–
	83	carbonates	4000–11,100	4–24	0.1–5000	30–89	0.32–6.0	28–45	25–28,300
Miscible HC	17	sandstone	4000–13,750	8–26	20–1500	25–80	0.3–73	19–41	200–80,000
	–	unconsolidated sands	–	–	–	–	–	–	–
	20	carbonates	4040–9150	8–18	3–5000	30–90	0.14–0.83	37–48	10–8810
Polymer	24	sandstone	625–5540	15–34	7–5000	45–82	5–5000	13–34	14–55,000
	–	unconsolidated sands	–	–	–	–	–	–	–
	–	carbonates	–	–	–	–	–	–	–
Combustion	1	sandstone	400–2065	32	650	94	660	19	240
	3	unconsolidated sands	3120–3450	28–30	8000–15,000	70–80	100–550	9.8–17	–
	11	carbonates	8300–9500	17–20	10–15	50–85	1.4–2	31–38	100–12,733
Surfactants	2	sandstone	625–14,500	12–17	45–50	36–51	0.5–3	27–39	70–350
	–	unconsolidated sands	–	–	–	–	–	–	–
	1	carbonates	4800	14	20–60	50	2.6	34	–
Nitrates	1	sandstone	7500–8100	25–30	20–2500	–	0.14	33	8800
	–	unconsolidated sands	–	–	–	–	–	–	–
	1	carbonates	2000–3000	50	0.1–1	50	2	30	860
Micorbial	3	sandstone	200–1572	17–26	180–200	54	19–31	23–31.5	–
	–	unconsolidated sands	–	–	–	–	–	–	–
	–	carbonates	–	–	–	–	–	–	–
Hot water	2	sandstone	1350–2100	32–34	1500–2000	15–48	900–3350	12–14	226–1450
	–	unconsolidated sands	–	–	–	–	–	–	–
	–	carbonates	–	–	–	–	–	–	–
Miscible acid gas	–	sandstone	–	–	–	–	–	–	–
	–	unconsolidated sands	–	–	–	–	–	–	–
	1	carbonates	4900	8	10–100	40	0.6–1.5	32–40	1000
Total	213	sandstone	–	–	–	–	–	–	–
	29	unconsolidated sands	–	–	–	–	–	–	–
	123	carbonates	–	–	–	–	–	–	–
	365	–	–	–	–	–	–	–	–

* Oil saturation at start-up.

Table 3. Available data set by field. (Courtesy: Sonangol EP).

Field	Depth	Net Thickness	Porosity	Permeability	Viscosity	API	Oil Saturation	Temperature	Pressure	Water Salinity	Formation Type
X_1	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
X_2	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
X_3	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_4	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_5	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_6	✓	✓	✓	✓	✓	✓	×	✓	✓	×	×
X_7	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_8	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_9	✓	×	✓	✓	✓	✓	×	✓	✓	×	×
X_{10}	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_{11}	✓	✓	✓	✓	✓	✓	×	✓	✓	×	×
X_{12}	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×
X_{13}	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
X_{14}	✓	✓	✓	✓	✓	✓	✓	✓	✓	×	×

Table 4. Rock and fluid properties for some of the Angolan oilfields. The area grouping is based on production allocation for the entire reservoir investigated Block K. (Courtesy: Sonangol EP).

Variables		Area 1			Area 2			Area 3			Area 4		
Type	Number	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
Depth (ft)	1011	5510	8107 51%	14,260	6318	7746 37%	12,631	4385	7175 5%	12,382	4370	8052 7%	12,644
API	205	15.9	27.6 39%	42.2	24.6	29.34 9%	37	25.4	31.6 32%	39.6	18.2	28.6 20%	39.7
Viscosity (cp)	146	0.6	1.94 43%	16	0.3	1.4 11%	2.1	0.2	0.96 25%	2.5	0.4	2.5 21%	10.7
Porosity (%)	170	15	26.2 51%	33	14	26.6 36%	35.7	22	29.5 4%	35	15	26.7 9%	38
Permeability (mD)	148	43	1026 65%	4875	1	1224 27%	4870	383	1813.2 3%	3350	108	1079 5%	2100
Oil Saturation (%)	159	54	82 55.4%	97	33	78 35%	99	71	86.32 3%	95	73	86.14 6%	92
Net Thickness (ft)	118	4	58 58%	245	6	121 25%	472	39	133 6%	246	7	79 11%	171
Temperature (°F)	106	140	168 35%	213	137	157 18%	207	132	184 25%	266	127	157 23%	195
Pressure (Psia)	928	2015	3706 53%	5296	227	3418 37%	4452	2202	3169 5%	5358	2133	3435 5%	5314
Salinity (ppm)	3	180,000	198,333 100%	230,000	0	0 0%	0	0	0 0%	0	0	0 %0	0
Formation type			ss, s			s, ss, cst			ss, s			ss, s	

ss = sandstone, s = sand, cst = claystone.

(**a**)

(**b**)

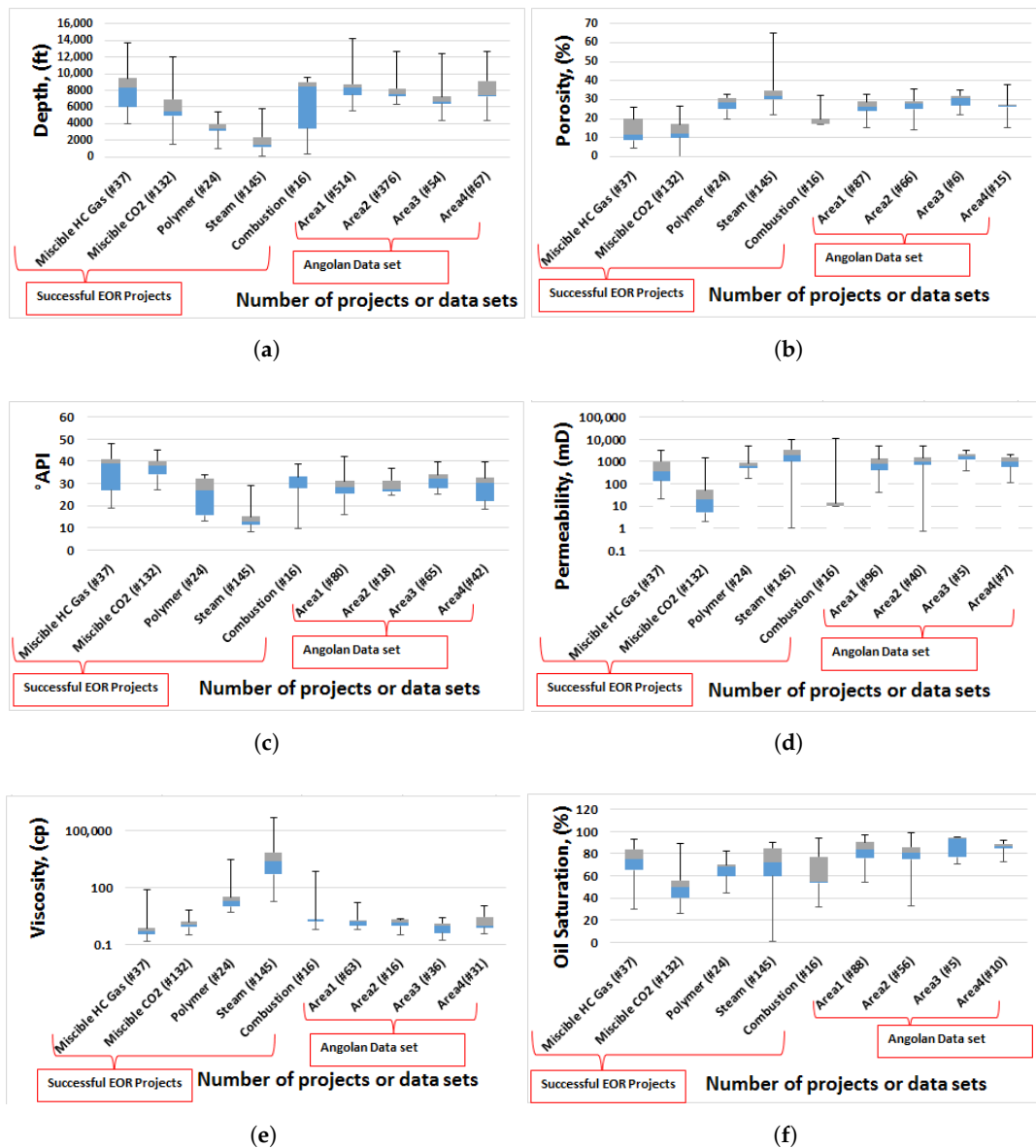(**c**)

(**d**)

(**e**)

(**f**)

Figure 10. Reservoir properties distribution vs. EOR methods. (**a**) Depth; (**b**) porosity; (**c**) API; (**d**) permeability; (**e**) viscosity; and (**f**) saturation. Data source of Worldwide successful EOR: [15,38]; Angolan oilfield data: Sonangol EP.

Besides box-plots, Equations (1) and (2) can also be used for data analysis. As an example, considering steam as an EOR technique (Tables 2–4 and Figure 10a), the lower and upper limit of the variable depth for successful projects are 250 and 5740 and for Area 2 are 6318 and 12,631; $[250 \cup 5,740] \cap [6,318 \cup 12,631] = \{\}$, which is an empty set. This implies that the depth range under investigation may not be suitable for steam. On the other hand, for steam as a technique and oil saturation as a variable for Area 1 (Tables 2–4 and Figure 10f), $[20 \cup 90] \cap [54 \cup 97] = [54 \cup 90]$, which means the values within the range of 20 and 90 may be suitable.

3.2. Neuro-Fuzzy Technique

The modelling process consists of three main stages: training, validation and testing. Data was grouped by variables from each EOR technique (Table 5). The set of options which generates the least RMSE and NDEI 80% (4/5) of the data set were selected at random for the training and the remaining 20% as the validation (prediction) set. This set of data 20% (1/5); which generates the least RMSE and

NDEI is used as validation data set for the testing process. 45 runs for each variable and totaling more than 1350 runs for the six variables of five EOR techniques were generated. Figures A1–A5 summarise the best selected simulation results. Figure 11 illustrates five options run out of forty five runs of Depth for steam.
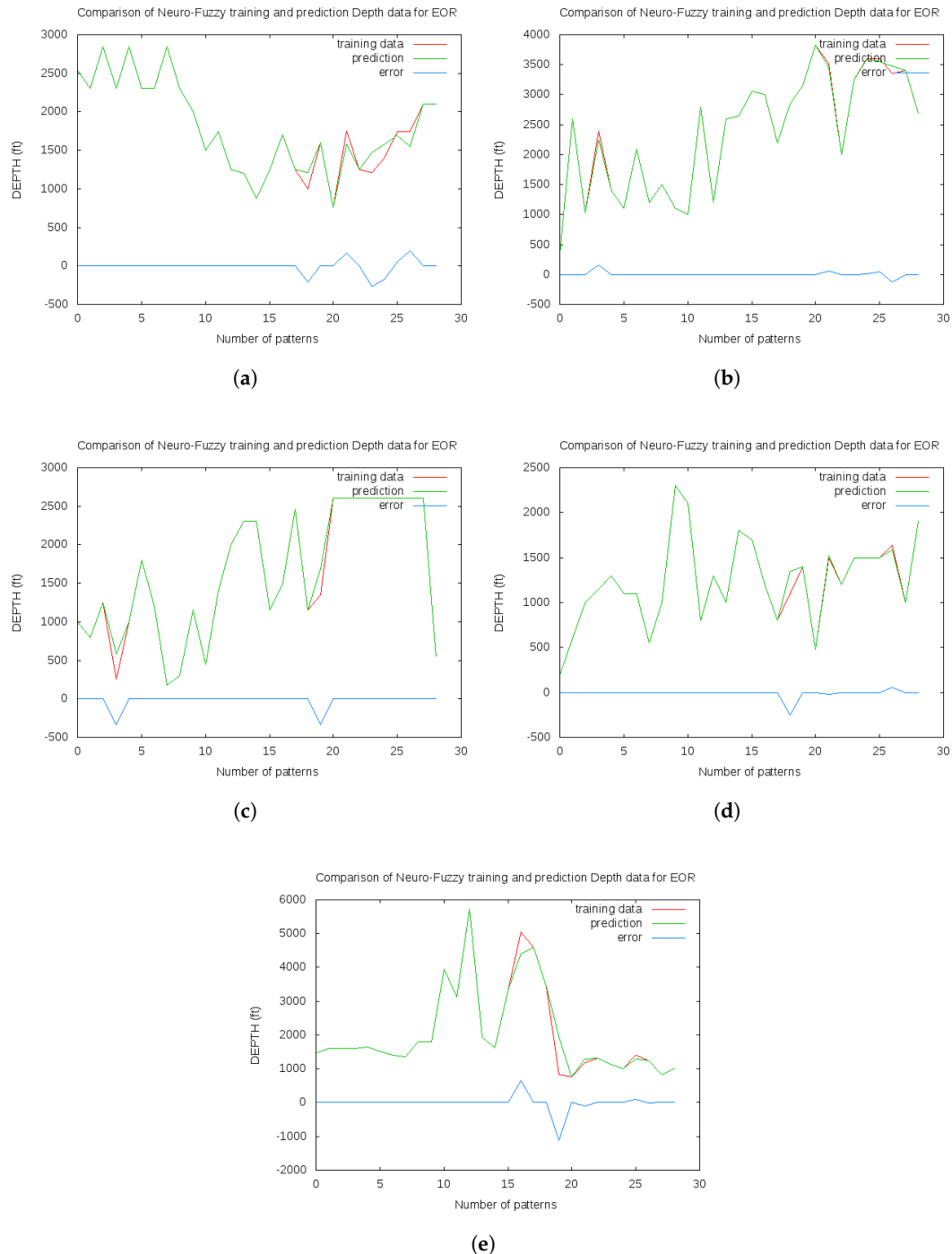

(**a**)

(**b**)

(**c**)

(**d**)

(**e**)

Figure 11. Plots of depth for the weighted training data, prediction data and associated error versus number of patterns for steam: (**a**) option 1; (**b**) option 2; (**c**) option 3l (**d**) option 4; and (**e**) option 5.

Table 5. Worldwide successful EOR data base by variables. Data source: [15,38].

	° **API**	**Depth (ft)**	**Permeability (md)**	**Porosity (%)**	**Saturation (%)**	**Viscosity (cp)**
Steam	145	145	134	145	138	141
CO$_2$	131	130	129	130	107	128
Miscible Gas	37	37	36	37	33	36
Polymer	24	24	24	24	18	21
Combustion	16	16	14	15	15	15
Surfactants *	3	3	3	3	3	3
Nitrates *	2	2	2	2	2	2
Microbial *	3	3	3	3	3	2
Hot water *	2	2	2	2	2	2
Acid gas *	1	1	1	1	1	1
Total	364	363	348	362	321	352

* Techniques not investigated due to insufficient number of successful EOR projects data set.

The test data set (Angolan oilfield data), we used random selection and tested with the already validated data set from the training process. The results of simulation determines the EOR techniques suitable for Angolan oilfield according to the methods and variables investigated. Figures A6–A8 summarise the results of the simulation using the Angolan oilfield data set. The sample testing simulation results for steam are illustrated in Figure 12. However, this is not binary decision operation and hence the engineering expertise and knowledge from the previous operations in the area will be invaluable in evaluating the sensitivity of each variable for decision making.
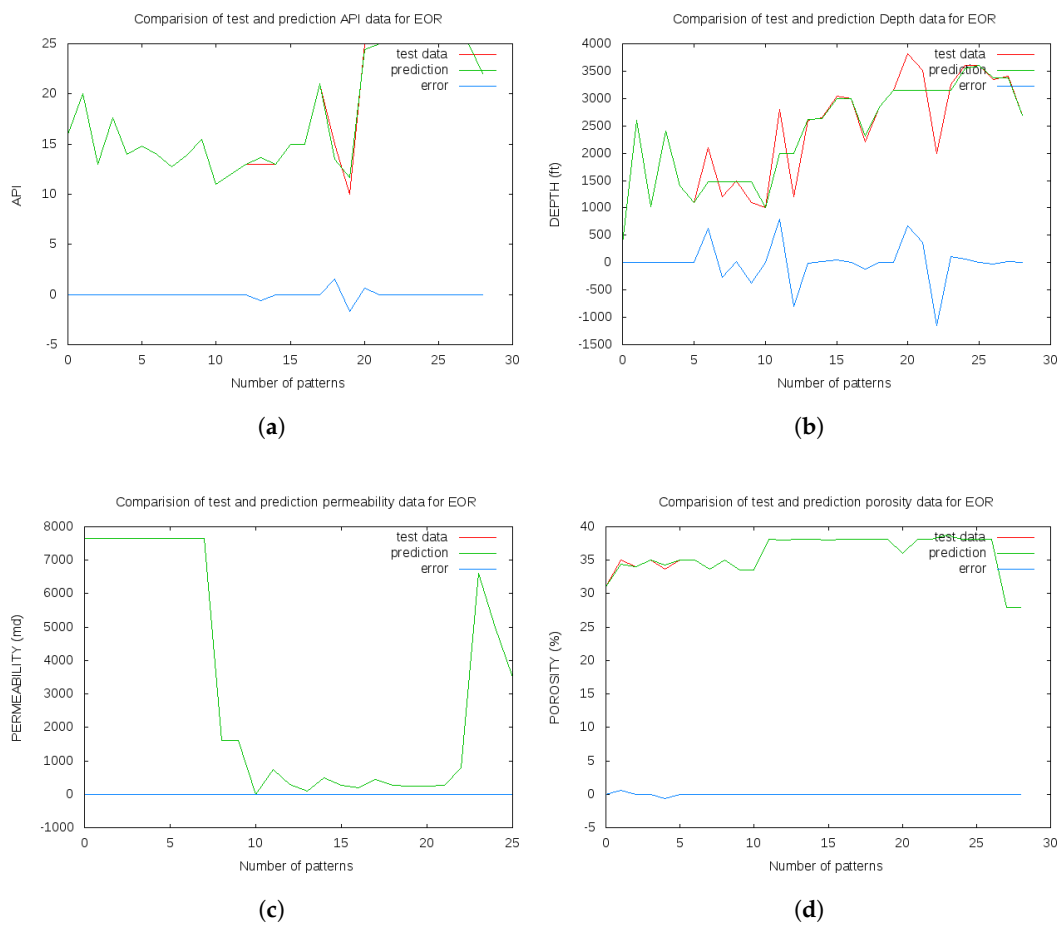

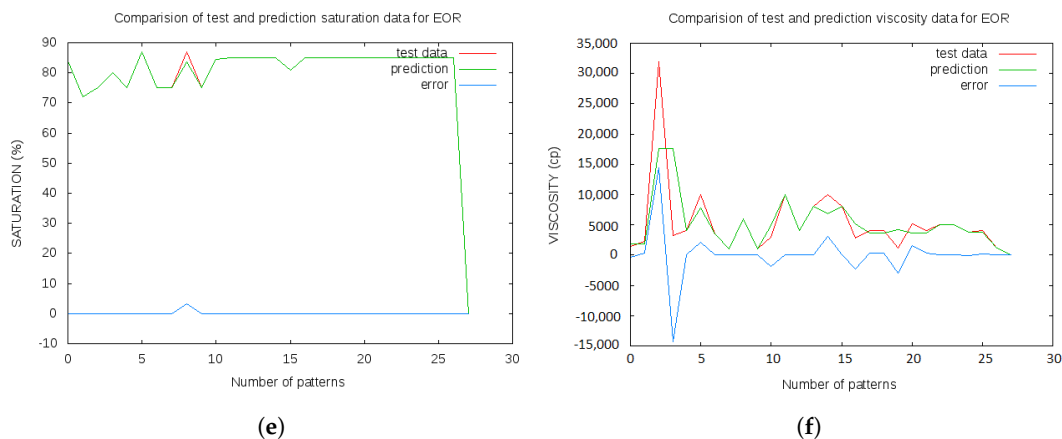
(**a**)

(**b**)

(**c**)

(**d**)

Figure 12. *Cont.*

Figure 12. Plots of the weighted testing data, prediction data and associated error versus number of patterns for steam (Area 1): (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

4. Results and Discussion

The data base from the worldwide successful EOR projects was maximised by tuning the parameters (number of patterns, epochs, mean and standard deviation) of each variables associated with each five (5) different EOR techniques; steam, CO_2, miscible hydrocarbon gas, polymer and combustion. Based on the identified patterns reinforced by the available data set, five unique values of mean and standard deviation were computed. The weight values were added to the results and then used to predict the degree of success of different EOR projects. The sample size of the available data becomes crucial to minimise the error and optimise simulation outcome.

In this study, the values of the NDEI and overall RMSE associated with the investigated successful EOR projects of the training process with corresponding oil and reservoir properties were computed. Figure A1 shows the NF model for steam matches the predicted depth data with NDEI ranging between 0.04 and 1.8, respectively. The RMSE varies from 40 (minimum) and 1183 (maximum). The best match (RMSE = 40, NDEI = 0.04) corresponds to option 2 (see Figure 11 and Figure A1). The predicted or validated data set of this option is then used as predicted set on testing process of the steam for the depth.

The training process was performed for the other parameters and EOR techniques. The best results of each training process are summarised in Figures A1–A5. The error computation is critical to ensure that the NF technique is suitable for the EOR process or technique under investigation. The developed model performed satisfactorily when run with enough training, verification and testing data sets. Each of the groups must have equal number of data sets. The degree of suitability of a typical EOR project obtained from the model prior to full field implementation as well as permits to segregate more oil properties and reservoir characteristics that could impact on EOR projects. The formation type is not included the in model. However, this can be determined by screening criteria from the successful EOR worldwide field data set (Table 2).

Data from Angola reservoir fields was tested against this trained and validated data. Table 4 presents the data of some of the Angolan oil reservoir fields which consists mainly of sandstones formations. No carbonates reservoir was encountered in the area investigated. Six variables such as depth, API, viscosity, porosity, permeability, and oil saturation were investigated. EOR methods such as surfactants, microbial, nitrates, hot water, miscible acid gas (Table 2) were not investigated due to the reduced number of the sample size. Figure 12 presents a testing process for steam process resulting from Area 1 of Block K. There is a good matching results for saturation (RMSE = 0.29, NDEI = 0.018), porosity (RMSE = 0.16, NDEI = 0.053). API matches with RMSE and NDEI of 0.42 and 0.08 whilst , depth (RMSE = 363, NDEI = 0.38), viscosity (RMSE = 1875, NDEI = 0.322), and permeability (RMSE = 2.25, NDEI = 0.0007). This procedure was performed for the four areas of the Block K (Area 1,

Area 2, Area 3, Area 4) of the six variables investigated (API, depth, porosity, saturation, permeability and viscosity) for five EOR techniques (miscible gas, steam, CO_2, polymer and combustion) and results are summarised in Table 6.

Table 6. Simulation results from NF model with the least root mean square error (RMSE) and non-dimensional error index (NDEI).

Block	Area	Steam	Misc. Gas	CO$_2$	Polymer	Combustion
Scenario 1 $20 < \text{NDEI} \leq 30\%$	Area 1	$\times$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
	Area 2	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
	Area 3	$\checkmark$	$\times$	$\checkmark$	$\checkmark$	$\checkmark$
	Area 4	$\times$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Scenario 2 $10 < \text{NDEI} \leq 20\%$	Area 1	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
	Area 2	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
	Area 3	$\times$	$\times$	$\times$	$\checkmark$	$\checkmark$
	Area 4	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
Scenario 3 $\text{NDEI} \leq 10\%$	Area 1	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
	Area 2	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$
	Area 3	$\times$	$\times$	$\times$	$\checkmark$	$\checkmark$
	Area 4	$\times$	$\checkmark$	$\times$	$\checkmark$	$\checkmark$

$\checkmark$ = suitable; $\times$ = not suitable.

In order to determine the suitability of a particular technique in EOR project, variables are considered based on their degree of variance. It is understood that variables such as permeability can vary by up to 3 or 4 orders of magnitude in a geological formation [40]. Three scenarios were investigated: (1) the least RMSE combined with $20 < \text{NDEI} \leq 30\%$; (2) the least RMSE combined with $10 < \text{NDEI} \leq 20\%$; (3) the least RMSE combined with $\text{NDEI} \leq 10\%$ (Table 6). As this is not a binary decision operation, engineering knowledge of the process is required in decision making. As an example, variables like viscosity and depth for thermal process (steam and hot water), pressure for gas and steam injection, temperature for chemical and hot water are very sensitive and critical [13]. Permeability is not a critical variable for gas injection [5,6]. Based on the available data and the screening results, the summary of the main results for the investigated techniques are presented in Table 6 and Figures A6–A8.

Scenario 1, polymer is the most suitable EOR methods for the areas investigated. Combustion is also suitable, however, due to the reduced number of the successful EOR projects, the results obtained may need further laboratory test for confirmation before execution. Miscible gas and CO_2 are suitable in three out of four areas, whilst steam is suitable in one out of four areas investigated (Table 6).

Scenarios 2 and 3, the results of polymer, miscible hydrocarbon gas, and combustion remains the same except for steam and CO_2 that are not good candidates, because most of the parameters investigated present more than 50% NDEI that is not within the range of the investigated variables. However, more study is recommended for CO_2 technique due to its importance in CO_2 sequestration (Table 6).

Comparison of Simulation RMSE and NDEI Output with Analytical Method

Figures A10 and A11 show the comparison of the RMSE (Equation (7)) and NDEI (Equation (8)) for the variables investigated (depth, porosity, API, permeability, viscosity, and saturation). The computed values for the simulated and analytical calculation are conducted for non-regression and five different regression methods: linear, exponential, logarithmic, polynomial, and power. The same set of equations (Equations (7) and (8)) that was used for the model simulation was used to verify the code analytically. Expectedly, the simulated and analytical calculations matched very well (Figures A10 and A11).

5. Conclusions

A NF model provides a powerful technical screening tool for reservoir fields within Angola or around the world. The data set of 365 successful EOR projects from 10 different EOR technologies

in which five were investigated. Sixteen major oil producing countries were used in the developed model based on six different reservoir parameters and could be extended to other reservoir parameters. The model was tested using oil reservoir fields from Angola and can be used to test any data worldwide.

Box plots were used as data analysis and a quick look of technique suitability. However, use of box-plots do not reflect the degree of suitability or the behaviour of given parameter within the investigated range. The trained and validated data were used for comparison of simulation RMSE and NDEI output with five different regression methods; linear, exponential, logarithmic, polynomial, and power law. The regression models matched the simulation output to varying degrees. The caveat in the use of regression techniques is that some data points could be potentially excluded during the fitting process. The non-regression simulation approach adopted in this study, however, allows for automated error decay with the defined tolerance limit.

The Angolan field reservoirs from Block K under investigation are good candidates for polymer and combustion, followed by the miscible hydrocarbon gas. The screening methods are simply used to determine the suitability or chance of success of an EOR technique. Before stating with confidence that the selected EOR technique will likely be technically successful, additional evaluations such as core analysis, reservoir simulation and field pilots are required.

Abbreviations

The following abbreviations are used in this manuscript:

NNs	Neural Networks
MFs	Membership Functions
ANFIS	Adaptive-Network-Based Fuzzy Inference System
DST	Drill Stem Test
PI	Productivity Index
Mbbls/day	Millions of barrels per day
POP	Pseudo outer-product
HC	Hydrocarbon
NDEI	Non-dimensional error index
RMSE	Root mean square
TSK	Takagi and Sugeno
FL	Fuzzy-Logic
NF	Neuro-Fuzzy
MMP	Minimum miscibility pressure
GEP	Gene expression programming
BPNN	Back-propagation neural network
RBFNN	Radial basic function neural network
LSSVM	Least square support vector machine
IFT	Interfacial tension
COA	Cuckoo optimization algorithm
TLBO	Teaching learning based optimisation

Appendix A

Appendix A.1. SI Metric Conversion Factor

g/cm^3 = $^\circ$ API 141.5/(131.5 + $^\circ$ API)
cp = mPa.s
m = ft $\times$ 0.3048
g/L = 1000 ppm

°C = °F (°F − 32) × 9/5

KPa = Psi × 6.894757

μm^2 = md ×9.869233 × 10^{-4}

D = 9.869233 × 10^{-13} m^2

1.E(x) = 1 × 10^x

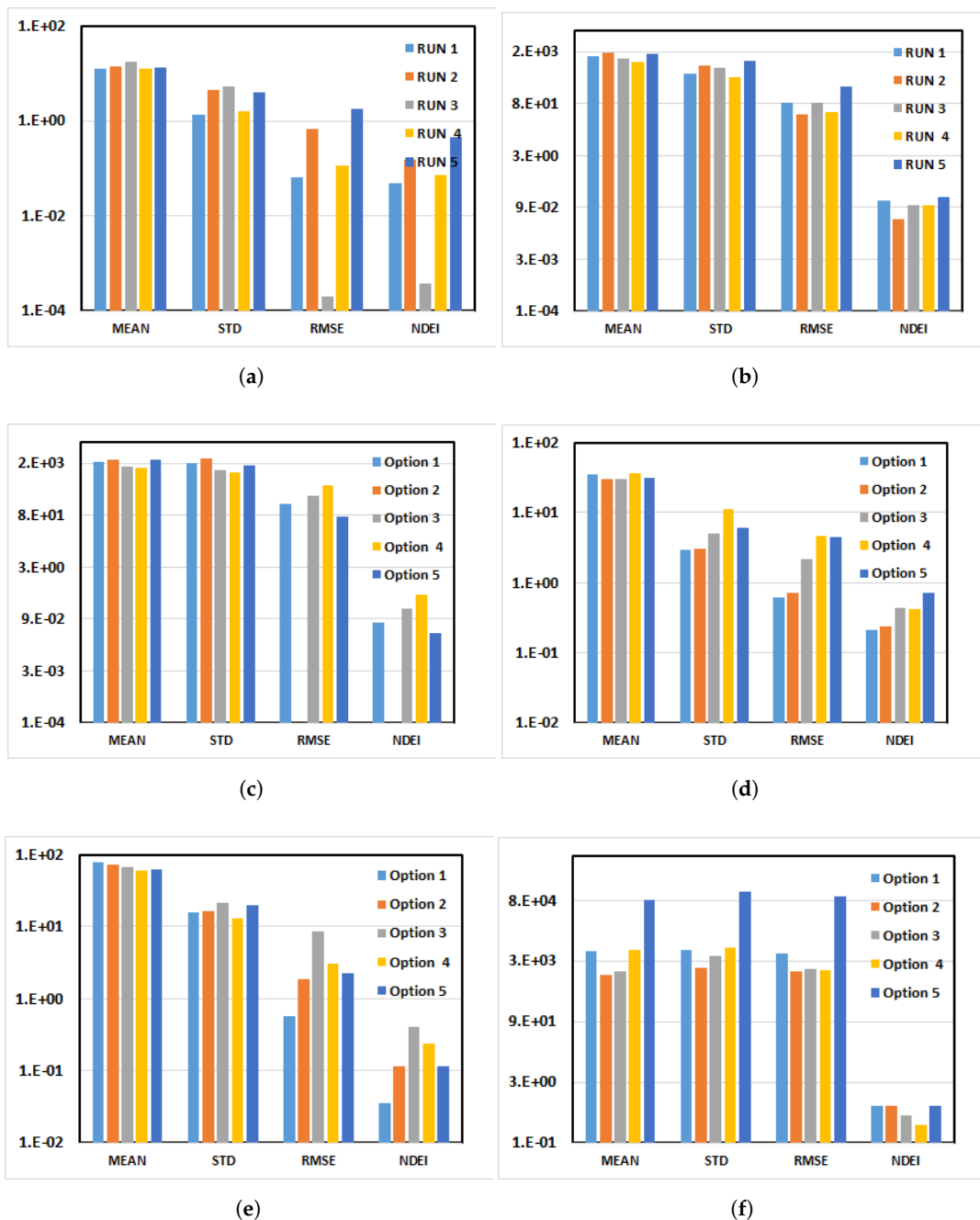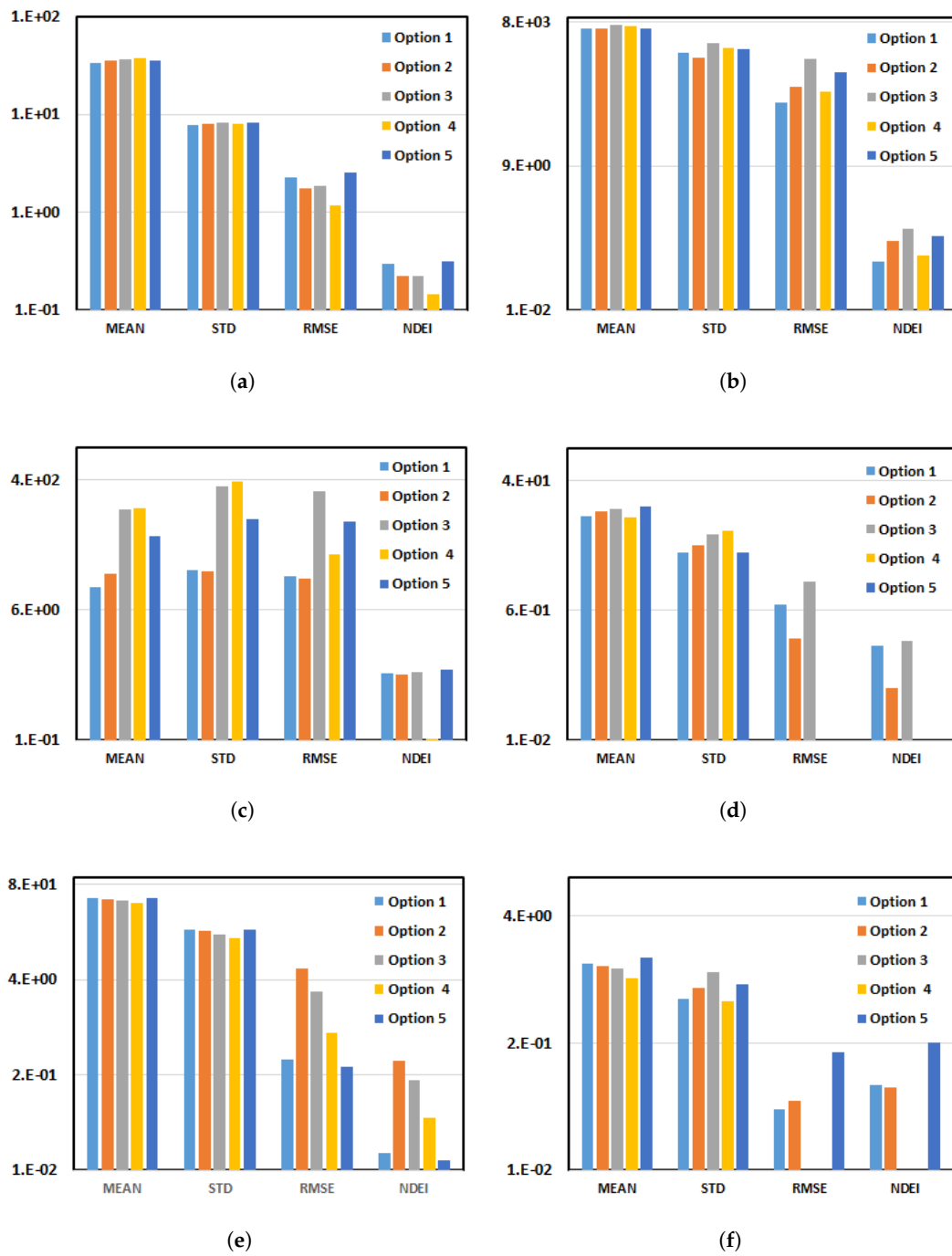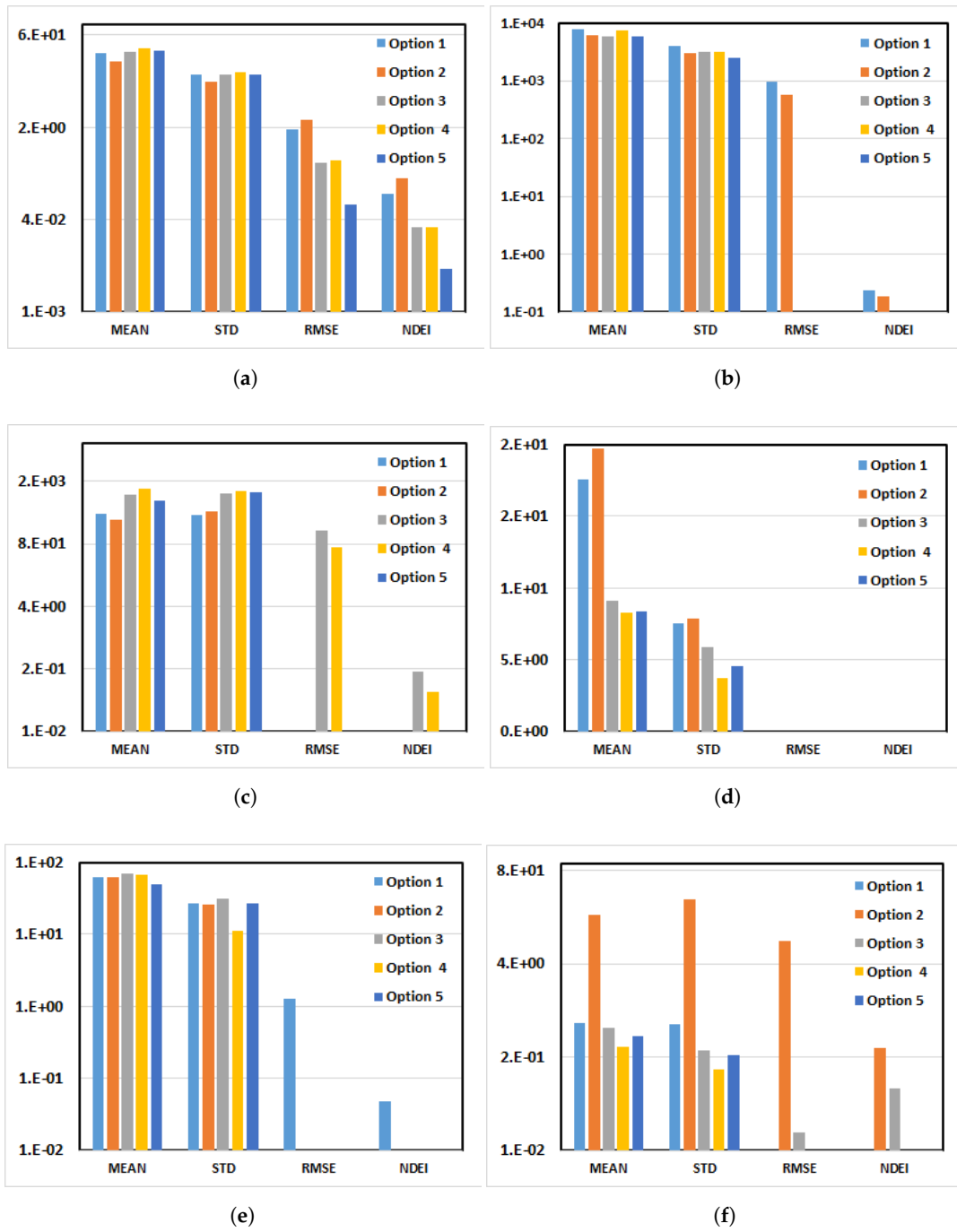*Appendix A.2. Statistical Data of Worldwide Successful EOR Projects*

Figure A1. Statistical data plots of worldwide successful steam injection EOR projects for the variables: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

Figure A2. Statistical data plots of worldwide successful CO_2 injection EOR projects for the variables: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

Figure A3. Statistical data plots of worldwide successful gas injection EOR projects for the variables: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.
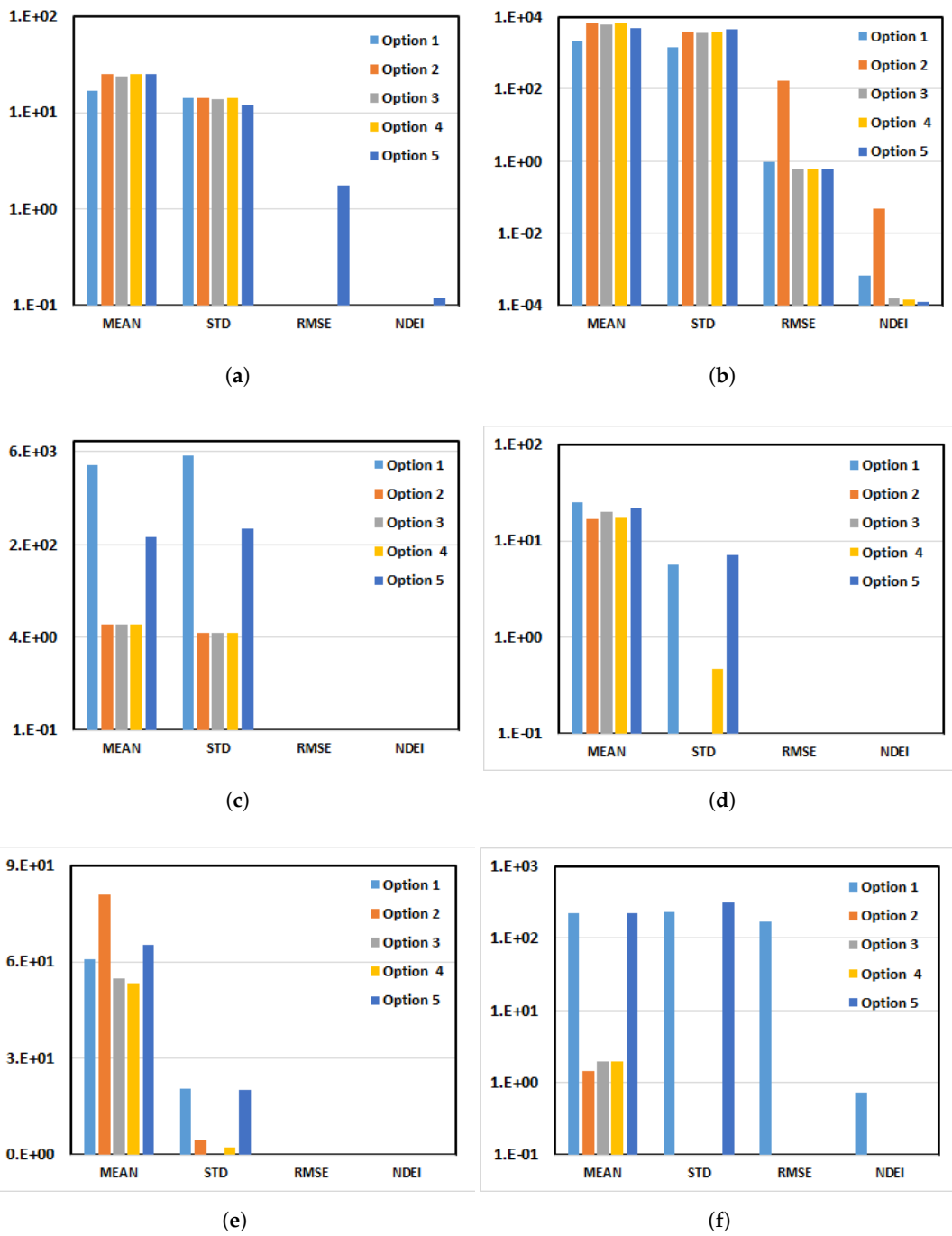
Figure A4. Statistical data plots of worldwide successful combustion injection EOR projects: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.
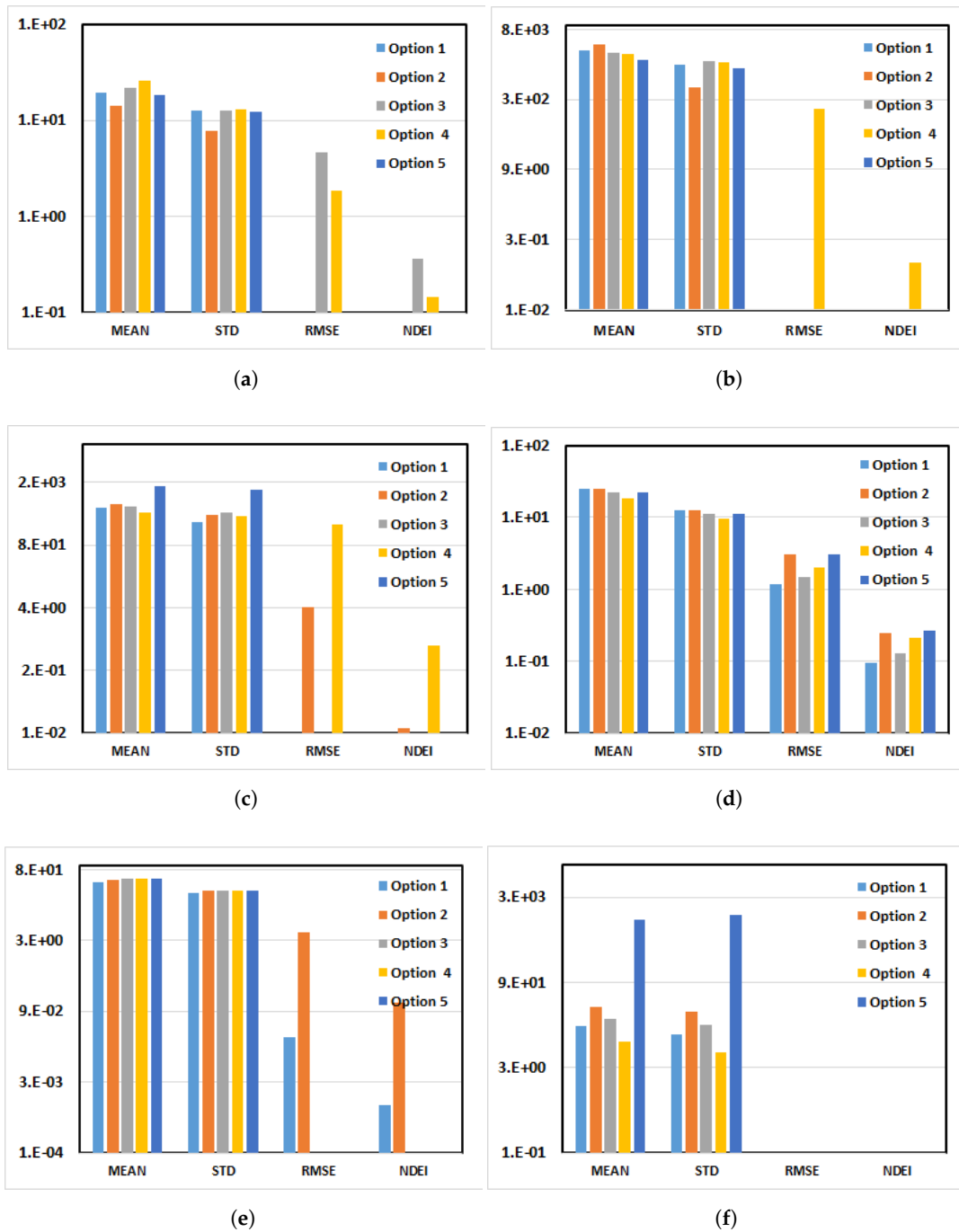
Figure A5. Statistical data plots of worldwide successful polymer injection EOR projects: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

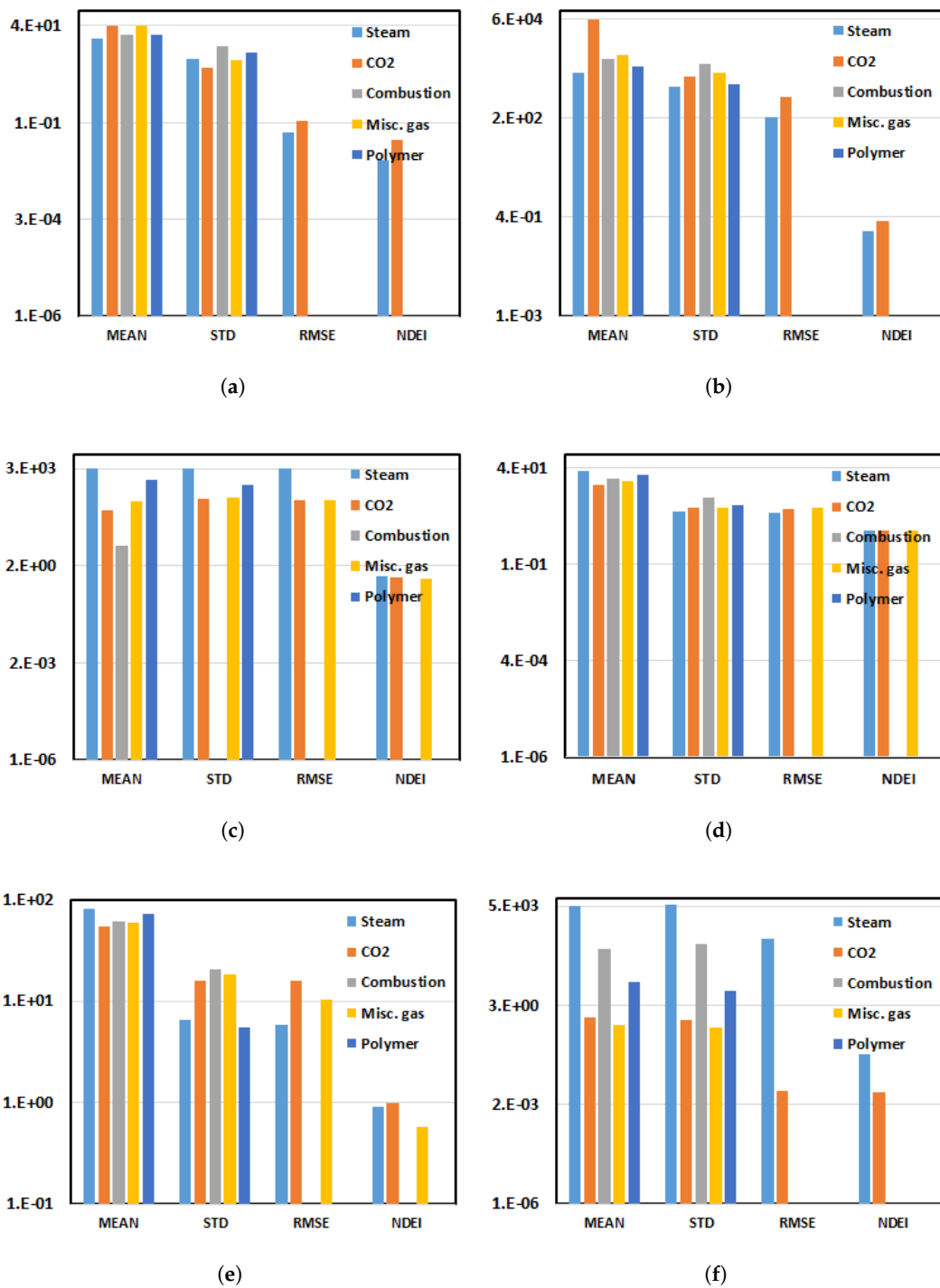*Appendix A.3. Statistical of Angolan Oilfields of Block K*
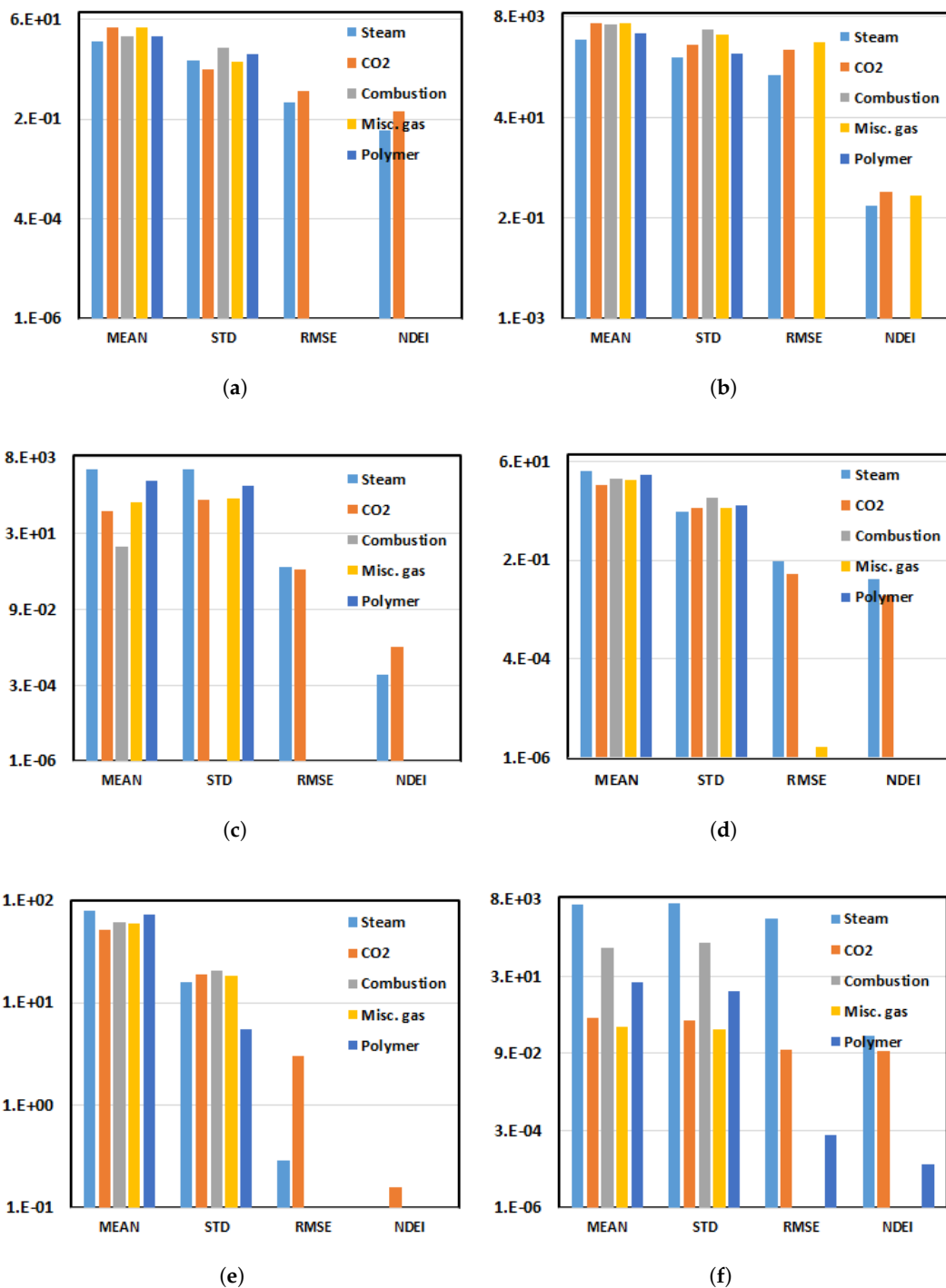
Figure A6. Statistical data plots of steam, CO_2, combustion, miscible gas and polymer injection for Area 1 of the Angolan oilfield (See Table 4 for the area clarification). Variables include: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.
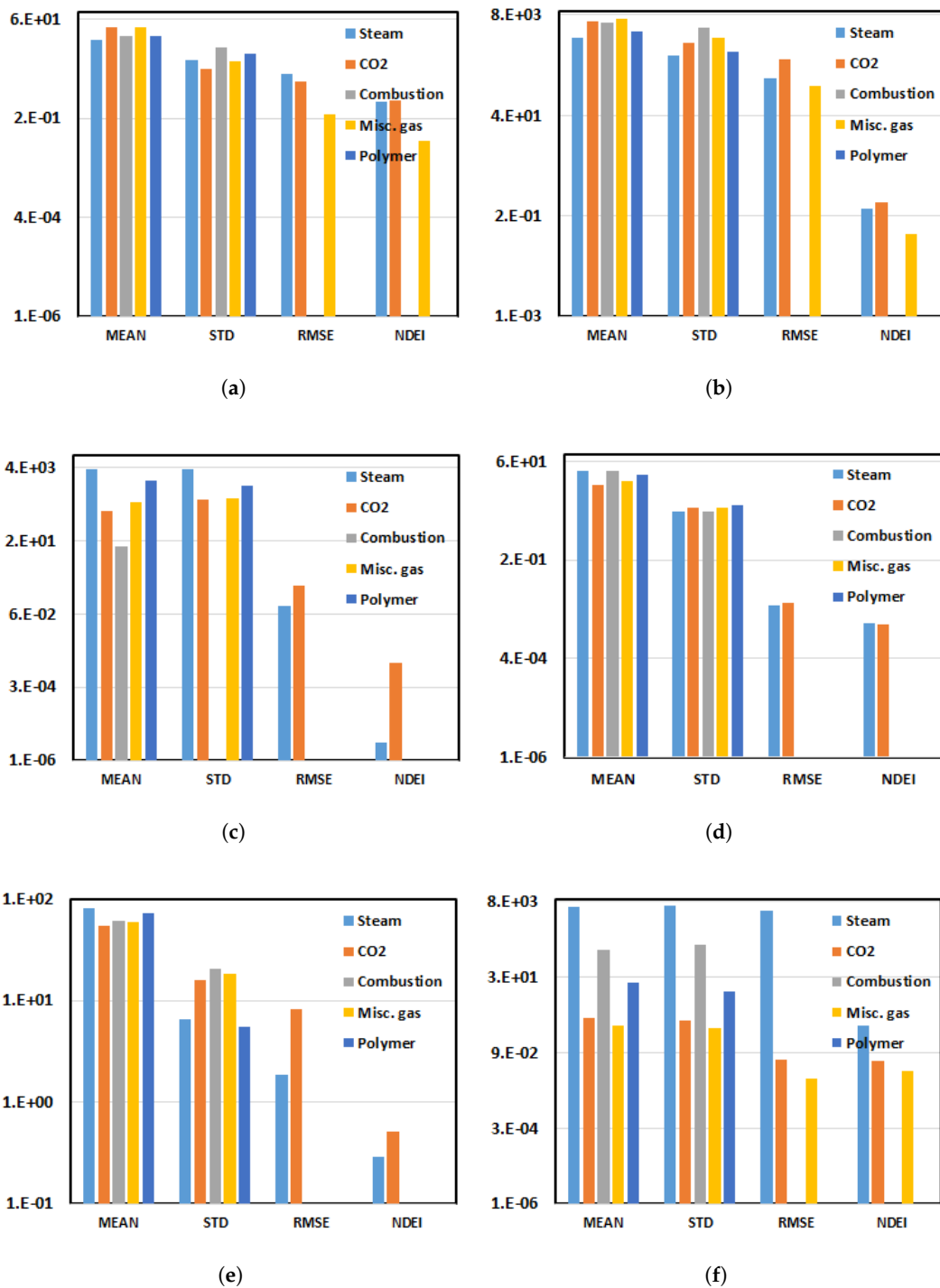
Figure A7. Statistical data plots of steam, CO_2, combustion, miscible gas and polymer injection for Area 2 of the Angolan oilfield (See Table 4 for the area clarification). Variables include: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.
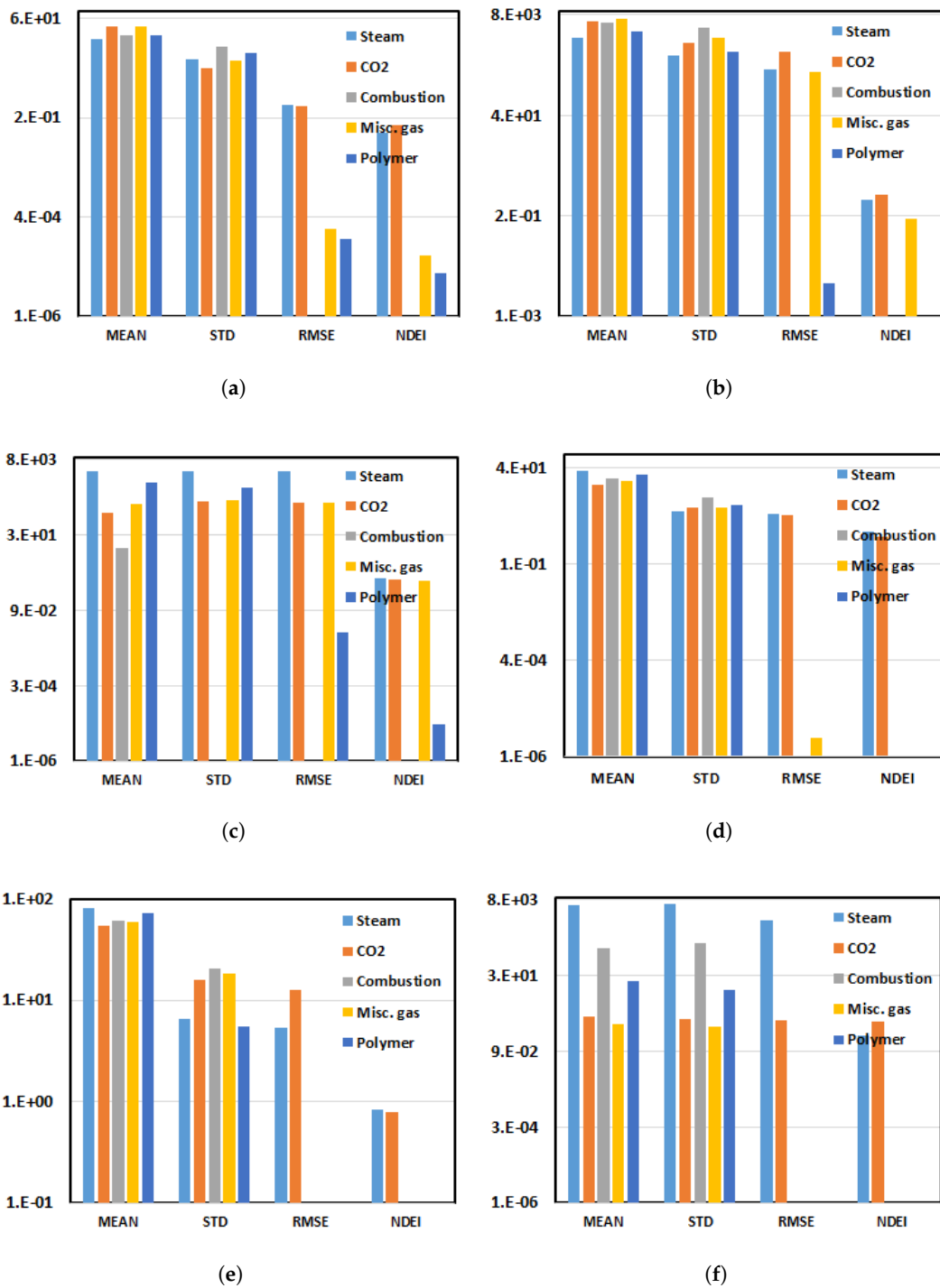
Figure A8. Statistical data plots of steam, CO_2, combustion, miscible gas and polymer injection for Area 3 of the Angolan oilfield (See Table 4 for the area clarification). Variables include: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

Figure A9. Statistical data plots of steam, CO_2, combustion, miscible gas and polymer injection for Area 4 of the Angolan oilfield (See Table 4 for the area clarification). Variables include: (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

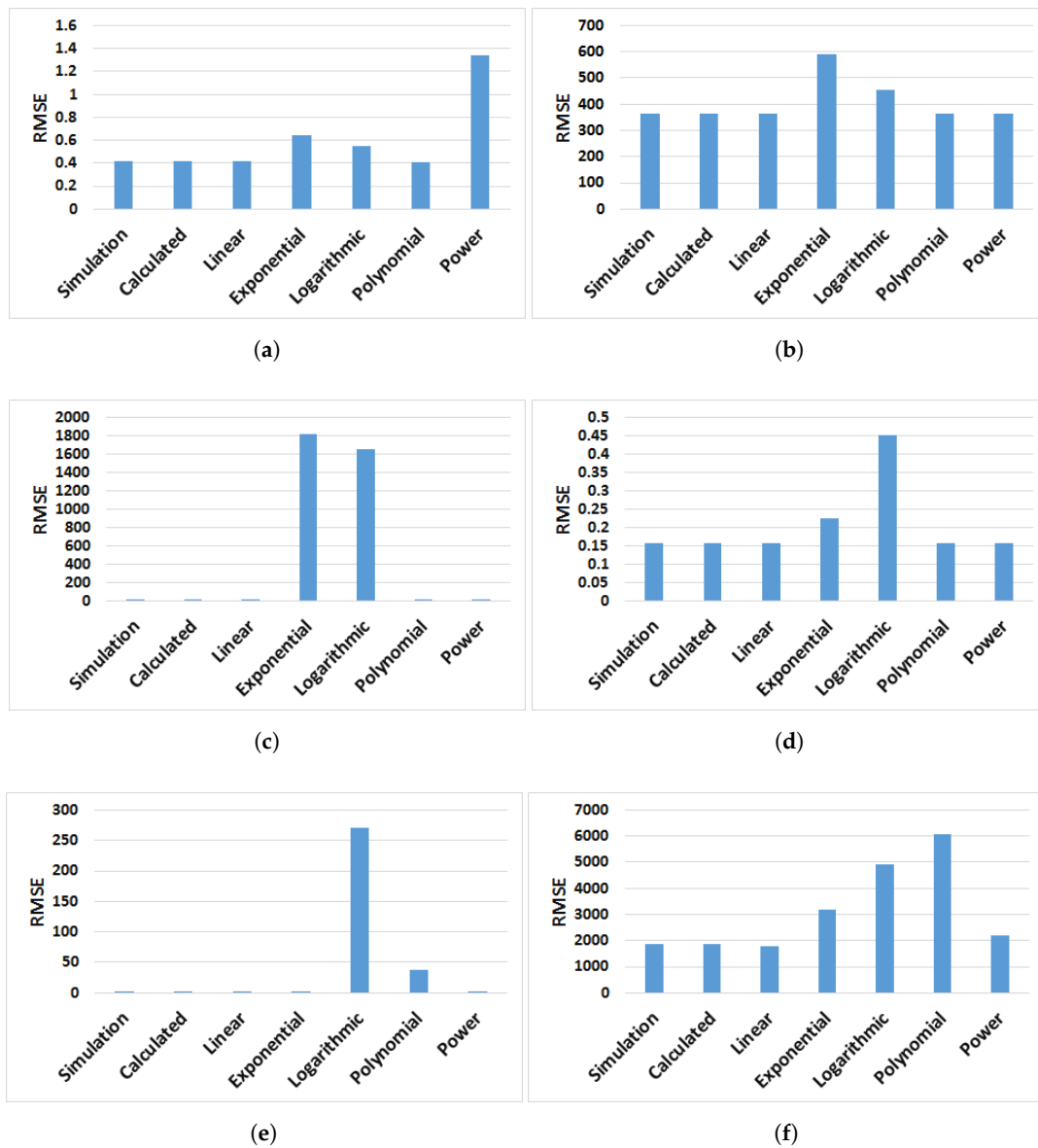*Appendix A.4. RMSE and NDEI Comparison between the Results from Simulation and Analytical Calculated Values*
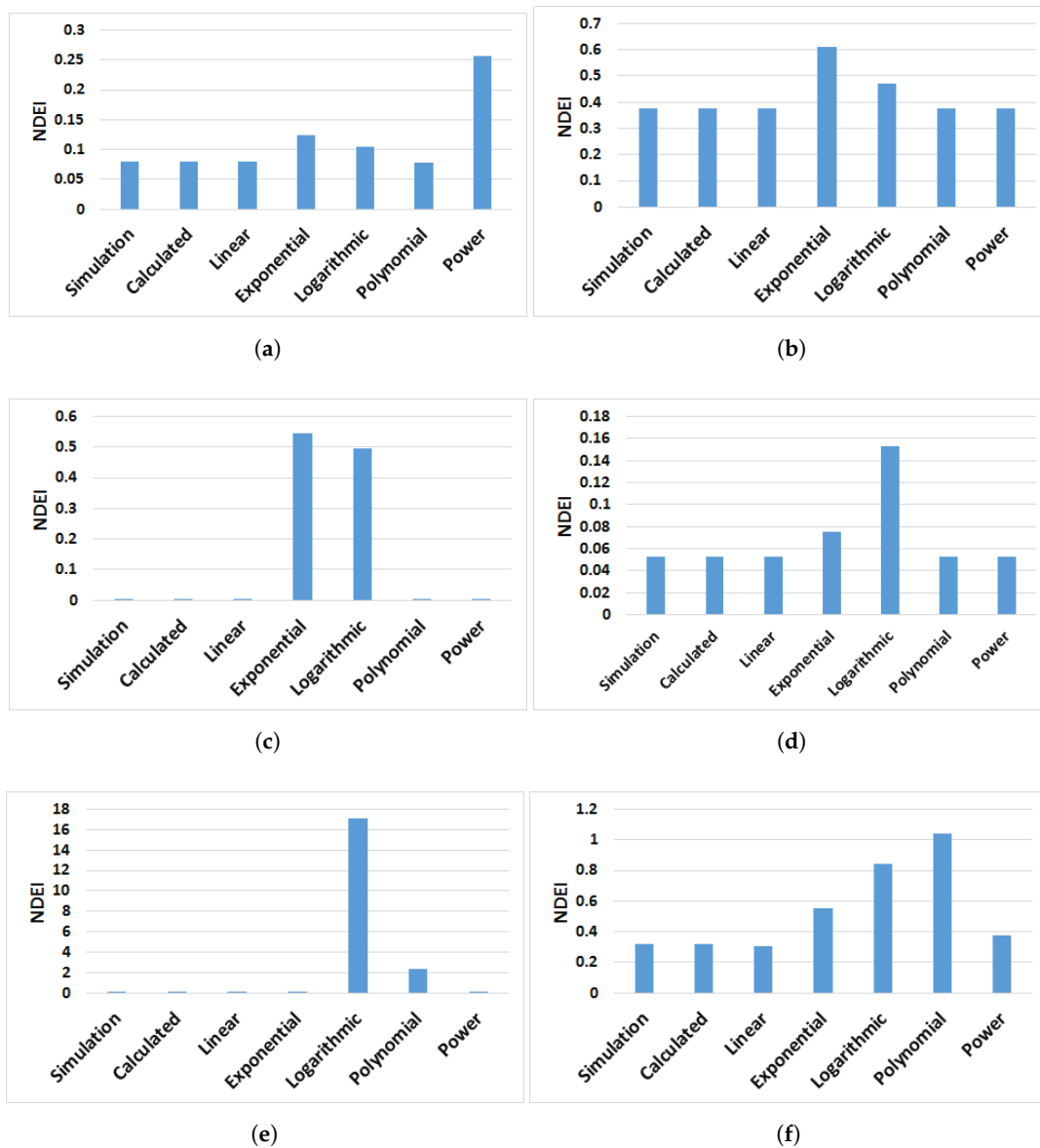

Figure A10. RMSE comparison between the results from simulation and analytically calculated values for steam (Area 1): (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

Figure A11. NDEI comparison between the results from simulation and analytically calculated values for steam (Area 1): (**a**) API; (**b**) depth; (**c**) permeability; (**d**) porosity; (**e**) saturation; and (**f**) viscosity.

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