

Electrofacies classification of a mixed carbonate-siliciclastic reservoir using machine learning techniques



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Abstract. Many scientific fields, including the geosciences, have successfully employed machine learning to address numerous significant issues. Current studies show that the application of machine learning within the geosciences is still in its early stages, and there is a huge potential for this technique that need to be explored. This research focuses on the Late Permian Beekeeper Formation from the Perth Basin, Australia. It aims to improve our understanding of the application of machine learning to characterise subsurface rock formations. The objectives of this study are threefold: (1) to conduct cutting, crossplot, and modern machine learning analyses on a mixed carbonate-siliciclastic reservoir; (2) to compare the results from the aforementioned analyses and to interpret the electrofacies and lithofacies; and (3) to understand the degree of accuracy of the application of machine learning in the characterisation of the subsurface rock formations. Cutting, crossplotting, and modern machine learning analyses have been conducted to achieve the aim and objectives of this study. Seven electrofacies, associated with nine lithofacies, were identified within the studied data, and these were classified into carbonate-dominated facies group, siliciclastic-dominated facies group, and mixed carbonate-siliciclastic facies group. Results also show the presence of stratal and compositional mixing within the Beekeeper Formation. A combination of cutting, crossplot, and machine learning analyses can provide a better, more accurate, and more reliable interpretation of the facies of the Beekeeper Formation. This study is expected to advance our understanding of the application of machine learning in geosciences.

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INTRODUCTION

Machine learning has transformed our modern society and greatly impacted our culture. Many fields of science, including computer sciences, engineering, education, healthcare and medical sciences, accounting and finance, business and marketing, agriculture, and geosciences, have now used machine learning to help tackle many issues related to their particular field [1, 2]. Within the geosciences, this relatively new approach has successfully been applied to solve various problems such as slope failure prediction, and geohazard modelling [3-5], seismic processing and interpretation [6, 7], subsurface formation evaluation [8, 9], hydrocarbon exploration and production [10-12], seismology and

earthquake sciences [13, 14], and mineral prospectivity mapping [15-17]. Despite all these advancements, the application of machine learning in geosciences is still considered in its infancy, with many opportunities to develop and expand its application in geosciences.

Electrofacies, defined as "the set of log responses that characterise a bed and permit it to be distinguished from others" [18], are commonly studied in hydrocarbon exploration to better understand subsurface rock formations. In the past several decades, many geoscientists have relied on the traditional crossplot of the wireline log data following the method by Schlumberger [19, 20] to conduct an electrofacies analysis. The success of this method relies heavily on the



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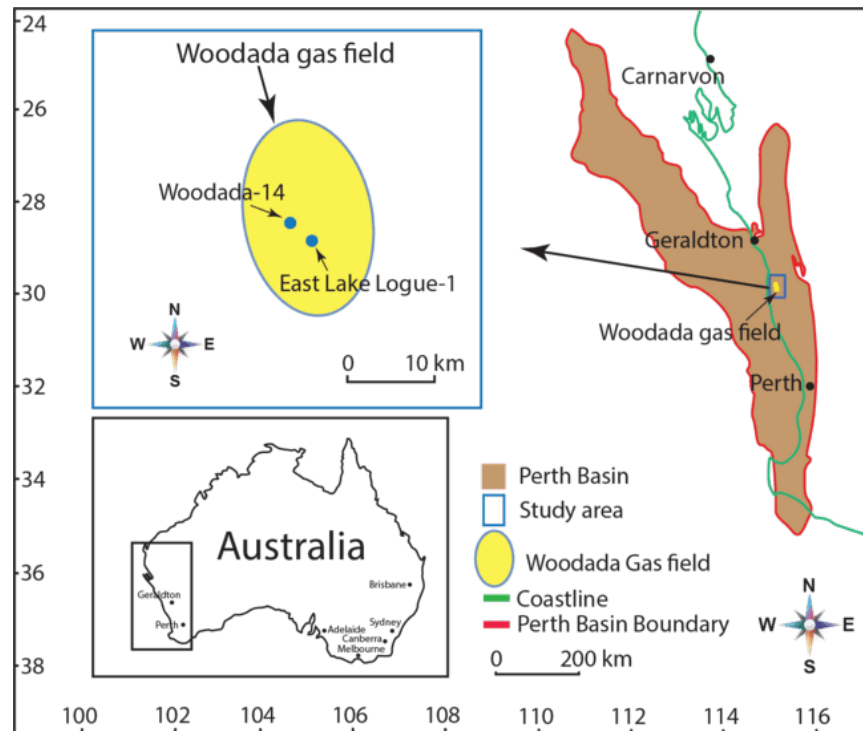


Figure. 1. Location of the study area. The Beekeeper Formation is a proven gas reservoir in the Woodada gas field, located onshore of northern Perth Basin. Available subsurface data from Woodada-14, and East Lake Logue-1 were used for this research.

interpreter's expertise and knowledge. Human error in interpretation can lead to significant inaccuracies or misinterpretations in the interpretations generated by this method. Moreover, applying this crossplot method may require a long period of time, and this may also impact the companies'/institutions' budget due to the responsibility to spend more money to cover the related interpretation costs.

Recently, many companies/institutions have adapted and used machine learning, a relatively new method to help interpret subsurface rock formations [21, 22]. This method strongly relies on machines to interpret subsurface conditions, producing relatively accurate and acceptable results in a short period of time, which can significantly reduce the budgets of companies and institutions [11, 23]. This machine learning method has become a "darling" of many geoscientists in interpreting electrofacies, mainly due to its effectiveness, efficiency, reliability, and acceptable results [24].

This study focuses on the Beekeeper Formation, a proven hydrocarbon reservoir of Western Australia. Many earlier researchers have tried to characterise the subsurface condition of this formation; however, their studies mainly rely on traditional geological analyses such as petrographic analysis, cross plot analysis, and sedimentary analysis [25-28]. Moreover, some researchers have tried to apply artificial intelligence analysis to study the Beekeeper Formation for log estimation purposes, which is different from the aim of this research [23]. In this study, we proposed a relatively new method, machine learning analysis, to better characterise and visualise the subsurface condition of the

Beekeeper Formation. Here we rely on the machine to automatically classify and group the well log data, and then the results are compared with real subsurface cutting and core data.

This research aims to improve our understanding of the use of machine learning to characterise subsurface rock formations. The objectives of this study are threefold: (1) to conduct traditional crossplot analysis and modern machine learning analysis on a mixed carbonate-siliciclastic reservoir; (2) to compare the results from both the aforementioned analyses and interpret the electrofacies; and (3) to understand the degree of accuracy of the application of machine learning in the characterisation of subsurface rock formations. Results from this study are expected to improve our understanding of the ability of machine learning in tackling various geoscience issues and to encourage geoscientists to explore the many possibilities of applying machine learning in solving problems.

This study focuses on the Beekeeper Formation of the Perth Basin, Western Australia (Fig. 1). The Perth Basin is about 1,000 km long, an average of 120 km wide, and covers an area of ~45,000 km² onshore and ~50,000 km² offshore [29]. This basin is divided into three parts based on the main geological characteristics, which are the northern Perth Basin, the central Perth Basin, and the southern Perth Basin [30-32]. The geological evolution of the Perth Basin is related to some major global events that occurred during the Early Cretaceous, which are the break-up and movement of Gondwana, the formation of the Indian Ocean, and the rifting of Greater India and Western Australia [33-37]. Various tectonic

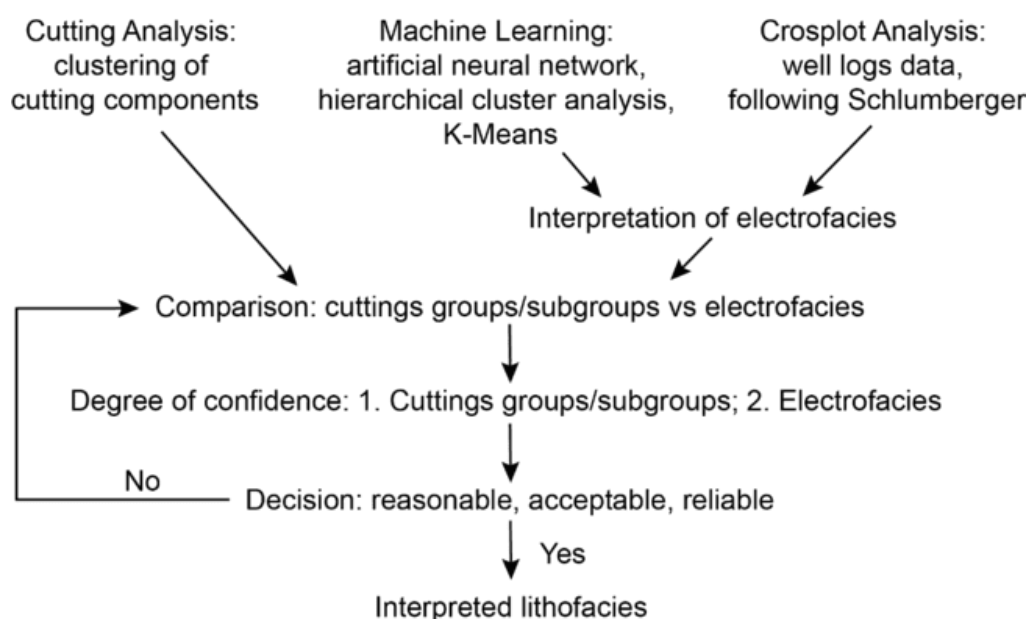


Figure. 2. Workflow of data analysis used in this study. Lithofacies were interpreted on the basis of the results from cutting, machine learning, and crossplot analyses.

deformations influenced the development of the Perth Basin, and these include the planar normal faults; tectonic inversion recognised by extensive uplifts, erosions, and foldings; Late Jurassic to Early Cretaceous dextral strike-slip movement; and listric faults associated with rollover structures [38, 39].

The geological age of the Beekeeper Formation is considered Upper Permian based on the brachiopod fossil [40], the presence of the *Dulhuntyspora* microfauna assemblage that was found in several wells [41], its close association with the underlying Carynginia Formation and from palynomorphs [26]. The Beekeeper Formation was deposited in the northern Perth Basin and has been identified as the producing reservoir in the Woodada and Beharra Spring fields [31]. This formation was formerly known as the limestone member of the Carynginia Formation or the Carynginia Limestone and was renamed to the Beekeeper Formation [26].

The Beekeeper Formation is a mixed carbonate-siliciclastic rock composed of limestone, dolostone, sandstone, and shale with spectacular fracture systems [42-44]. The Beekeeper Formation is considered to have developed as an anticline structure, which was formed by wrench-induced compression that occurred during the separation of the Indian Plate from the Yilgarn Block [45]. The Beekeeper Formation is restricted to the subsurface areas on and around the Beagle Ridge high. It sits conformably with the overlying Kockatea Shale Formation (which consists mainly of shale) and the underlying Carynginia Formation (which contains abundant shale) [26].

METHODOLOGY

Cutting and wireline logging analyses were conducted on two (2) wells (Woodada-14, and East Lake Logue-1) from the Woodada gas field, northern Perth Basin, Australia. These wells were selected due to the presence

of the Beekeeper Formation as reported by earlier researchers [25, 27], the availability of subsurface data, and also due to these wells being considered as the best representative wells within the study area to achieve the aim and objectives of this study.

Cutting analysis was conducted on 84 cuttings data from Woodada-14, and East Lake Logue-1. Each cutting sample was examined and analysed using a binocular microscope, with additional tests to determine the primary compositions/minerals as needed. The primary components of the cutting data were determined based on physical qualities (colour, mineral type, grain size, hardness, lustre, streak, crystal form). The semi-quantitatively estimated percentage of the primary cutting components was given in a bar chart to help visualise the Beekeeper Formation's characteristics.

Five types of logs were studied, which are gamma ray log (GR), density log (RhoB), neutron porosity log (NPHI), photoelectric factor log (PEF), and sonic delta time log (DT). Acoustic impedance (AI) log was estimated by multiplying sonic velocity with bulk density. These types of logs were selected/estimated due to their ability to detect certain rock parameters/properties which can be used to identify the lithology and other important characteristics such as formation porosity and fluid content[46].

Two types of wireline logging analysis were performed: traditional crossplot analysis and modern machine learning techniques. The crossplots are two-dimensional with one variable scaled in the vertical (Y-direction) and the other in the horizontal (X-axis), with the resultant crossplots then interpreted by comparing them to the standard interpretation of Schlumberger [19, 20]. Modern machine learning techniques which rely heavily on the machine to do data processing were conducted using three different algorithms: hierarchical cluster, K-

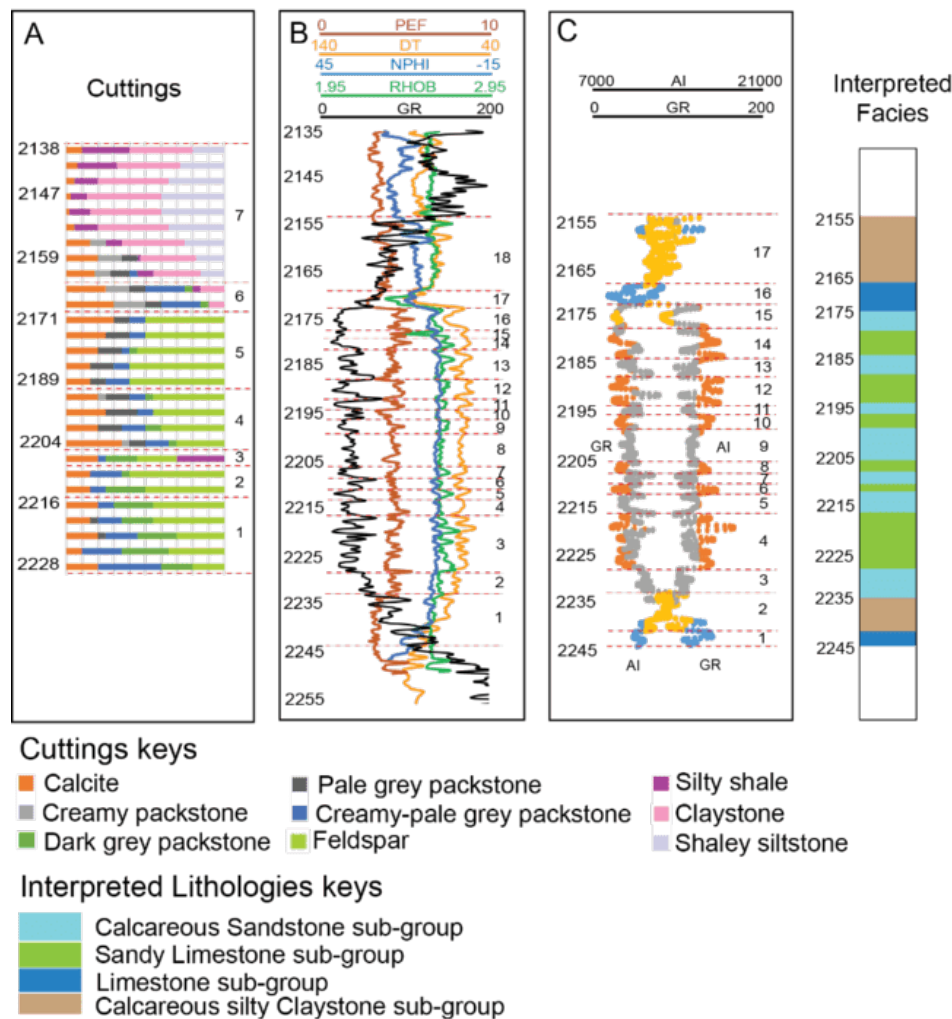


Figure. 3. Showing subsurface data of Woodada-14. A. Results from cutting analysis. B. Crossplot of wireline log data showing the presence of 18 intervals. C. Four clusters data, and 17 intervals were identified from machine learning analysis of Woodada-14. Cluster-1 is marked with yellow colour and is interpreted as calcareous silty claystone sub-group, Cluster-2 is marked with blue colour and is interpreted as limestone sub-group, Cluster-3 is marked with orange colour and is interpreted as sandy limestone sub-group, and Cluster-4 is marked with grey colour and is interpreted as calcareous sandstone sub-group

means (both are unsupervised techniques), and artificial neural network analyses (supervised technique). Each of the modern machine learning algorithms has its strengths and weaknesses; therefore, a combination of multiple machine learning algorithms is needed to improve robustness and the quality of the results [46]. Hierarchical cluster analysis groups the data into several clusters of data based on the similarities between the data, and the results are presented as a dendrogram [47]. K-mean analysis categorised the data into several clusters based on the nearest location of the data to the cluster centre/cluster centroid [46]. Artificial neural network analysis, which simulates the mechanism of learning in biological organisms, groups the data into several clusters of data using the deep learning algorithm [48]. SPSS software, a product of IBM (International Business Machines), was used to perform this modern machine learning analysis. Results from crossplot

analysis and machine learning analysis were compared to each other and then were grouped into several clusters of data (named as electrofacies) based on the similarities between their physical properties.

The level of confidence in the outcomes of the aforementioned analyses was evaluated using the available dataset and the types of analyses performed (Fig. 2). Cutting data from real subsurface rock formations is considered more reliable, whereas wireline logging analysis is considered less accurate due to its nature (estimation of physical parameters, numerous ambiguities). This consideration (decision-making process) is consistent with general knowledge in the field of geology and geophysics, where the real subsurface cores and cutting data are accepted as reliable sources of information for geological analyses [49, 50].

The cutting data, however, were collected every 3 m, and this generated an incomplete/ discontinued dataset. To overcome this, we relied on the data from wireline logging, which was recorded every 15 cm. A combination of the data and analyses from both cutting and wireline logging was used in the final interpretation of the electrofacies. When there is no consistency and/or a significant gap in the results, the interpretation was performed by combining cutting analysis and wireline logging analysis, and the results that are considered more reasonable, acceptable, and reliable (based on geological and geophysical knowledge) were chosen as the final interpretation.

RESULTS AND DISCUSSION

Thirteen (13) types of cutting components were identified within the Beekeeper Formation of the studied

wells. These components are dolomite, calcite, creamy packstone, dark grey packstone, pale grey packstone, creamy-pale grey packstone, pale grey lime mudstone, feldspar, quartz, silty sandstone, silty shale, claystone, and shaley siltstone. These cutting components were unequally distributed within the studied wells. The Woodada-14 consists of 9 cutting components (Fig.3), while East Lake Logue-1 composed of 12 cutting components (Fig.4). Data from Woodada-14 show that the cutting data can be grouped into 7 intervals (Fig.3), while in East Lake Logue-1 the cutting data can be grouped into 9 intervals (Fig.4).

Results from traditional crossplot of wireline logging data show that the Beekeeper Formation in well Woodada-14 can be classified into 18 intervals (Fig.3), whereas in well East Lake Logue-1 it can be grouped into 10 intervals (Fig.4). Each of these intervals were

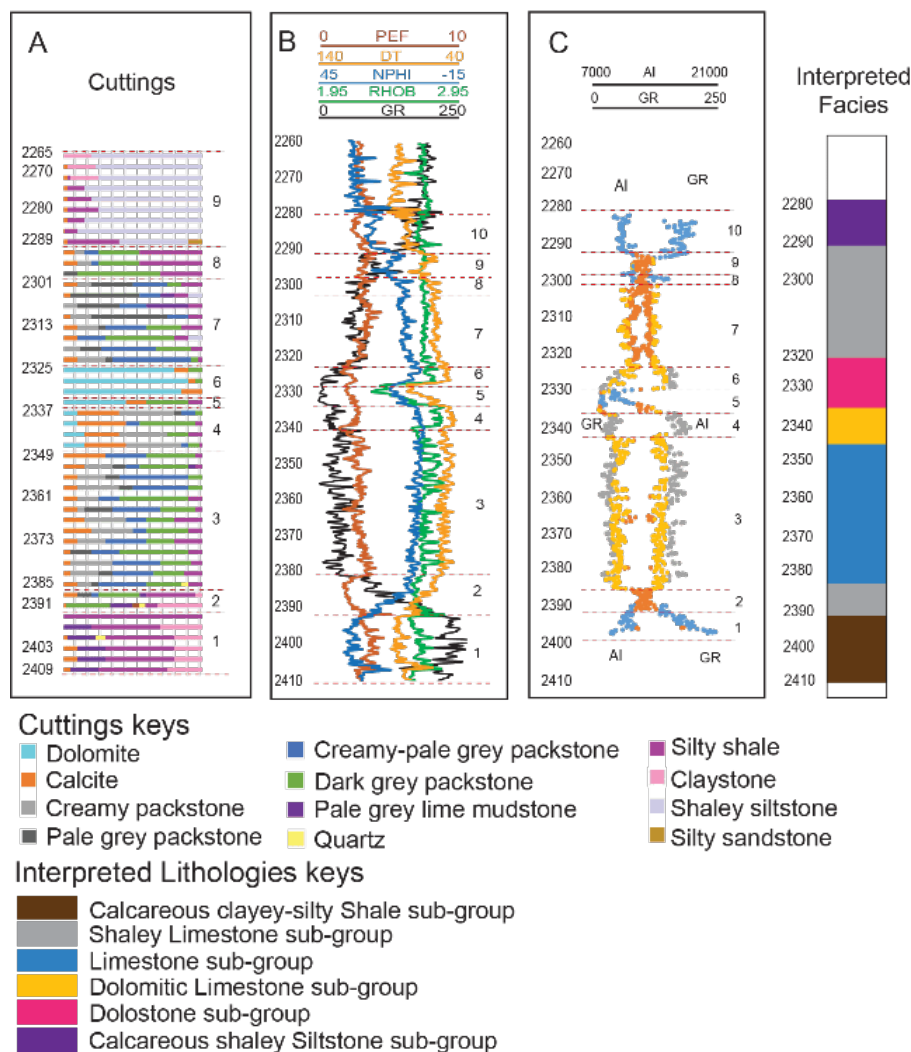


Figure. 4. Showing subsurface data of East Lake Logue-1. A. Results from cutting analysis. B. Crossplot of wireline log data showing the presence of 10 intervals. C. Four clusters data, and 10 intervals were identified from machine learning analysis of Woodada-14. Cluster-1 is marked with blue colour and is interpreted as calcareous shaley siltstone sub-group and/or calcareous clayey-silty shale, Cluster-2 is marked with orange colour and is interpreted as shaley limestone sub-group, Cluster-3 is marked with grey colour and is interpreted as dolostone sub-group and/or dolomitic limestone, and Cluster-4 is marked with yellow colour and is interpreted as limestone sub-group.

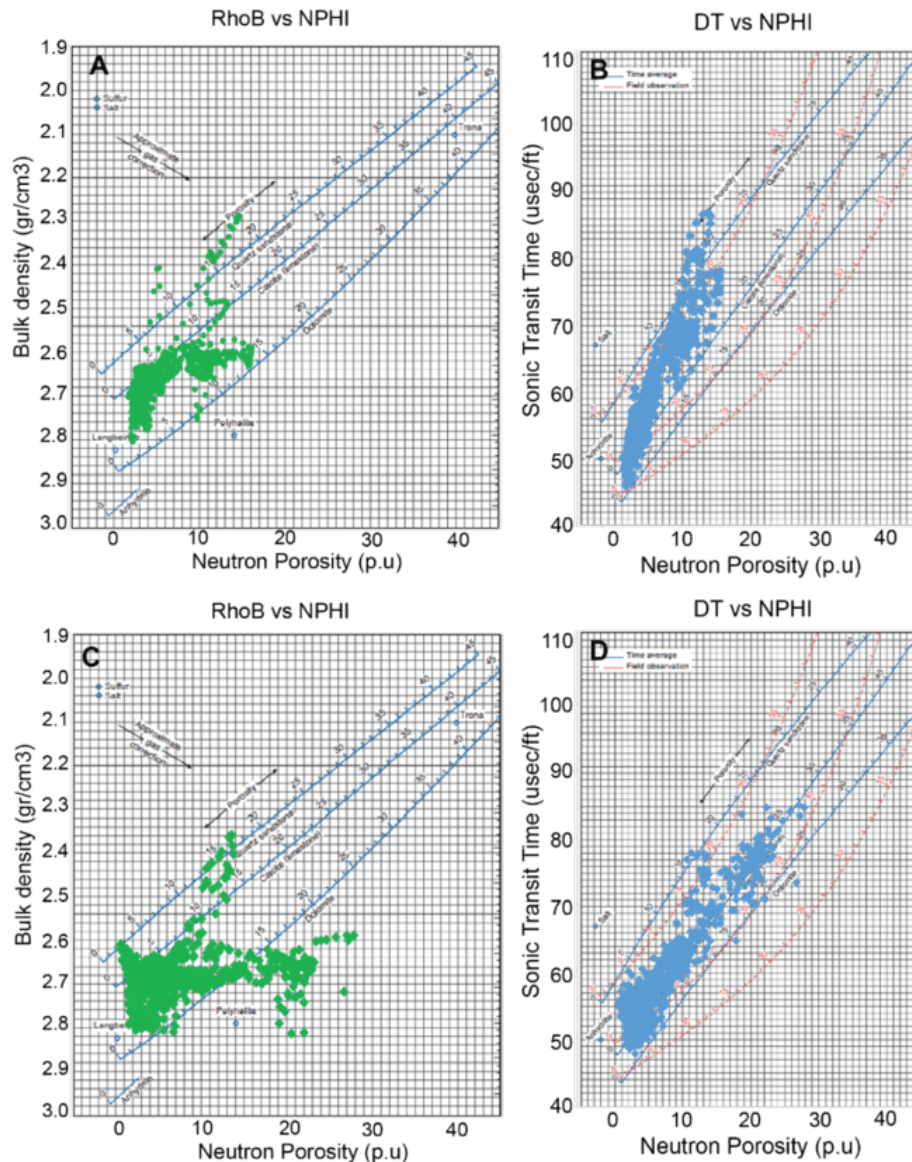


Figure 5. Traditional crossplot of the studied data. A. Plotting of RhoB vs NPHI for Woodada-14. B. Plotting of DT vs NPHI for Woodada-14. C. Plotting of RhoB vs NPHI for East Lake Logue-1. D. Plotting of DT vs NPHI for East Lake Logue-1. RhoB = Density log, NPHI = Neutron Porosity log, DT = Delta Time log.

distinguished on the basis of their petrophysical characteristics. Five types of well logs data (PEF, DT, NPHI, RHOB, GR) were used to assist in this characterization. Plotting of RhoB vs NPHI and DT vs NPHI shows that the Beekeeper Formation in Woodada-14 and East Lake Logue-1 composed mainly of calcite and dolomite components with minor-moderate quartz component (Fig.5).

Results from modern machine learning analysis (K-mean method) show that Woodada-14 can be distinguished into 17 intervals, with four clusters of data (marked with four different colours in Fig.3.C, and Fig.6). On the other hand, ten intervals were identified within East Lake Logue-1, also with four clusters of data (marked with four different colours in Fig.4.C, and Fig.6). Identification of these clusters were done automatically by the machine on the basis of the similarities of the physical properties of the input data that were provided.

The clusters identified from this study show similar characteristics for both Woodada-14, and East Lake Logue-1 (Fig.6).

Results from hierarchical cluster analysis (Fig.7.A) show that the data from Woodada-14 can be grouped into four different clusters. This is similar to the data from East Lake Logue-1, where the results also show the presence of four clusters of data (Fig. 8.A). Moreover, artificial neural network analysis provides similar results with other machine learning techniques, where four clusters of data were identified within Woodada-14, and East Lake Logue-1 (Fig.7.B, and Fig.8.B).

All of the aforementioned results from cutting analysis, traditional crossplot analysis, and modern machine learning analysis were combined and compared in order to see the similarities between the results. Based on these comparisons, we interpreted that the Beekeeper

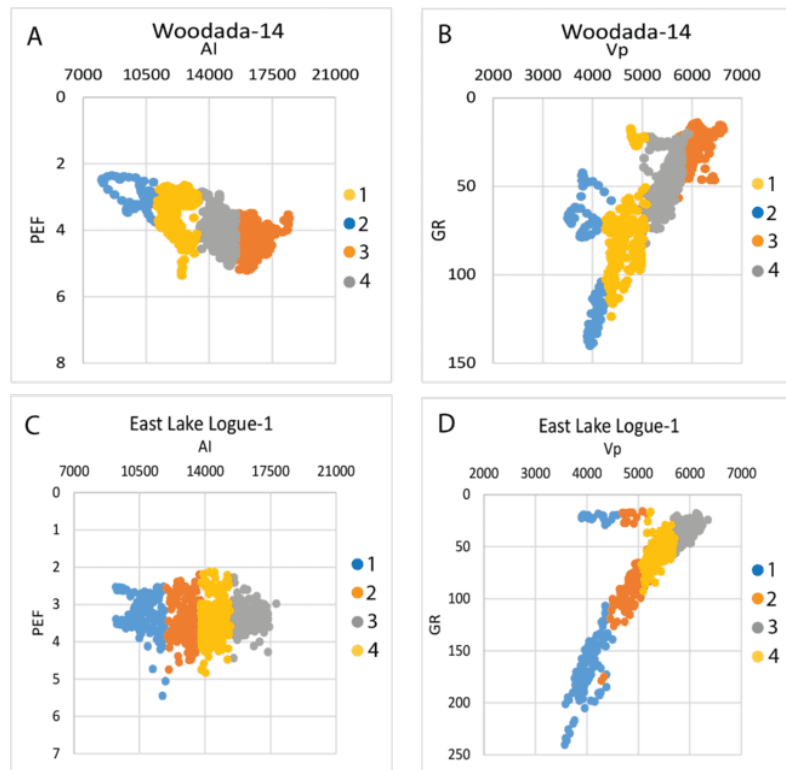


Figure 6. Distribution of the clusters of data from K-Mean method. Four clusters were identified from Woodada-14 (A-B), and also from East Lake Logue-1 (C-D). AI = Acoustic impedance, PEF = Photoelectric factor, GR = Gamma Ray, Vp = Primary porosity.

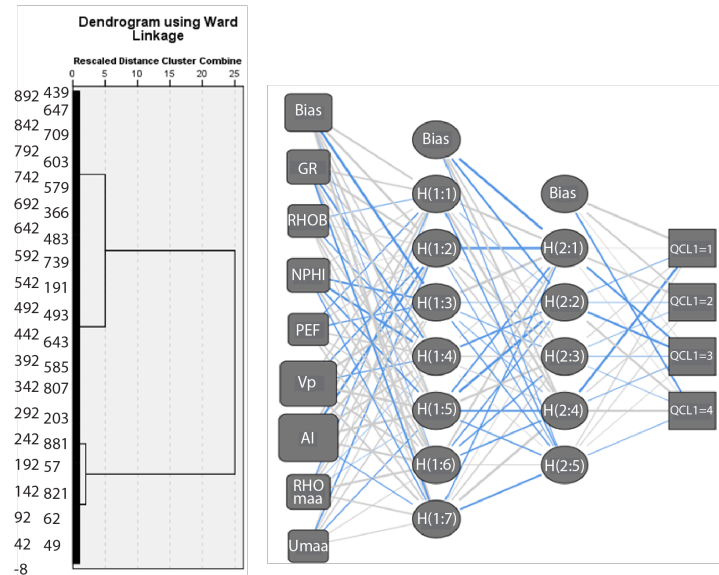


Figure 7. Results from machine learning analysis of Woodada-14. Results from dendrogram (A), and ANN (B) show the presence of 4 electrofacies. C. Cluster center for each electrofacies.

Formation within Woodada-14, and East Lake Logue-1 is composed of seven (7) electrofacies that are associated with nine (9) lithofacies (Table 1). Each of these electrofacies has its own characteristics (physical properties) that differs from others (detailed in Table 1). Electrofacies-1 is associated with limestone subgroup, and here we differentiated between limestone subgroup from Woodada-14, and those from East Lake Logue-1

due to the difference in their physical properties (electrofacies-1.A, and electrofacies-1.B).

Electrofacies-2 is interpreted to be associated with dolostone subgroup or dolomitic limestone subgroup. Electrofacies-3 is interpreted to be associated with sandy limestone subgroup. Electrofacies-4 is interpreted to be associated with shaley limestone subgroup. Electrofacies-5 is interpreted to be associated with

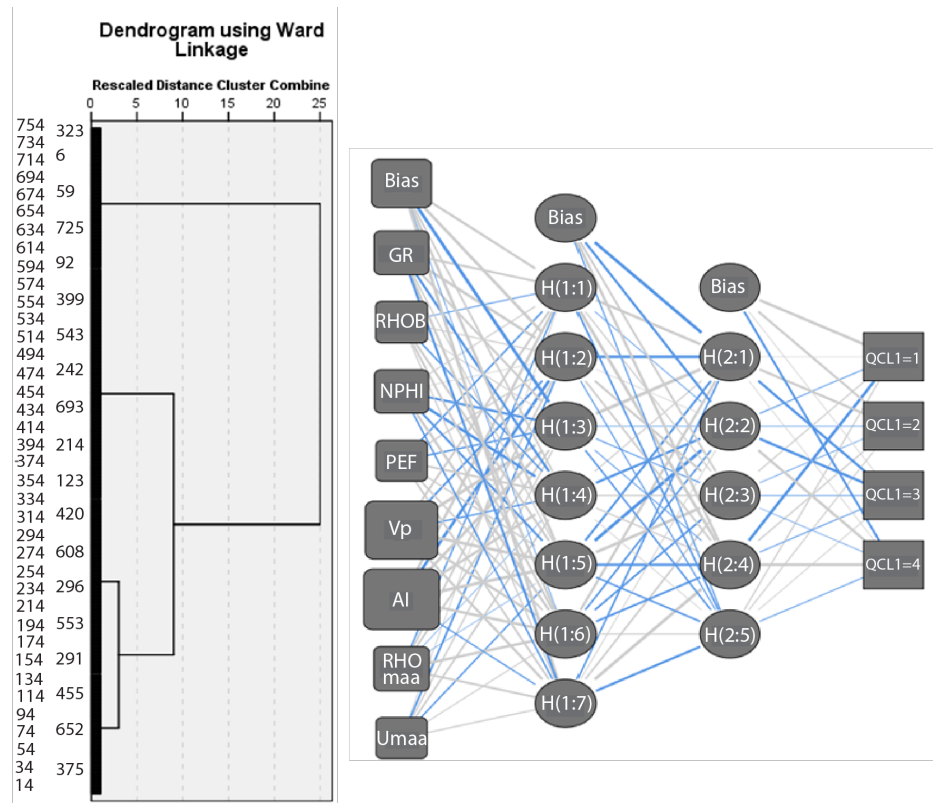


Figure 8. Results from machine learning analysis of East Lake Logue-1. Results from dendrogram (A), and ANN (B) show the presence of 4 electrofacies. C. Cluster center for each electrofacies.

Table 1. Cluster center of the electrofacies (EF).

	Cluster Centers						Interpretation
	GR	RHOB	NPHI	PEF	Vp	AI	
EF-1.A	96.3	2.5	13.0	3.0	3980.0	10078.6	limestone sub-group (Woodada-14)
EF-1.B	56.2	2.7	4.7	3.4	5385.4	14457.9	limestone sub-group (East Lake Logue-1)
EF-2	36.8	2.8	3.4	3.3	5893.7	16264.3	dolostone sub-group and/or dolomitic limestone
EF-3	29.2	2.7	2.8	4.2	6005.2	16320.5	sandy limestone sub-group
EF-4	84.4	2.7	9.2	3.5	4892.5	13085.5	shaley limestone sub-group
EF-5	44.9	2.7	4.1	4.0	5492.3	14634.5	calcareous sandstone sub-group
EF-6	141.8	2.6	18.1	3.3	4072.5	10710.5	calcareous shaley siltstone sub-group and/or calcareous clayey-silty shale
EF-7	77.7	2.6	8.8	3.5	4628.1	12139.2	calcareous silty claystone sub-group

calcareous sandstone subgroup. Electrofacies- 6 is interpreted to be associated with calcareous shaley siltstone subgroup and/or calcareous clayey-silty shale subgroup. Electrofacies-7 is interpreted to be associated with calcareous silty claystone subgroup.

Sedimentary facies of the Beekeeper Formation, on the basis of the results from the studied wells, can be grouped into three facies group: (1) carbonate-dominated facies group; (2) siliciclastic-dominated facies group;

and (3) mixed carbonate-siliciclastic facies group. Carbonate-dominated group composed predominantly of carbonate materials, and consists of limestone sub-group, dolomitic limestone sub-group, and dolostone sub-group. Siliciclastic-dominated facies group contains abundance siliciclastic materials and composed of calcareous sandstone, calcareous silty claystone, calcareous clayey-silty shale, and calcareous shaley siltstone. Mixed carbonate-siliciclastic facies group composed of moderate siliciclastic and carbonate

materials, and this group consists of shaley limestone, and sandy limestone.

This study has successfully identified seven electrofacies within the Beekeeper Formation that are associated with nine lithofacies. This finding has been compared with the real cutting data that were obtained directly from the petroleum drilling. The accuracy, and reliability of this result are considered high with minimal erroneous results. Similar studies of electrofacies using artificial intelligence/ machine learning by other researchers [51, 52] also showed the effectiveness of this machine learning technique with reliable and acceptable results. On this basis, therefore, it is considered that machine learning and/or artificial intelligence can be used to help with wireline logging analysis and in the identification of subsurface electrofacies of rock formations. Readers are, however, encouraged to be cautious when conducting the interpretation of the electrofacies mainly due to the potential of the overlapping physical properties values that could lead to misinterpretation of the results. Real subsurface data such as core data, or cutting data can be used as a control when interpreting the electrofacies [44].

Findings from this research show that the Beekeeper Formation consists of carbonate-dominated group, siliciclastic-dominated group, and mixed carbonate-siliciclastic dominated group. This is consistent with the results from earlier researchers [27, 42, 53] that proposed this formation as a mixed carbonate-siliciclastic system. Mixed carbonate-siliciclastic reservoirs are well known for its heterogeneities and complexities [54, 55], and findings from this study show that machine learning and/or artificial intelligence can be used to better understand the facies of a complex reservoir such as a mixed carbonate-siliciclastic system.

Two types of mixing of carbonate and siliciclastic materials within a rock formation were proposed which are strata mixing, and compositional mixing [54]. Within the Beekeeper Formation, we identified the presence of both types of mixing. This finding from our study strongly supports the classification of Chiarella [54]. Moreover, it is also clear from the results of this study that the This vertical partition is based on the main type of facies of the Beekeeper Formation, and this is consistent with earlier studies [42].

The lower, and upper parts consist predominantly of siliciclastic-dominated group, and/or mixed carbonate-siliciclastic dominated group; while the middle part composed mainly of carbonate-dominated group. We propose that these partitions to be associated with the development and evolution of the Beekeeper Formation. The lower part is related to the initiation of the Beekeeper Formation where certain type of substrates (e.g. silicate minerals, feldspars, quartz) are needed for the carbonate platform to develop. The middle part shows the growth stage of the Beekeeper Formation where carbonate biotas developed without any major disturbance. The upper part is associated with the demise of the Beekeeper platform

where consistent siliciclastic influx, and sea-level fluctuation may have influenced this formation.

Machine learning has successfully been applied to characterized the Beekeeper Formation, a mixed carbonate-siliciclastic reservoir. Similar studies by other researchers targeting a mixed carbonate-siliciclastic reservoir also show acceptable and reliable results [56]. This machine learning technique also applicable to other type of rock formation (e.g. Sandstone, shale) as shown by other studies [21, 57]. In several advanced studies, it is shown that machine learning can also be used to predict a reservoir's porosity and permeability and provide insights for reservoir quality [8, 58]. This is evident that machine learning it now slowly being accepted as an alternative for subsurface geological interpretation. Machine learning has now been successfully applied to characterize many type of reservoirs with acceptable results. Therefore, in order to avoid misinterpretation due to human error, and also to minimise the budget spending, we encourage the readers/researchers to use machine learning analysis to better characterize subsurface rock formations.

CONCLUSION

Electrofacies classification using machine learning techniques (artificial neural network, hierarchical cluster analysis, K-Means) shows similar results with the traditional geological crossplot analysis, and these results have been confirmed with the real data from cutting analysis. Cutting, crossplot, and machine learning analyses have been successfully applied to characterise the main facies, and electrofacies of the Beekeeper Formation from Woodada-14, and East Lake Logue-1. The results of these methods are considered reliable, and acceptable. Therefore, it can be concluded that machine learning analysis is suitable for studying subsurface geological data.

Thirteen (13) types of cutting components were identified within the Beekeeper Formation of the studied wells. These components are dolomite, calcite, creamy packstone, dark grey packstone, pale grey packstone, creamy-pale grey packstone, pale grey lime mudstone, feldspar, quartz, silty sandstone, silty shale, claystone, and shaley siltstone. The studied wells show that the Beekeeper Formation is composed of seven electrofacies (electrofacies 1 to 7), that are associated with nine lithofacies (limestone, dolostone, dolomitic limestone, sandy limestone, shaley limestone, calcareous sandstone, calcareous shaley siltstone, calcareous clayey-silty shale, calcareous silty claystone). These lithofacies were group into carbonate-dominated group, siliciclastic-dominated group, and mixed carbonate-siliciclastic group.

Both stratal and compositional mixing are present within the Beekeeper Formation, and this is consistent with similar mixed carbonate-siliciclastic reservoirs worldwide. Vertical succession of the facies of the Beekeeper Formation can be divided into three parts: lower, middle, and upper. The lower part is related to the initiation of the Beekeeper Formation, the middle part

shows the growth stage of the Beekeeper Formation where carbonate biotas developed without any major disturbance. The upper part is associated with the demise of the Beekeeper platform where consistent siliciclastic influx, and sea-level fluctuation may have influenced this formation. Facies of the Beekeeper Formation show that this formation composed mainly of siliciclastic-dominated group and/or mixed carbonate-siliciclastic dominated group within the lower and upper part, while the middle part of the Beekeeper Formation composed predominantly of carbonate-dominated group.

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