Visualization as a Big Data Artefact for Knowledge Interpretation of Digital Petroleum Ecosystems

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ABSTRACT

In the current upstream business environment, we examine the risk involved in the petroleum exploration and field development. Many sedimentary basins worldwide possess hundreds of petroleum systems with thousands of oil and gas fields, geographically scattered. A significant amount of unstructured heterogeneous and multidimensional data are locked up in many industrial applications and knowledge domains. Our objective is to bring the relevant data together, integrate and visualize for adding values to the existing interpretation. We simulate a Big Data guided digital petroleum ecosystem (DPE) approach, a digital oil field solution, a new direction in the analysis of a total petroleum system (TPS), in which multiple sedimentary basins may have been grouped, inheriting an interconnectivity between the systems. The DPE is articulated in a framework, organizing variety of data associated with the elements and processes of complex petroleum systems and integrating their data dimensions and attributes. We develop an ontology based data warehousing and mining artefacts. We present warehoused metadata, with slicing and dicing of data views for visualization of new prospects in the investigating area. We further investigate the risk of exploratory drilling campaigns and how the integrated framework, with visualization and interpretation artefacts can holistically support the delivery of high-quality products and services.

KEYWORDS

Digital Petroleum Ecosystem; Big Data; Data Visualization; Interpretation; Knowledge Discovery.

1. INTRODUCTION

Data visualization [13] is the study of the visual representation and graphical depiction of data, meaning thereby, the information is explored and processed in different schematic forms, with variables in different units. Data fusion is a sort of visualization, in which we describe the data instances in different graphic visuals, in a way the knowledge extracted from the metadata is interpretable. The goal of data visualization is an information delivery effectively through graphical means. The designers [13] focus on visuals, and their functionality ensuring new insights of information, especially in sparse and complex data areas in a more intuitive way. Without losing the clarity and perception, we obtain the knowledge through visual representations and graphic displays of geological and geophysical (G & G) and exploration and production (E & P) knowledge. The knowledge-based data structures [2] are of ontology focus. For transmission of data views geographically, data are structured in XML codes [2]. As described in [11, 4], various visualization techniques motivate us interpreting multiple datasets including various association mining rules. An oil and gas exploration with an application of data visualization technique is given in [3]. The visualization of frontier areas of petroleum prospects is described in Australian sedimentary basin [6] contexts with 4-D seismic technologies. We examine various issues of exploitation of reservoirs, structural and strati-structural plays under different geological settings [3]. The risks of exploratory drilling, and under-explored areas are given in [1]. Aside from brief discussions on data structuring of the resources data, there is a limited literature available on ontology application in oil and gas industries, especially the implementation of DPE in the oil and gas industry. In this context, we introduce the Big Data paradigm

though as a hype [7], but emerging as a think-tank in the context of DPE in which the volume and variety characteristics play a dominant role in particular the unstructured data representation more explicitly through visualization and interpretation artefacts.

2. RESEARCH OBJECTIVES

We aim at analysing the digital ecosystems focusing the following data visualization and interpretation objectives:

1. How are the correlations, trends and patterns of data views extracted from metadata structures visualized and presented for interpretation?
2. How to present and visualize the explored data for knowledge discovery, extracting new value of information.
3. Whether the visualized data views extracted from metadata structures, can be interpreted using the existing interpretation procedures?

To share common understanding of the data structure among entities: It is one of the common goals in developing ontologies. Several websites contain geographically varying volumes of oil and gas data and information. If these websites share and publish similar ontological descriptions of the data entities, in a way the computer agents can extract and aggregate information more visually. The agents can use the aggregated information to answer user queries or as input data in other applications.

Models from several domains need to represent the notation in space and time: This representation includes the notions of time-intervals, points in time, relative measures of time, and so on. If one group of researchers develops such ontology in detail, others can reuse it in their domains and contexts. As an example, the domain knowledge acquired from a particular model of a particular conventional oil and gas field, may be reused in the same ecosystem for an unconventional field. Additionally, if a large ontology description is needed to be built, several existing ontologies can be integrated describing the portions in the larger domain.

The domain assumptions are made more explicit: Make necessary changes as per the interpretation and implementation and just in case the knowledge about the domain changes. Explicit specifications of domain knowledge are useful for researchers and investors who must learn what terms or entities/dimensions in the domain mean to earth science systems.

Existing known operational knowledge among entities or dimensions is separated from the undiscovered knowledge among the emerging conceptualized and contextualized entities or dimensions. To generate the domain knowledge, we use the following visualization and interpretation methodologies.

3. DATA VISUALIZATION METHOD

In this section, we use several visual tools, providing an effective means of communication, with highly developed 2D and 3D pattern-recognition capabilities that allow processing and perceiving the pictorial digital data efficiently. We summarize the data, highlighting the visualization trends. Unknown phenomena are uncovered through various kinds of graphical representation. Several visualization techniques use volumes and varieties of Big Data including spatial-temporal multidimensional datasets that exist in the DPE contexts. We exploit the following visualization methods:

One method of visualizing the results of data search is through scatter- plot display in a three-dimensional grid. A scatter plot is a visualization technique that shows each data point as a color sphere, or bubble. Scatter plots are referred to as bubbles in these visualizations. The size, shape and color of the bubble, each is used to represent a variable in the data. The three axes in the visualization ideally should be able to describe any dimension within the same data plot and should be able to be randomly selected and modified by the user. The user can choose to explore more fully those data points using visual methods or perhaps click on the data and see a traditional numerical display in a spreadsheet. The volume of data points can also be rotated to observe clusters in different areas. By preparing and presenting the data graphically, the user can uncover properties of the data quickly and easily detecting any patterns or deviations from expected results.

Bubble charts are other ways of presenting data, because they convert pages of hard-to-understand numerical and textual data into something that is easily comprehensible to analyze. Bubble plot is a simple example of the use of graphics to quickly convey information about the data what they describe. This bubble plot, representing bubble sizes, densities and trends, suggests several inferences such as structure, reservoir and production attributes, their strengths and magnitudes that can bring out the qualitative and quantitative properties of reservoirs.

The visual data are typically read in as a 3D block of data, called a volume. Workstations do read the data in chunks because of voluminous and variety of data. Each point of data in the selected area represents a physical location (i.e., an X, Y, Z position) in the 3D space

represented by that particular field. The value at each data point represents many attributes or properties (such as amplitude, phase, frequency, velocity). A collection of surrounding values in a given area is in turn identified (to a certain degree of probability) as the type of entity (or object) or a dimension at each geographic location. A value is assigned to each data point (or more typically to a range of data points) corresponding to a color attribute to display in that range of values or instances. All the points that fall within the selected range of values have the same color. In a 3D representation of the object, the colors smooth out to form layers. We use similar visuals [4, 8] for discovering numeric association rules among the structured resources business data. These rules assign various color attributes for visualization.

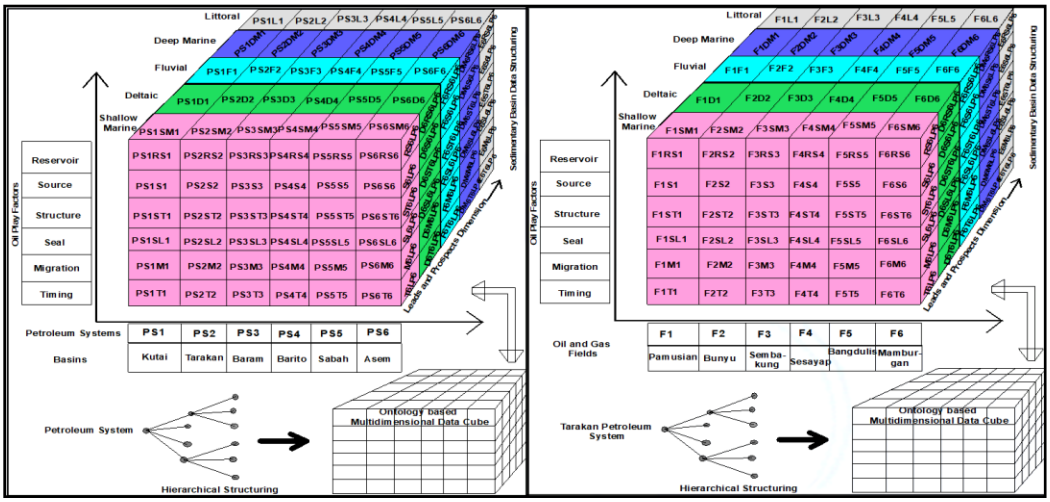

Figure 1: 3D Cube multidimensional representation of matured fields with reference to the elements of a petroleum system

We focus on data visualization, keeping in view its increasing demand in presenting the data views in various graphic visuals. The visualization explicitly facilitates the domain-specific data interpretation from fine-grained metadata volumes. Visualization is a display of multiple views, such as map, plot, chart, bubble plot views and how multiple dimensions and all the data patterns, trends and correlations are visualized in a single plot more explicitly. OLAP visualization is a presentation of metadata views from warehoused G & G and E & P data sources. As shown in Figure 1, we display both periodic and geographic dimensional data views for visual interpretation. The cloud computing systems (synonymous to network of systems in the present context) accommodating various data organizations distribute the data views and deliver products and services of good quality visuals to the data interpreters and oil and gas explorers. We use the visualization workflow as given in Figure 2 to process the graphic visuals for business analytics, delivering quality and interpretable information to variety of users. Business and data analytics and presentation of processed data in desired visuals are significant criteria. The new knowledge convey the information that needed in identifying the oil and gas prospective locales, but broadly in the DPE and TPS scales.

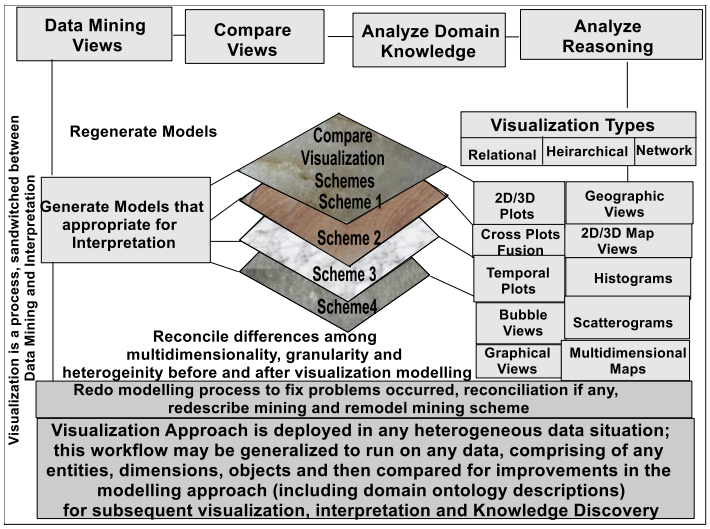

Figure 2: Visualization modelling – workflow

Information represented in the form of graphics, audio and video, makes use of spatial-temporal data and other multidimensional datasets from warehouse repositories. Visualization modelling has an impact in any application domain [8, 10] for which creative thinking, product ideation, and advanced business analytics are envisioned. Questions such as "what" to explain the "why" of engineering graphics, are incorporated within the design of visualization models. During data visualization process, data views, extracted from the warehoused metadata ensure with users' requirements so as to interpret them for knowledge discovery. As described in Figure 2, various visualization schemes are attempted to best fit the current interpretation and knowledge.

4. DATA INTERPRETATION METHODOLOGY

As a part of implementation in the present study, we propose several interpretation methodologies. We interpret the extracted data-views for evaluating the effectiveness of integrated framework and data models designed in different knowledge domains and contexts. The Cognitive Big Data as introduced in [7] is a new data interpretative research with several baseline scenarios and contexts. The rationale behind this approach is to bring together and integrate different contexts. Data analysis is crucial, in addition to testing the validity of data models, data warehousing and mining and the effectiveness of visualization. Qualitatively, the trends, patterns and correlations observed among various data events are interpreted in the knowledge enhancement domain. Besides, we describe the relevance, effectiveness, efficiency, impacts and sustainability criteria. Extent and duration of usage of data models and integrated framework including implementation of contextual, short- and long-term research outcomes among latitude and longitude dimensions are other interpretation objectives.

Data analysis and interpretation are meant for transforming the processed data into critical knowledge guaranteeing the research outcomes for descriptive analysis. The measure, consistency and effectiveness of multidimensional and heterogeneous data organization, modeling, mapping, data mining including effectiveness of data visualization are the other tests. Interpretation is either qualitative and or quantitative and the data patterns, trends and correlations interpreted, lead to the discovery of knowledge, implementing it in multiple domains. Interpretation made for evaluating the data models follows the criteria:

Relevance: methodologies, models, data mining, visualization are relevant to support the analysis in different application domains.
Effectiveness: achieved the research objectives.
Efficiency: within the available resources, to achieve maximum targets and goals.
Impacts: there is an immense impact in the implementation of data models in various application domains.
Sustainability: the scope of models, methodologies and implementation in other domains
Impact based evaluations are refined based on the use of our models in multiple domains and applications with the criteria:

1. ***Extent of use*** – how many stakeholders identified this approach and what degree outcome of research findings used

2. ***Duration and extent of usage*** – will the models, methodologies and implementations continue to be in multiple dimensions, such as geographical and periodic; to use in multiple countries and historical periods

a. Interpretation of Cross-sectional and Longitudinal Data Dimensions

Interpretative research is part of design science information science (IS) research. Data views represented in multidimensional views provide insights of interpretation and anticipated domain knowledge. Multidimensional metadata and their data views are interpretative in systems analysis and development scenarios. Big data in geographically spread countries and historical periods are significant in testing the current data models. Knowledge is built based on both short and long-term outcomes for interpretations. It is good idea evaluating the implementations of short and long term outcomes separately, so that we experience a fair assessment, examination of time-frame and resources needed for the projects and sustained impacts at different stages.

b. Contextual Implementation

Interpretation of results or implementation outcomes are possible in proper contexts, which include what outcomes are expected from current implementations, based on similar implementations that may have been made in previous visualization models.

c. Knowledge Modelling

Based on the domain application, interpretation objectives are chosen. But in the present context, we narrate methodologies as described in Figures 3 and 4. Knowledge is built based on the analysis and interpretations. Data mining rules focus on interpretation of attributes. The anomalies are deviations from the common rules or standardized or expected values. Interpretation and qualitative analysis of anomalies are the basis of building knowledge, such as attitude attributes of petroleum systems' elements and or processes. We perform the quantitative analysis by measuring the thicknesses of reservoirs and the areal extents of structures.

Data Interpretation Techniques	
Qualitative Interpretation	Data Knowledge Data Relationships Area Knowledge Data Analytics: Features Anomalies Categories Classifications Patterns Trends Correlations Similarities Dissimilarities
Quantitative Interpretation	Description of Parameters: Depth Thickness Distance Time Period Velocity Extent of Damage Sizes and Areal Extents

Figure 3: Interpretation methodologies

Data views extracted for visualization and interpretation are examined for anomalies and their evaluation for corroborating a particular model that achieved the knowledge presentation objectives. For this purpose different interpretation approaches are adapted for evaluating the qualitative and quantitative anomalies for knowledge discovery. We attempt several interpretation schemes for achieving the set of objectives of interpretation as narrated in Figures 3 and 4. Focusing on the number and type of property attributes, we reconcile the differences before and after the interpretation modelling, the best scheme in the current domain application. The domain ontologies and their modelling help facilitating both the visualization and interpretation schemes that ultimately provide new knowledge interpretation of prospective areas.

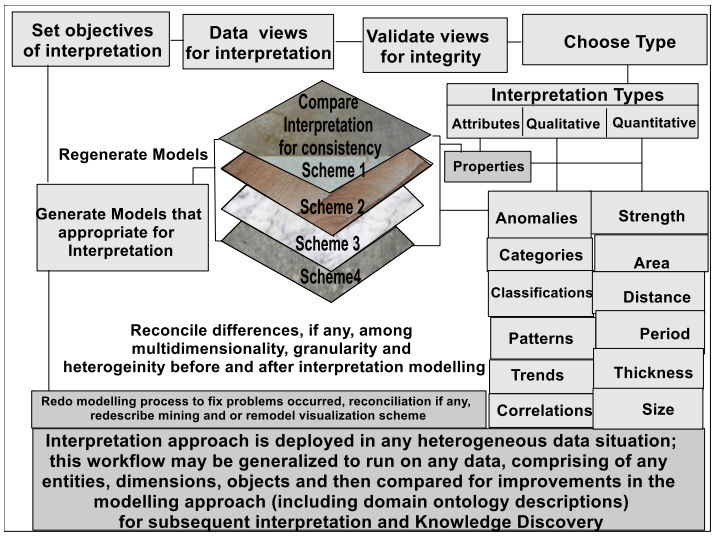

Figure 4: Data interpretation modelling – a workflow

We iterate the advantage of ontologies for representing the knowledge and modelling the domain knowledge. Ontology supports storage and manipulation of knowledge, including drawing inferences and making decisions. Mechanism of generalization and specialization including classification facilitate the semantics and fine tuning of knowledge representation. Selected data views consist of interesting patterns and trends, which may be descriptive and or predictive. The data attributes are either qualitative or quantitative. Attributes that depict the spatially and periodically varying properties are used for interpreting the data inferences in different knowledge domains and contexts. Bid Data as a cognitive approach support the inferences. We use data views for extracting domain knowledge for interpretation in support of knowledge-based systems.

As demonstrated in Figure 4, various data views are derived from metadata. Knowledge obtained in all case studies, is ensured with meaningful interpretations and implementation of metadata in different application domains. For example, an element of a petroleum system is found to be more productive and its areal extents discovered is large enough, such that similar strength of attributes is predicted in other fields of associated systems. The creation and discovery of knowledge play a decisive role on increased availability of knowledge from a system and effectiveness of the knowledge in its associated systems. Knowledge acquired in a system has an impact in perceiving knowledge of other related (or associated) domains, for which the data models described for mining, visualization and interpretation are effective.

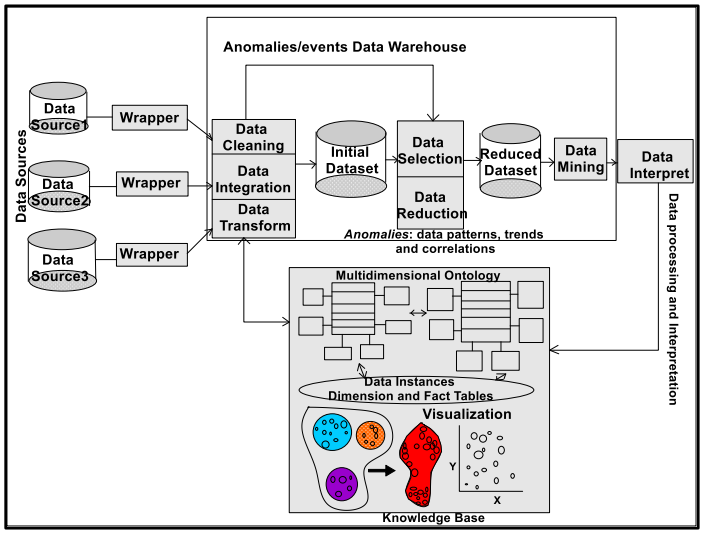

Figure 5: Knowledge building process model

A generalized knowledge process model as given in Figure 5 depicts a workflow from modelling of data sources to interpretation and then implementation of knowledge. Data exploration, prospecting, appraisal and development stages produce enormous amount of knowledge at multiple levels of systems' investigation and analysis, each level adding information for knowledge, interpretation and its analysis.

The current literature is not sufficient enough to interpret domain knowledge and its use in oil and gas industries. Though operating and service companies have their own proprietary interactive interpretation software, the interpretation methodologies are either developed based on user needs or problem solutions. But still, qualitative and quantitative interpretation methodologies are popularly used in many domains including oil and gas domains. Data views extracted from warehoused metadata, are validated for interpretation and the type of interpretation is chosen for its consistency and knowledge discovery. Data are either qualitatively or quantitatively interpreted based on the objectives of interpretation and project goals. Models computed from statistical mining are used for interpreting their properties, more often for qualitative interpretation. Implementation of the data models in different knowledge domains is carried out, addressing the issues of heterogeneity. Metadata that represent demographic, geographic and periodic data instances, is interpreted to have a meaningful information for decision support systems that assist in understanding system's behaviour, further analyse for future improvements. Merits and demerits of the systems and performances are analysed. Measures, strengths and anomalies of the properties of the attributed dimensions are analysed using different models and methodologies for interpretation. We analyse the domain knowledge and its limitations in the digital ecosystems.

5. MAPPING THE DOMAIN KNOWLEDGE

The warehoused metadata [5] are explored for implementing their data views in the strategic knowledge management. In the oil and gas industries, in particular exploration entities, "domain knowledge" is commonly used during interpretation of elements, processes and chains of petroleum systems and their ecosystems. Translating the existing knowledge with new knowledge, using the new attribute dimensions interpreted in multiple domains is a key focus. The data views extracted from warehoused metadata generate several prospective locales in the investigating area. As described in Figures 6a and 6b, several data attributes and their instances of geological structure, seismic data attributes are interpreted to identify new prospective areas. Structural highs, thicker isochrones- packs and their attribute visualizations when superimposed each other, can provide better areas for detailed drilling campaigns. The acoustic impedance attribute visualizations can contribute to better interpretation.

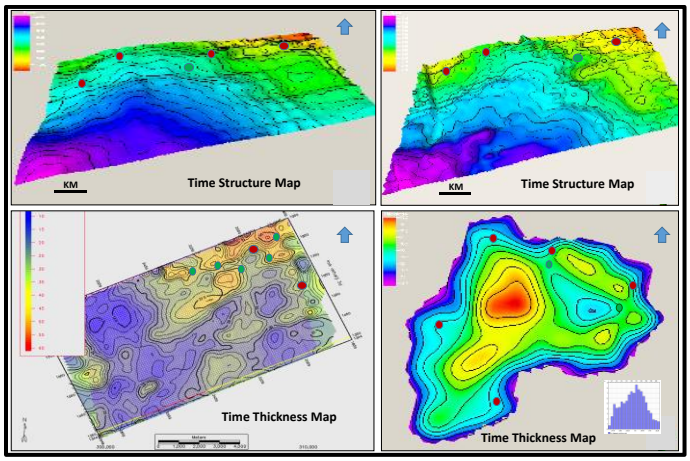

Figure 6a: Visualization of geological structure data-views

Use of "domain knowledge" in the context of petroleum systems, and oil and gas industries is uncommon and implicitly understood in spite of that several domain applications are involved in the upstream business environments. Though literature is available in this context in public domain, it is highly commercialized.

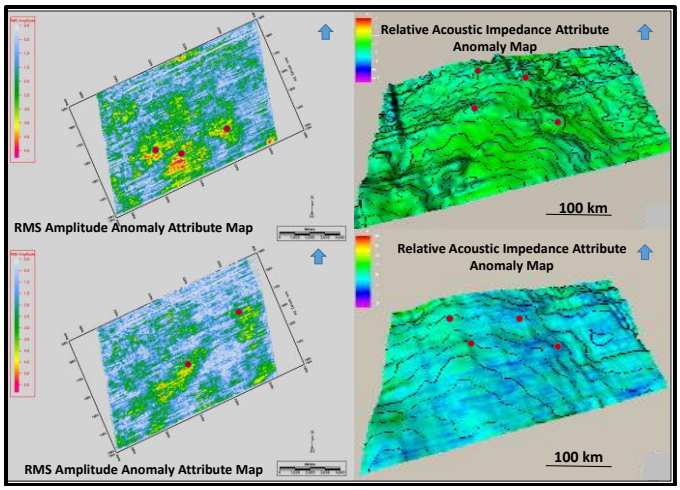

Figure 6b: Visualization of well-driven seismic attribute data-views

6. DIGITAL ECOSYSTEMS

The research objectives are further examined, exploring the scope of developing the visualization models for digital ecosystems of the other petroleum bearing basins worldwide. As demonstrated in [11, 12], several sedimentary basins described in Australia, India, Indonesia, Uganda, Middle East and USA are considered in the current research, keeping in view the intricacies and complexities of data sources in these regions. Our focus is on conventional, unconventional and matured oil and gas fields of these basins, exploring a scope of analysing huge volumes of heterogeneous and multidimensional data and their visualizations.

Australian sedimentary basins: There is an immense scope of integrating and analysing many sedimentary basins of Australian onshore and offshore basins, especially Western Australia, which produces more oil and gas deposits than elsewhere in Australia. Sedimentary basins possess heterogeneous and multidimensional data sources as shown in digital form [11]. Integrated framework and workflows explore the use of exploration and production datasets for risk minimizing the oil and gas business in Australia. Super Westralian basin, a total petroleum system (TPS), such as North West Shelf (NWS) possesses the shelf, slope and deep geological events, which appear to have a connectivity through phenomena of a digital ecosystem. Besides, this super basin has a multitude of sub-basins, each basin is associated with multiple petroleum systems, and each system with unknown or limited areal extents. Each petroleum system contains various oil and gas fields, with the hierarchical structuring of data dimensions and their associated attributes. North West Shelf in the Western Australia possesses unstructured heterogeneous and multidimensional data [11], we explore the scope of analysing their dimensions, attributes and instances in a warehousing environment with data mining and visualization opportunities exploiting untapped reservoirs of these basins.

Arab Gulf basins: Petroleum digital ecosystems and their embedded systems are described in the context of Arabian Gulf Basins (Middle Eastern onshore and offshore basins, [11], demonstrating the necessity of ontology structuring in the integrated workflows and their implementations. There is scope of specification of conceptualization and contextualization analysis in modelling and integrating multidimensional and heterogeneous data sources in Arab Gulf basins. Ecology, petroleum system and geomorphic systems cannot be isolated, which are otherwise are embedded, demonstrating an ecosystem, with multiple systems' connections. In this context, an integrated methodology proposed in Gulf basins enables us to understand the ecosystem phenomena through interconnected multiple digital ecosystems and their visualizations.

Indonesian basins: Indonesia is an island country with more than 30000 islands, with scattered sedimentary basins [9], in huge geographic regions and areal extents. They inherit volumes of multidimensional and heterogeneous data sources. Indonesian petroleum ontology (PO) descriptions can make good use of integrating oil and gas data sources of Indonesian sedimentary basins in different knowledge and application domains. These descriptions facilitate digital oil field solutions and visualizations in these regions.

***East African Rift System (EARS)*:** Several data sources exist within East African rifted basins. As a part of demonstrating the concept of digital petroleum Ecosystem (PDE), we identify ontology-based data warehousing associated with multiple petroleum systems, in the context of Albertine Graben (located in the Western Uganda, [10, 11]. Albertine Graben is considered as super basin with sub type basins. Each sub-basin consists of multiple petroleum systems and each is associated with multiple oil and gas fields. The super basin concept is simulated as an ecosystem, in which all petroleum systems and their embedded oil and gas fields have a connectivity. Volumes and varieties of data available in these basins facilitate the demonstration of emerging petroleum ontologies (PO) in the rift systems. The emerging visualizations have a further scope of analysing a large number of productive basins starting from southern Sudan in the north to the Malawi rift in the south-eastern parts of Uganda.

Unconventional Energy Scenarios in the USA: Several shale gas projects are developed [10] in the southern parts of USA to meet the demand energy resource. Because of growing demand of energy sources and the steady depletion of the current conventional oil and gas resources, there is an increasing quest for unconventional oil and gas business. Shale gas occurs within fractured shale reservoirs. Data sources associated with fractured shales do exist in many company situations, but unsuitable for an integrated framework because of the heterogeneity and multidimensionality. Problems associated with drilling and production, especially in the fracture development areas may be resolved with fracture visualizations, their associated subsurface lithologies (geological sense) and their connectivity.

Oil & Gas Deposits in the Indian Sub-continent: In the context of Indian sub-continent [11], there is immense scope of analysing different sedimentary basins for risk minimizing the exploration & production tasks in onshore and offshore regions. Data mining and visualization are used for building knowledge and effectively managing geographically scattered petroleum systems. The Cambay Basin, KG Basins, Cauvery Basin, Bombay Offshore Basins and several onshore basins of the North Eastern India, where several matured fields reported wealth of the data. These petroleum provinces and their linked data are suitable in designing and implementing the visualization modelling and knowledge interpretation methodologies.

7. CONCLUSIONS

Based on the visualization and interpretation of various data views of the PDE and TPS of multiple sedimentary basins, we have made the following conclusions:

1. Data visualization is a successful and widely used technology for viewing the resources data hidden under great depths. Data mining is an iterative process, implying that each time it refines the resultant data, a better visualization attribute is observed. This technology supports the Big Data cognitive approach.
2. Interpretation models drawn in the present studies are useful for the resources industries in terms of predicting the drillable exploratory locales.
3. It is recommended to use the data warehousing and mining technologies together with visualization and interpretation artefacts that supported by Big Data.
4. The map views are valuable tools for interpretation and implementation in the upstream business.
5. SQL and classical statistical mining are quite useful for mining and visualizing the multidimensional data, including geographical and periodic dimensions.
6. Heterogeneous data sources located in government and private enterprises, national and multinational companies can successfully be used in building multidimensional models.
7. Petroleum digital ecosystems (PDE) and petroleum information systems are digital oil field solutions in Big Data scale for various producing companies and multinational service companies.
8. There is immense scope of extending the current research application in worldwide sedimentary basins.

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