Warehousing of Object Oriented Petroleum Data for Knowledge Mapping

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Abstract

Australia produces a-third of world's natural resources. Enormous amounts of energy and financial resources are expended in order to tap these natural reserves from the earth's surface. Vast amounts of these resources, however, remain unexplored and under exploited. Data pertaining natural resources, such as mineral and petroleum, are, in general, heterogeneous and complex in nature. Volumes of these types of data are geographically distributed among many companies in Australia and abroad. The existing historical resources data are logically and physically organized using warehousing techniques. Entity-relationship (ER) and object oriented (OO) data mapping techniques are used for analyzing the data entities, dimensions and objects. In this paper object oriented data and warehousing of object class data models have been described. Data mining techniques can be employed to explore many more resources hidden, under great depths of the earth's crust, without additional efforts of exploration and development. Warehoused object oriented resources data can significantly reduce the complexity of the resources data structuring and enhance the data integration and information sharing among various operational units of the resources industry. Large amount of financial inputs can be saved if these technologies are successfully implemented in the resources industry.

1 Introduction

Resources business data, categorized as various entities, dimensions and object classes, vary with time and space. Business applications that involve complex modelling and mapping are driven by data warehouse systems and third party software packages. In recent years, it has been recognized that business applications of warehoused resources data put forward a fast growing business for desktop data warehouse market and with usage of online analytical tools. The data warehouse is aimed at analyzing business situations locally and globally, particularly to handle the periodic fluctuations in demand and supply of petroleum resources. *Exploration*, *drilling* and *production* data entities are often dealt with for meeting the demand and supply of petroleum resources.

Resources business data that frequently involve spatial objects and their reference (navigational) systems are diverse in nature and their values change with time. Relationships that exist among the complex resources data are mapped with varied petroleum business situations and constraints. But these traditional mapping approaches have definite limitations in handling the heterogeneous resources data, because of which data integration and access are increasingly becoming difficult. Warehousing of resources data is warranted for simplifying complex heterogeneous data structures. Before discussing the object oriented modeling in a warehousing environment, authors review the ER modeling application in resources industry, highlighting its merits and limitations. The problem statement, methodologies attempted to solve these problem issues with analytic views of resources warehousing, have been discussed in the following sections.

2 Previous Literature

Concepts of object oriented databases have been described in [7], [1], [6], [8], [11] and [21]. These authors narrate importance of object oriented data in a warehousing environment with simple data structuring cases. Several case studies are available in the existing literature and few of them involve the time dimension. For example, the papers [2], [4], [5], [9] and [10] illustrate health and insurance data presentation with period (time) dimension. Temporal data, using entity-relationship mapping approaches are analyzed in [12] and [18]. A comparative study between relational and object oriented database systems has been done with case studies in [20]. ER and multidimensional data structuring methodologies have been demonstrated in ([13], [14], and [17]) using petroleum and mineral exploration and production data. These heterogeneous data structures have been examined in [15] and [16] using ontology approach. They make comparative study among ER, multidimensional and OO approaches for managing the petroleum exploration and production data. Issues of multidimensionality and granularity have been examined in [19], where temporal data are dealt with in industrial situations. More issues of petroleum exploration and production database management have been published in [3]. The current problem statement is discussed in the next section.

3 Problem Statement

Not much literature is available on warehousing methodologies of object oriented and multidimensional structuring of the resources data, interpreted as object classes in a warehousing environment. Shortcomings of the present methodologies in handling the heterogeneous resources data have been discussed. Issues, such as storage, programming, data manipulation, data access and search, in particular with resources databases, have not been discussed in the previous literature. Data integration and interoperability are also key issues which have special significance in a warehouse design and development of resources industry, through which enormous financial resources can be saved. Information sharing and data access are intended to improve through data warehousing and mining, if successfully designed and implemented. Following methodologies have been reviewed.

4 Methodologies

Keeping in view the limitations in the data structuring methodologies for handling the present heterogeneous resources data structures, authors propose object oriented and multidimensional approaches that can manage different types of object classes as described in Fig.4. ER data structuring methodologies have been discussed in the next section, narrating merits and demerits, followed by an object oriented approach.

4.1 Entity Relationship Mapping Approach

Since their success during 1980's and 90's, relational database management systems (RDBMS) have become an accepted [7] technology for primary data storage and access platform for knowledge-tone applications. Data structuring with appropriate logical and physical designs, data manipulation procedures, such as SQL and stored procedures are important ingredients of RDBMS. RDBMS manages data as a collection of tables, in which all data relationships are identified and represented by common values of related tables. ER modeling and normalization processes are routinely carried out for designing database structures and for constructing traditional data warehouse. Issues related to indexing like primary and foreign keys are also analyzed during normalization process. Traditionally, architecture of data warehousing is optimized by an approved RDBMS, especially for decision support systems.

Initially, conceptual modelling (as shown in Fig.1), narrating generalization and specialization processes and mapping have been carried out for building RDBMS for a resources company. Entities, attributes and relationships have been identified and created tables of *navigation/satellite*, *exploration*, *drilling*, and *production* and for other support service functions (Fig. 1). As stated before, *exploration*, *drilling*, *production* and *marketing* are important business functions of the resources industry.

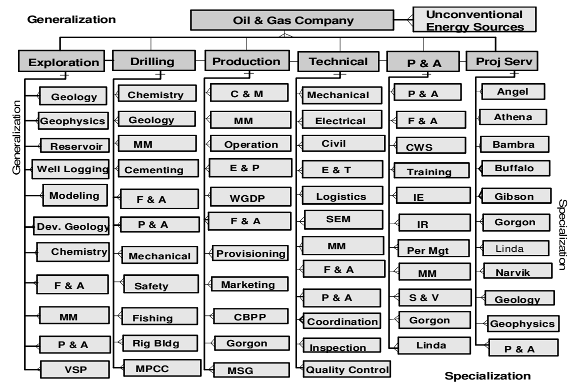

Fig. 1 Metadata model of oil and gas business with super type and subtype entities

Each of these high-level operations has several other lower-level operations, such as *exploration* entity has *geology*, *geophysics*, *well logging*, *reservoir* and *geochemistry* subtype entities. A logical model and a sample of such ER diagram for petroleum exploration and production database is shown in Fig. 2. In the present study, a group of entities and their corresponding attributes have been considered for resources industry to draw ER models. All the conceptual models have been transformed into various logical schemas, which narrate structural description of entities with several constraints. Most commonly database models describe relationships as one-to-many and many-to-many relationships. Cross-reference keys link the tables, representing the relationships between entities. Primary and foreign keys provide an easy access to the databases. Similar to the petroleum resources data structuring, mineral resources data also possess several high-level and low-level business operations. Accordingly, data items of mineral databases possess definite relationships among their entities or dimensions and attribute values, which are beyond the scope of this paper. As shown in Fig. 2, a diamond marked, indicates a relationship or an associative entity shown along with cardinality constrained features. This is a mere generalized logical data model, which is further detailed with higher order multidimensional structural features later in the paper.

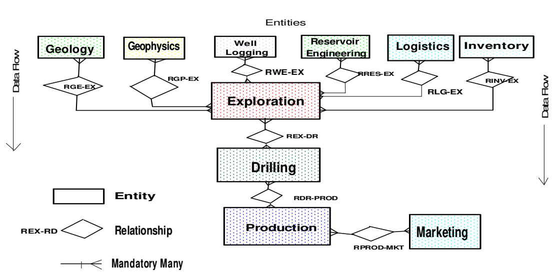

Fig. 2 Typical conceptual model for a petroleum company

Resources data represented in entities and attributes are mapped for ER models. One of such ER model drawn for survey-contractor relationship is shown in Fig.3.

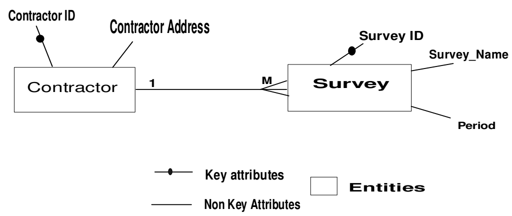

Fig. 3 A simple ER diagram for petro2-surveys showing one-to-many relationships

Often these *surveys* (*exploration*) data are accessed through *navigational* data, which are space-temporal in nature. There are many *points*, *survey lines* and *regions* (object subclasses in our case) described with these types of *exploration* data. Traditional methods of data mapping approaches, such as ER modeling, have inherent limitations of handling these heterogeneous types of data. Because of these reasons, each and every data entity of petroleum industry is now depicted as an object class and few of the object classes used in the present study are described in Fig. 4. An added advantage is that these object classes can easily be programmed using object oriented languages. All the resources data entities, discussed so far are represented in object classes, keeping in view the storage requirements, data manipulations, programming convenience, data accessibility and interoperability issues as well.

4.2 Resources Data as Objects for Warehouse Development

Application of data warehousing, combined with business intelligence concepts to resources industry data, yields interesting results, especially when resources information technology (RIT) is coupled with non-resources information technologies (e.g. coupling a RIT with a data warehouse). Issues, such as slow response times, poor image or map navigation capabilities, data fusion bottlenecks need to be resolved. Data warehousing linked with resources information technology, is thus a problem solution. RIT does mostly transactional processing with less interpretation and hardly supports decision-making applications. However, user point of view, functionalities and response times of both spatial (such as RIT) and non-spatial technologies are tuned for compatibility. These technologies are intended to handle complex heterogeneous data structures of resources databases.

In case of resources databases, different types of data, such as *exploration*, *drilling* and *production* data are stored as object classes along with their associated sub classes in a warehouse environment. Data are processed by separate analytical tools. Typically these data are in the form of numeric and spatial with several geometrical shapes. Semantic data pertained to RIT, are stored separately in tune with multidimensional data structuring with separate semantic data mart servers. Nowadays, with the arrival of universal servers, it has become efficient to store *exploration*, *drilling* and *production* data together and perform basic analyses with a single high powered server. Special geo-scientific modules are needed, if one wishes to perform high speed processing (such as seismic data processing and 2D/3D data interpretation) with more advanced analysis and interpretation. Such solutions remain transaction oriented and do not satisfy decision support requirements. Additional concepts needed for the current multidimensional approach are discussed in the following sections.

In an *exploration* aggregation entity, spatial or coordinate data dimensions have more significance in the resources data computations, since various types of geometrical and non-geometrical data, are generally referred to earthly (navigational) positions and thus to make up geo-scientific databases. When building a geo-scientific data warehouse with a multidimensional approach, one may have to consider three types of dimensions (in multidimensional sense), according to the theory of scale measurement (nominal, ordinal, interval and ratio scales, where each scale allows for richer analysis than its precedent one [12]. Each type of dimension is considered, if it deals with a geometric spatial reference such as X, Y coordinate systems (i.e. quantitative data of the interval and ratio scales), with a semantic spatial reference such as place names (i.e. qualitative data of the nominal and ordinal scales) or with combination of both, such as *survey* coordinates, *survey name* and *survey line*, *basin* name; *permit* number and name of a particular *basin* (which is a combination of quantitative and qualitative data, where the quantitative data are located precisely and or interpolated along the linear axis identified by the qualitative data). The type of dimension involving the geo-scientific database system, supported by the warehousing/decision-support technology, influences the type of spatial dimension one may use, or in other words, the type of hierarchy of a dimension:

Non-geometric spatial dimension: This dimension contains only non-geometric data. For example, *survey names*, *survey line numbers*, *well numbers*, *survey IDs* and *well IDs* and *permit IDs* and numbers etc… are constructed for the geo-scientific warehouse as a dimension containing only nominal data to locate a phenomenon in space. Such a dimension could start with the names of *exploration permit* names, *survey line* numbers and *basin names*, which are non-geometric such as *state* and *country* names. Such a solution can be implemented as long as navigation representation is not required.

Geometric-to-non-geometric spatial dimension: As shown in Fig. 5, an *exploration* aggregation component, which has several dimensions or entities, are further represented by several object elements characterizing with several patterns. This is a dimension, whose prehistoric level data is geometric but whose generalization, starting at a certain high level, becomes non-geometric. For example, a *survey line* represented by a polygon (in the Canning basin, map not presented here), that is geometric data, is the finest granularity level of this spatial dimension. However, each *survey line* is generalized to some value which is solely nominal, such as Canning *survey line 1*, Canning *survey line 2* etc… and its further generalization remains nominal, thus playing a similar role to a non-geometric dimension at coarser granularities [19] of this spatial dimension. Using such design technique, resources DW users are facilitated with the generalization potential of the measurement scales i.e., qualitative measurements carry less details than quantitative measurements.

Fully geometric spatial dimension: This is a dimension whose primitive level and all of its high-level generalizations are geometric elements. For example, polygons of equi-type or value onshore survey *regions* data (such as equal property of *gravity*, *magnetic* or *seismic survey* data) or for offshore *regions* data are geometric shaped object classes (see Fig. 4). It could also be polygons of equal elevations or altitude regions are geometric data, and every generalization, such as elevations covering 0-700m, 700-1000m and so on… are also geometric. Geometric elements are presented in different object classes. It is demonstrated with the conceptualization of the real world spatial objects [18] through object oriented data modeling reducing the complexity of object data structures. For example, *geological field* samples are represented in *point* objects. "*Seismic survey lines*" is another spatio-temporal view showing occurrence of spatial events in different *basins* represented in *line* objects. *Navigational* data of the resources in different polygons and *net oil pay sand thickness* contours (2D surface, type of object), representing maps as *region* objects, are other views of geometric elements as shown in Fig. 4.

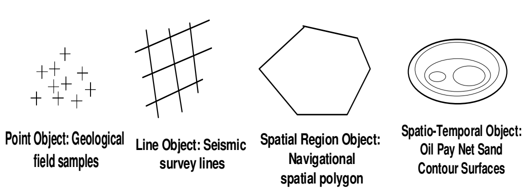

Fig.4 Process of representing spatial views of geometrical elements of resources data

The last two types of spatial dimensions of geo-scientific data indicate that geometric data may have more than one way of being generalized to high-level concepts, and the generalized concepts can be geometric, such as maps representing larger regions, or non-geometric, such as named areas or general descriptions of the regions. These can be used as alternate ways to go from fine granularity to coarser granularity [19], even within the same spatial dimension.

Data that have been analyzed are presented in cubes [7]. In multidimensional data modeling, two types of measures can be distinguished within a cube:

Numeric measure: This contains only numeric data. For example, daily exploration costs, roll-up may get the total costs by quarterly or yearly (with *period* dimension).

Spatial measure: This measure contains a collection of points to spatial objects. For example, during generalization of (or roll-up) in a spatial data cube, the areas in a *basin* (Australian basins, under study now), having equal *gravity*, *magnetic* or *seismic* data values are grouped into the same cell, and the measure so formed contains a collection of pointers to those areas under investigation. *Survey lines* (sometimes in straight lines or curvilinear) and contour lines (equal property values alignment) are collections of *points* derived or computed from the data warehouses, which have geometric measures.

Having described, the data sources and types of resources industry ([13] and [14]) in an entity or dimension or spatial domain, then complex nature of resources data items are represented in object-oriented modeling, which have been discussed in the following sections.

4.3 Representing the Aggregated Exploration Entity as Spatial Object

So far entities in the ER modeling, dimensions in the multidimensional modeling and types of data and measures involved in a typical petroleum industry have been discussed. As stated earlier, in the resources industry, the data types are in the form of numeric and or geometric measures. An object in the spatial data modeling is equivalent to an entity or dimension that has well-defined role in the application domain as well as state, behavior and identity. An object class [7] is taken as a concept or abstract, or thing that makes sense in an application context. Entities in the ER modeling are represented as object classes in the object oriented model, if one wishes to model spatial objects such as *survey lines* or *well locations* or *gravity or seismic contours*. Data of these types are easy way of representing in object classes for data storing and manipulations. In addition to storing information, an object also exhibits its behavior, through operations that examine or affects its state.

As an example, a petroleum company is an aggregate object class consisting of several component objects. *Navigation*, *geology*, *geophysics*, *reservoir engineering*, *well logging* are component sub class objects of the aggregate *exploration* object class. Similar object classes are identified in other aggregated objects such as *drilling*, *production* and *marketing* object classes of the resources industry. As shown in Fig. 5, an *exploration* object is an aggregation of several component object sub classes. Authors notice that aggregation involves a set of distinct object instances, one of which contains or is composed of the others. It is a stronger form of association relationship and is represented with a hollow diamond at the aggregate end. Further, more component object classes and or subclasses are added, when business needs arise and even if one component is missing, still the aggregated object class still survives.

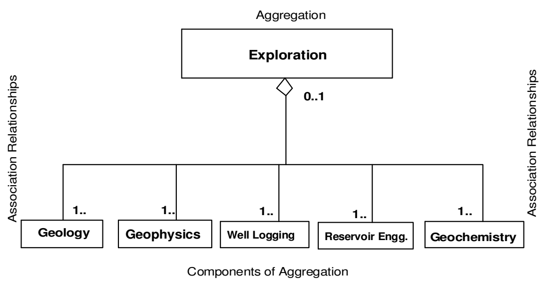

Fig. 5 Representation of the aggregated exploration component

Each component of object subclasses of *exploration* aggregate object class has measures of numeric and spatial data. As discussed earlier, data from each of the object component is processed and stored in the resources data warehouse. These data must have been pre- or post computed and stored in the storage components. As shown in Fig. 5, each component of the aggregated object can have multiple sub-components (sub classes), such as *geology*, *geophysics*, *well logging*, *reservoir* and *geochemistry* (with multiple sub classes), indicating several types of operations and their corresponding data types.

4.4 Composite Aggregation of Petroleum Database Objects

As shown in Fig. 6, the diamond (shaped symbol) at one end of the relationship between *basin* and *survey lines* is not hollow, but solid. A solid diamond represents a stronger form of aggregation called composite aggregation. In composition, a part object belongs to only one whole object; for example, a *survey line* is part of only that particular *basin* that is under study. Therefore multiplicity on the aggregate end may not exceed one. Parts may be created after the creation of the whole object; for example, *survey lines* may be added to the existing *basin*. However, once a part of the composition is created, it lives and dies with the whole object class. Deletion of the aggregate object cascades to its components. However, it is possible to delete a *survey line* before its aggregate *basin* dies.

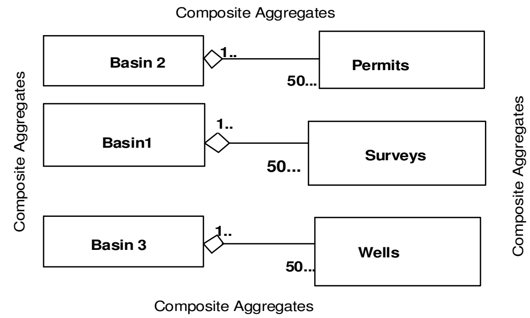

Fig. 6 Representing the composite aggregates of petro2-surveys database

4.5 Spatio-temporal Resources Data Object Modeling

Fig. 7 describes a conceptual database structure enabling the resources data user to model the spatio-temporal variations of *reservoir region* units. The data structure with multiple arc-node structures [18] on the logical level can be designed, but inconsistent with ER mapping approach. Authors deal these data types as object classes in object oriented approach. The basic problem is derived from the *reservoir* units from certain geological *regions* that may only be valid for a certain period of time, since all the world oil or gas *reservoirs* have definite life span. These *reservoir pay* aerial or *region* objects vary with time and space as well. When they originally produced petroleum, they possess definite boundaries, but with increasing time, they have differing boundaries. A spatial unit may evolve from either one or the combination of several spatial units. It may loose or gain area from several units. The spatial *reservoir* units are also characterized by spatial and temporal attributes as well as their relationships to the neighboring reservoir unit objects. Here each object class is related to other object categories: an *oil-producing basin*, which has been leased to state owned resources company. Each object is described by attribute data, which may carry a *period* dimension, such as the lifespan of the *region* object. ER models when converted into a star schema multidimensional model, these spatio-temporal object resources data structuring in a warehouse environment becomes more consistent and flexible with varied data dimension and fact constraints.

Accessing complex data types stored in data warehouse environment can also become efficient with better inherent architectural features of the warehouse. Petroleum exploration and production, in particular, the reservoir data are typically, heterogeneous in nature and authors examine these types of data that affect the architecture design as discussed in the following sections.

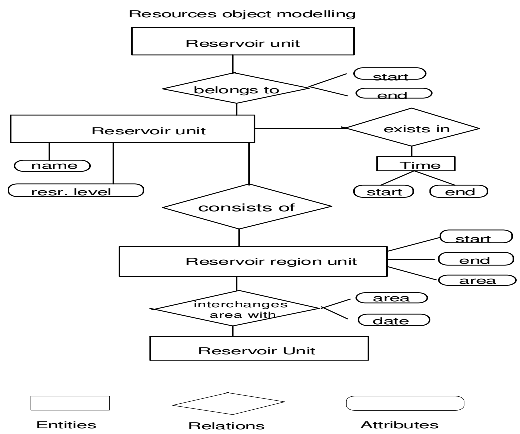

Fig. 7 ER model of reservoir region units representing resources data

5 Resources Data Warehouse Architectures

Entities, dimensions, objects and facts of these resources data that have been captured from various operational units and other sources have been stored in relational data structures. Star schema is one of such schemas used describing the structure of tables, columns and rows, views and constraints for mineral and petroleum Industries. Nowadays multidimensional modeling has become more popular and convenient for designing the data warehouse (DW). There are various data warehouse architectures evolved at different times for their operational conveniences. Some of the features of these architectures have been described in the following sections.

Data Mart: is a smaller and more focused data warehouse. In many cases, resources companies find it more useful to create data marts for specific business units that have equally specific data analysis needs. For example, *Exploration* or *drilling* or *production/marketing* business units may have their specific focuses on their own data needs to explore for specific purpose. Although the larger data warehouse could support these needs, the enormous bulk of data contained within a typical data warehouse could reduce the efficiency of a consistently focused data analysis effort. As shown in Fig. 8, the data mart established for a specific online analytical effort is both, the target of the data delivery and the direct source of data, accessed by end users associated with that data mart. Data mart as an access tool has a role in the data warehouse and its position is discussed in Figs. 8 and 9**.** Fig. 9 indicates that the data warehouse feeds data to the organizational business units of data marts. In turn, the data warehouse is fed its data from the legacy applications. As shown in Fig. 10, a logical data mart and active warehouse architecture is practical for only moderate sized data warehouse [7]. Logical resources data marts are not physically separate databases, but rather different relational views one physical, slightly denormalized relational data warehouse. Resources data are moved into the data warehouse rather than a separate staging area to utilize the high performance computing power of the warehouse technology.

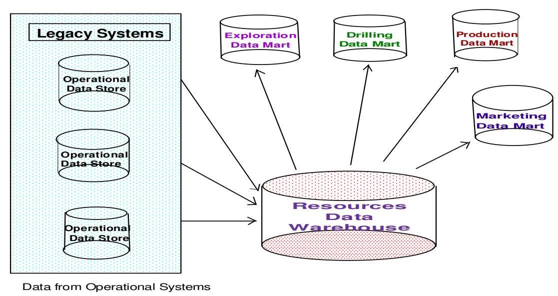

Fig. 8 Architectural positioning of the data warehouse and data mart

Despite their obvious similarities, data marts and data warehouses have a number of fundamental differences as shown in Fig. 9.

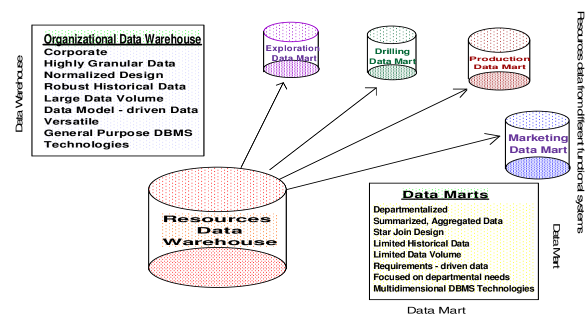

Fig. 9 Fundamental differences between resources data warehouse and data mart

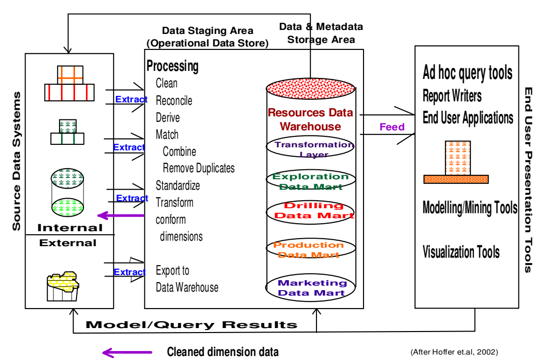

Fig. 10 Logical resources data mart and active warehouse architecture

6 Analysis and Discussions

Typically resources data consist of *pointed*, *line*, *region* or other spatial objects (Fig. 4), with several other entities or dimensions and measures. These have been identified and the likely entity and or object relationships have been mapped. The data stored in the resources data warehouse with object oriented data structures; have been mined for drawing out correlations and trends among various resources data items. Construction of such data warehouse has been briefly discussed in the following sections.

6.1 Exploration of resources business data

It is often used to capture, store and access resources data and their hidden dimensions of strategic information surrounded in different operational units. To make use of the potential information available in different operational units of the resources company, the data stored as a part of everyday work, have to be selected, consolidated and aggregated. Other associated object classes are processed or aggregated first, before they are of use for analytical or prognostic purposes. Nevertheless, all the operational data stored are usable, but the content or information from datasets is of immense use during data mining stage. In the end, the resources data warehouse provides the user pre-structured data and tools to access and explore the information content. Design process flow of a data warehouse is discussed in Fig. 11.

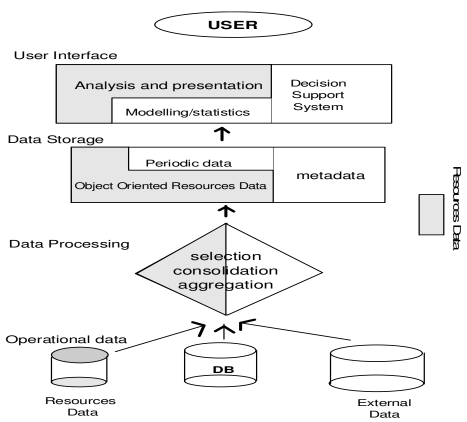

Fig. 11 Structure of the object oriented resources data warehouse

The aggregation of resources data, especially when they involve space-time components and continual update of such spatio-temporal data from the operational processes is an essential task of the resources data warehouse. Even under changing circumstances like new spatial divisions, the data warehouse must be able to provide the user spatio-temporal resources data that the user needs. It is important to mention that spatio-temporal changes are frequently updated and integrated in the data warehouse, both as means of data collection, processing and storage as well as a tool for the exploration of spatio-temporal resources data trends, correlations and patterns. Metadata modeling of the resources warehouse has been narrated in Fig. 11. Data mining of resources data warehouse is carried out using analytical analysis tools, based on which several multidimensional views are processed and presented for interpretation purposes. Knowledge is built from one of such multidimensional object model view as demonstrated in Fig. 12. Explorers and drillers are thrilled to have this model view to finalize their drilling plans and exploit the petroleum resources. This model visualization is of immense help to petroleum engineers for computing volume of reservoirs.

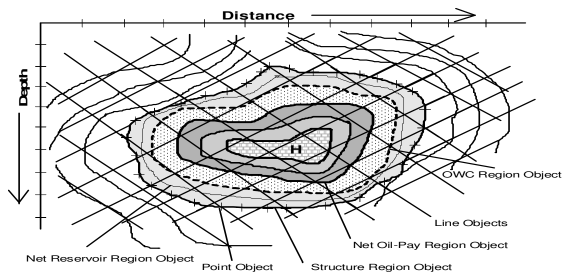

Fig. 12 Knowledge mapping model from warehoused resources data

7 Summary, Conclusions and Future Scope

Selection of data sources and other data requirement analysis are prerequisites for multidimensional structure modeling as this process permits to identify inappropriate and redundant information and thus can save operating time and costs. The entities, dimensions and object classes of petroleum exploration data have been identified and interaction between these data types within various operational units has been examined and thus built a conceptual model. The demand for spatial and temporal database management is high in resources industry. For warehousing purposes, logical ER, multidimensional and object oriented data models have been drawn from conceptual models. Merits and limitations of ER models in handling space and temporal data have been described. The proliferation of complex resources data types and the need to store, index, search and manipulate such data have provided multidimensional data structuring combined with object-oriented technology, an edge over other database methods. Similar data models can be designed and implemented for *drilling* and *production* object classes.

With the growing need in organizations to store and manipulate resources data, in applications ranging from computer aided design and manufacturing to geographic information systems, object oriented DB systems are gaining popularity, especially with petroleum resources data that carry temporal dimension. Literature is available for the information systems researchers, especially in the areas of petroleum industry, as discussed next section.

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