CHAPTER 2

REVIEW OF LITERATURE

In early twentieth century, the exploration for petroleum was carried out by geologists, especially petroleum geologists, whose prime concern was on geological structure details, and reconstruction of geologic model putting together the past and present, to be able to provide meaningful inferences regarding presence of hydrocarbons. The uncertainty involved in choosing potential drilling sites, and the high expenditure involved provided the suitable environment for use of seismic surveys in exploration.

The principle use of seismic exploration is to find potential oil and gas traps primarily by mapping geological structure. It has been a well-acclaimed geophysical tool for hydrocarbon exploration since 1930s. The field has continually been in the top research arena ever since then, with regular research updates.

In seismic exploration, an acoustic energy source radiates elastic waves into the earth from the surface. On the surface, there are receivers that detect acoustic energy reflected from geological interfaces within the earth. The recorded data is put through a series of processing steps in order to reduce its noise component, and further convert it into a reasonable form fit for analysis and interpretation. Seismic interpretation process is the interface between the exact mathematics of seismic data processing and inexact geological reasoning **[Denham, 1984].** To reduce ambiguity of interpretation, he used geological data obtained from exploration wells along with seismic data.

The concepts of physics became a prime additional requirement for successful analysis of seismic records. This gave rise to a new generation of experts, the 'geophysicists'. The skilled personnel having suitable background of geology and geophysics took up positions as 'seismologists' / 'seismic interpreters' , and worked on interpretation of seismic records to come up with meaningful inferences concerning sub-surface geology **[Sternbach, 2002].**

The development of computer technology, with increased sophistication in recording, processing and displaying techniques, created a perfect environment for the growth of seismic technology. The availability of multitude of color coding and printing facilities further added to increased clarity in the interpretation process.

Digital displays were preferred because of their superior color rendering and depth effect. But paper displays were still used for practically understanding the seismic section and interpreting it. It was easier to look at the paper than digital shows. Moreover the paper display was easier to carry and manage **[Sternbach, 2002].**

Analytical tools were developed for interpretation once computer processed data became available. The most elementary but very powerful technique was statistical cross-correlation of amplitude from one trace with the adjoining trace. This allowed the user to move across the traces but along the same reflecting horizon **[Herron, 2002].** What appears as reflecting horizons on seismic maps could be confirmed with this technique. This allowed tracking all significant horizons in an area with high level of confidence as long as there were no discontinuities.

Cross-correlation techniques used in interpretation ran into trouble when stratigraphic units differ in thickness or are truncated due to erosion, faulting or thickness changes from differing rates of sedimentation. Stretching of zones alone or moving-window correlation, or a combination of both, failed to ensure geologically meaningful correlation. Research in this area turned to pattern recognition of structure and artificial intelligence techniques **(Davis et al., 1981), Bonnet and Dahan, 1983).** The difficulty in these approaches is that integrated induction, reasoning, and judgment of contrary evidence played an essential role in geological interpretation. The problem is basically an intellectual one, and it was generally accepted that the common numerical processing techniques cannot effectively deal with such problems. The key to computer geointerpretation was to explore the logic of human interpreters and follow this logic in designing the computer software. The relevant techniques such as pattern recognition, expert systems, and image analysis have been under development for more than two decades. A software named "PROSPECTOR system" **[Duda et al., 1979]** was developed to provide consultation services for mineral exploration. Although many other powerful algorithms were published during this time, they could be applied to the problem with caution, as their underlying axioms did not always coincide with the way geointerpretation of log data is to be done. A well-log interpretation system was developed at this time using artificial intelligence techniques to show what a computerized stratigraphic interpretation system can do. There were two major subtasks: contact recognition (zonation), and interval (zone) identification **[Wu and Nyland, 1987].**

In seismic data interpretation horizon picking is important for structural analysis, feature recognition and site appraisal. However, horizon picking is still commonly done by hand, is error-prone and time-consuming. Attempts to automate this process were hindered due to absence of a clear, robust and universal picking algorithm. A new method was devised by Harrigan et al., (1992) which combined a traditional approach to horizon picking with a new technique using a trained artificial neural network. This method made better use of general properties of horizons, and is more robust than conventional pattern recognition techniques, and facilitated a solution to the problem of tracking through conventionally difficult regions containing faulting and other geophysical anomalies, where horizons are discontinuous **[Harrigan et al., 1992].**

The conventional seismic trace can be viewed as the real component of a complex trace which can be uniquely calculated under usual conditions. The complex trace permits the unique separation of envelope amplitude and phase information and the calculation of instantaneous frequency. These and other quantities can be displayed in a color-encoded manner which helps an interpreter see their interrelationship and spatial changes. **[Taner et al, 1979]**. Additionally, the instantaneous phase and envelope could also be used to track the horizons even across faults.

A seismic attribute is a quantitative measure of a seismic characteristic of interest. These play a significant role in providing information useful in seismic interpretation. Success of 3D surveys brought popularity to seismic attributes. Attributes are valuable for gaining insight from the data particularly when displayed spatially over interpreted horizons. However, all the many attributes available are not independent pieces of information but, in fact simply represent different ways of presenting a limited amount of basic information. The key to success lies in selecting the most applicable attribute for the problem. Moreover, statistical analysis using attributes must be based on understanding and not simply on mathematical correlation. The attributes could be poststack, those that are obtained from stacked and migrated data volume, and loaded on the workstations or they could be prestack, which means they have been derived from amplitude variations with offset (AVO) measurements **[Brown, 2001].**

Advances in seismic technology include voxel pickers (a voxel-based commercial software) that use multiple criteria of attribute, phase, frequency, and similarity to create very fast horizons [**Meyer et al, 2001].** These works explained how the interpreter can peel away the seismic reflectors he does not want and highlight the important parts without putting any hand-driven bias in the interpretation. This is called as 'data sculpting'. This is the ability to extract out seismic attributes that correlate to hydrocarbons and make the computer do the work of rendering it and quantifying it [**Strenbach, 2002].**

During the past 30 years, seismic attributes have evolved beyond simple measures of amplitude, frequency, and phase to include measures of waveform similarity, amplitude variation with offset (AVO), spectral content, and structural deformation. Although neural networks and geostatistics are effective ways of combining the information content of these many attributes, such analysis cannot replicate the pattern-recognition capabilities of an experienced interpreter. For this reason, careful visualization and display of multiple attributes remains one of the most powerful interpretation tools at our disposal. The two most important color display models are based on red, green and blue (RGB) or hue, lightness and saturation (HLS). Transparency/opacity provides a fourth color dimension and additional attribute modulation capabilities. Sometimes these combinations can be achieved using commercial voxel-based interpretation software. By careful use of color and transparency applied to modern volumetric attributes, one can display the strike of faults and flexures in three dimensions, isolate collapse features, and quantitatively display the geomorphology and thickness of channels [**Guo et al, 2008].**

Good seismic attributes and attribute analysis tools are expected to mimic a good interpreter. Over the past decades, it has been witnessed that attribute developments have achieved breakthroughs in horizon tracking, reflector acquisition and mapping, fault identification, bright-spot identification, frequency loss, thin-bed tuning, seismic stratigraphy and geomorphology. More recently, interpreters have used cross-plotting to identify clusters of attributes associated with either stratigraphic or hydrocarbon anomalies. For a computer-assisted seismic stratigraphy analysis, an interpreter trains the computer on a suite of structural or depositional patterns and asks the computer to find others like them. In near future, it should be possible for an interpreter to seed a channel on time slice, after which the computer paints it in 3D and eventually, we can expect computers to be able to duplicate all the repetitive processes performed by an interpreter. However, it may be difficult for computers to replicate the creative interpreter imagining depositional environments, structural evolution, diagenetic alteration, and fluid migration. **[Chopra and Marfurt, 2005].**

Coherence measures applied to 3D seismic data volumes have proven to be an effective method, for imaging geological discontinuities such as faults and stratigraphic features. By removing the seismic wavelet from the data, seismic coherence offers interpreters a different perspective, often exposing subtle features not readily apparent in the seismic data **[Gersztenkkorn and Marfurt, 1999].**

Cross-correlation, semblance, and eigenstructure algorithms have been used to estimate coherency. The first two algorithms calculate coherency over a multiplicity of trial time lags or dips, with the dip having the highest coherency corresponding to the local dip of the reflector. The original eigenstructure algorithm calculated coherency along an implicitly flat horizon. Although generalizing the eigenstructure algorithm to search over a range of test dips allowed to image, coherency in the presence of steeply dipping structures, it was found that this generalization also degenerated the quality of the fault images in flatter dip areas **[Marfurt et al, 1999].**

A more robust, multi-trace, semblance based coherency algorithm allows analyzing data of lesser quality than the original three-trace cross-correlation based algorithm. This second-generation, semblance-based coherency algorithm provides improved vertical resolution over the original zero mean cross-correlation algorithm, resulting in reduced mixing of overlying or underlying stratigraphic features using as narrow a time window as possible, typically determined by highest usable frequency in the input seismic data **[Marfurt et al, 1998].**

The automatic tracking of seismic horizons widely available in commercial software provided first insight into the problem of interpretation automation for geological faults. It became obvious with horizon auto-trackers that the tracking frequently breaks down at fault boundaries. There are gaps observed in the resulting interpreted surface visible as non-picked areas and there are large time jumps when the auto-tracker picks an erroneous event. When the horizon being tracked encounters a fault that has a displacement equal in time to some multiple of dominant frequency, the algorithm is not able to distinguish the alignment of seismic character across the fault without additional information given regarding the presence of faulted surface being recognized. Using a larger window, encompassing more of the wave train could potentially capture the offset on neighborhood events. Or a more sophisticated approach could use simultaneous tracking of multiple horizons, reducing the likelihood for misalignment.

Most automatic horizon tracking applications included cross-correlation or waveform based tracking algorithms to capture the seismic character over a user-controlled window length. These methods also compute a 'quality factor' attribute associated with the horizon pick position, which gave a further indication regarding areas of faulting. The combination of interpretation gaps, large gradient trends, and connected regions of low quality factor produced an excellent visual isolation of the fault geometry, relative to the background horizon structure.

While the fault expression was made visible from the horizon auto-tracking method alone, the means to extract this fault information directly and automatically was not available. A clever approach to isolate the fault information from an auto-picked horizon was to take the inverse of the surface, that is, show only areas where the interpretation does not exist. The fault boundaries for the structural extent of the horizon were clearly visible. This technique is applied to each surface and then linked from between one surface to the next, if a complete fault surface is required. It is not really an automatic process, but does allow an un-biased extraction of faults from a statistically consistent auto-tracker **[Pepper and Bejarnao, 2005].**

In about 1990s there was a community of seismic interpreters who increasingly adapted to tracking horizons in seismic data, using computer based cross-correlation techniques like Zap, 3D Hunt etc. These were user-guided programs basically making use of amplitude similarity. A very good review of the strengths and weaknesses of this method is provided by Don Herron (2000). One of the problems with these auto-tracker programs was the cumbersome task of assigning names to horizons and faults. Further, hand interpretation was appallingly prone to human and machine contouring error. During this time exploration industry had a very high demand for software developers to upgrade the current capabilities of computer-based interpretation **[Stenbach, 2002].**

Le and Nyland (1990) worked on pattern analysis of seismic records and devised three steps in the automated analysis of seismic records as trace-matching, event detection and seismic zoning. The algorithm matches traces by comparing sequences of neighboring traces and edits pairs of peaks identified as similar for consistency in trend across and down the record. By combining connected pairs, the laterally coherent events of varying quality are obtained which divide a record into zones that may have lithologic significance. These zones can be obtained automatically by applying cluster analysis to seismic attributes and other discriminating properties of these events.

Seismic signal processing advanced rapidly during the 1990s, allowing to approach, the problem of fault interpretation in a similar vein as the horizon interpretation was attacked. Bahorich and Farmer (1995) presented 'The Coherency Cube' **[US Patent Number 5,563,949]** technique for imaging discontinuities. They noted that the fault surfaces are distinctly separated from neighboring data, both visually and numerically, enabling auto-picking with the existing horizon auto-tracking software. Lees (1999) directly demonstrated this methodology using voxel-picking algorithm on ‘Seismic cube’ processed with a ‘Semblance’ attribute. Crawford and Medwedeff [**1999, US Patent Number, 5,987,388]** demonstrated extracting the 3D seismic cube by performing linear feature detection on lateral slices through the seismic discontinuity volume. These methods all help us recognize that the fault expression in seismic, after discontinuity processing, is most visible in the time-slice or horizon-slice orientations. Neff et al **[2000, US Patent Number 6,018,498]** introduced a method that uniquely combined many of these elements by estimating a probability factor that a fault exists at a specific spatial location using parallel estimation planes, within the seismic volume, and then following this procedure with an orientation and extraction method based on linear feature detection on time slices.

These attributes indicated that a vertical seismic section may not be the best background canvas for fault interpretation. The processing of seismic attributes highlighted the spatial extent of each fault, allowing accurate manual fault picking on these time-slice images. By connecting the line interpretation on just a few time-slices, a high quality fault surface could be constructed.

An early effort for semi-automatic fault interpretation came from Landmark Graphics Corporation when they introduced FZAP technology in 1997 **[Hutchinson; Simpson et al., US Patent Number 5,537,320]**. This technique allowed users to begin their fault interpretation task by simply ‘seeding’ one or more fault segments on a vertical seismic section, and the automatic operation would perform a cross-correlation on a series of slanted traces derived parallel to the seeded fault segment. The method could be used both for tracking, where no previous fault interpretation existed, or snapping, where an existing fault interpretation would be corrected based on the slant trace cross-correlation algorithm. Each fault surface extracted would need an initial seed point.

The small additional step of executing seeded fault auto-picking on these edge volumes, has been developed more recently. The reason for this technology delay may be in the historical approach of using the seismic interpretation workstation to emulate the 'paper' interpretation from previous years. Seismic workstations have been characteristically used to pick 'fault sticks' on vertical seismic sections and then link the intersection of these fault sticks with the interpreted seismic horizon to develop fault traces. Fault contacts are transferred from their position in the vertical seismic section to their spatial position on a basemap for contouring of the seismic horizon **[Pepper and Bejarnao, 2005].**

A 'seedless' approach to fault segment extraction was presented by **van Bemmel and Pepper [US Patent, 1999, Number5,999,885],** where the gaps and sharp gradients from a horizon interpretation were subjected to a connected body analysis followed by feature testing to deduce likely fault candidates. Through the analysis of multiple horizons, the entire fault framework could be extracted.

More than one hundred of seismic attributes have been invented and more appear each year **[Brown, 2001; Chopra and Marfurt, 2005].** Their great number and variety are daunting and make it difficult to choose which ones to use. Many seismic attributes duplicate each other, or are obscure, unstable, or unreliable, or are purely mathematical quantities, or are not really attributes at all. These unnecessary seismic attributes can be identified through inspection aided by crossplots, histograms, and correlation. Discarding redundant and useless attributes leaves a much-reduced set of attributes that is easier to use **[Barnes, 2007].**

Oil and gas exploration decisions are made based on inferences obtained from seismic data interpretation. The interpretation task is getting very time-consuming as seismic data sets become larger. Image processing tools such as auto-trackers assist manual interpretation of horizons visible boundaries between certain sediment layers in seismic data. Auto-trackers assume data continuities; therefore, their assistance is very limited in areas of discontinuities such as faults **[Admasu and Toennies, 2006].**

A new seismic interpretation methodology based on cognitive vision helps in associating visual characteristics that allow easy identification and detection of geological objects like horizons, faults etc. This is a successful method and easily integrated with Shared Earth Modeling workflows **[Verney et al, 2008].**

With the recent interest and enthusiasm in the industry towards smart wells, intelligent fields, real-time analysis and interpretation of large amounts of data, petroleum industry's need for powerful, robust and intelligent tools has significantly increased. Operations such as asset evaluation, 3-D and 4-D seismic data interpretation, complex multi-lateral drilling design and implementation, log interpretation, the building of geological models, well test design, implementation and interpretation, reservoir modeling, and simulation are being integrated in order to facilitate comprehensive reservoir management. In recent years, artificial intelligence, a branch of computer science, in its many faceted flavors from neural networks to genetic optimization to fuzzy logic, has been taking solid steps towards becoming more and more accepted in the main stream of the oil and gas industry. Artificial Neural Networks have been increasingly used for the process of seismic data interpretation in many ways **[Palaz, 1986; Lacoss et al., 1990].** These systems once provided with appropriate training on the data sets are capable of working with unknown data and providing reasonably accurate response. ANN-based models can assist petroleum engineers in solving some fundamental petroleum engineering problems, such as formation permeability prediction from geophysical well log responses with accuracy comparable to actual core analysis and well test interpretations. They are also capable of addressing case specific problems that may be encountered in the field **[Mohaghegh and Ameri, 1995].** ANNs are interdisciplinary information processing techniques rooted in biology, physics, mathematics, and many other fields of science **[Liu and Liuz, 1998].**

The origin of neural networks can be traced back to the 1940s when psychologists began developing models of human learning, but their use in petroleum industry is quiet recent. With the advent of the computer age in the 1950s, researchers began to program neural network models to simulate the complex interconnections and interactions between neuronal cells in the brain. These models successfully exhibited various types of human learning behavior. However, in 1969, Marvin Minsky (Minsky, 1969) one of the founding fathers of artificial intelligence, showed that the simple neural networks, were incapable of solving simple problems.

This caused stillness in the neural network research for over a decade. It was not until 1980s that these mathematical difficulties were surmounted by introduction of more complex neural network architectures. It was around this time that people began to realize the potential value of neural networks as general purpose problem solvers, over and above their use as biological models. Today, there are several dozen different neural network paradigms available. Neural networks have been exploited to solve exploration and production tasks that were previously only done by humans **[McCormach, 1991].**

The ability of ANNs to track horizons across discontinuities largely depends on how reliably data patterns characterize these horizons. While seismic attributes are commonly used to characterize amplitude peaks forming a seismic horizon, some researchers in the field claim that inherent seismic information is lost in the attribute extraction process and advocate instead the use of raw data (amplitude samples). Benbernou and Warwik investigated the performance of ANNs using both characterization methods (seismic attributes and raw amplitude data), and demonstrated how the complementarity of both seismic attributes and raw data can be exploited in conjunction with other geological information in a fuzzy inference system (FIS) to achieve an enhanced auto-tracking performance **[Benbernou and Warwik, 2007].**

The nonlinearity in engineering systems, the explosion of data, and the fuzziness of information constituted the basic scientific and technological background for the rapid development of ANN theory and applications in late nineties. Zhau and Mendel (1988) presented a seismic signal de-convolution by the Hopfield Network. Baldwin et al (1989) applied neural network simulators to problems in well-log interpretation. There was lot of research work done during this time, applying ANN in fields of seismic data processing, well-log analysis, and gravity and electrical surveys. All branches of geophysics got significantly benefitted by the ability of ANNs to perform non-linear mapping and pattern recognition **[Liu and Liuz, 1998].**

Pattern recognition feature of ANNs was used in seismic interpretation when the multilayer percepteron neural network was trained as a classifier and was applied by Huang (2001) for recognition of three classes of seismic patterns, the bright spot, pinch-out, and horizontal reflections. Seven moments that are invariant to translation, rotation and scale, were employed for feature generation of each seismic pattern. The training set included noise-free, low-noise, and misclassified seismic patterns. The test set included seismic patterns with various noise levels. The multilayer percepteron was initially trained with the training set of noise-free and low-noise seismic patterns. Some misclassified patterns with higher noise level were added to the training set for retraining. The classification and training process was repeated through several stages. This retraining significantly improved the robustness of the network. The converged network at each training stage was applied to the real seismic data at Mississippi Canyon, and the bright spot pattern was detected after retraining at higher noise level. These experiments showed the capability of multilayer percepteron in recognition of seismic patterns **[Huang, 2001].**

Li from University of Saskatchewan, Canada presented multi-attributes pattern recognition for reservoir prediction (Li, 2008). He described a new classification technique to recognize and predict reservoirs from seismic data using support vector machine (SVM) pattern recognition. As the method is data-driven it is especially suitable for use with non-linear multiple-attributes. The method has good generalization ability for cases where the populations are small. Li applied this technique to a 3D seismic dataset for the 'Large Save' oilfield. SVM was trained using 3D seismic multiattributes at known well locations with well test results. The resulting SVM structure was used to make predictions away from the wells. It was demonstrated that this method is less subject to overtraining difficulties and can be used to distinguish between oil and gas reservoirs **[Li, 2008].**

AI (Artificial Intelligence) methods have been used to successfully match all the selected horizons across normal faults in typical seismic images. Work done by Aurnhammer and Tonnies described a model based approach which reduces uncertainties in horizon correlation across faults by introducing global features based on geological constraints. Two optimization methods were examined, an exhaustive search algorithm that reliably delivers the optimal solution and the genetic algorithm **[Aurnhammer and Tonnies, 2000].**

Expert systems are truly the commercial exploitation of the power of AI. Edward Feigenbaum has been considered as father of Expert Systems. A new conceptual approach was presented by Whitney to show use of expert systems to assist in decision making process **[Whitley, 1990].** Main objective of the expert systems is to gather expert knowledge, represent it in appropriate format and make use of it like a human expert to take decisions. The system is also made capable of providing justifications and explanations for the decisions taken **[Angeneyulu, 1998].**

Era of expert systems began with the development of MYCIN used for diagnosing infectious blood diseases. Researchers have since then considered explanation to be one of AI's most valuable contributions. The user's confidence in the derived conclusion can be significantly increased by revealing internal rules that led to it. MYCIN also had a very well organized mechanism of providing explanations for the diagnosis. The explanation queries of MYCIN form the foundation of most expert system explanation systems today. MYCIN presented two forms of explanation – why and how. Users may ask why the system asks a particular question. The system may respond by indicating the rule that it is currently considering. The users may further desire to know, how a system has come up with a particular conclusion, and the expert system needs to justify its conclusion by putting forth, the line of reasoning it has followed **[Wick and Slagle, 1989].**

Object-oriented Modular Expert System Shell (OOMESS) is an expert system shell which was designed with the objective of integrating a production system with object-oriented language. The OOMESS presents itself in the form of a collection of objects with the capability to communicate with each other. It provides system support for the modularization of a large rule base into smaller groups through message passing. The functionality provided by OOMESS includes the accessibility of other rule groups, user-defined objects and the underlying language from the production rules of a rule group **[Cheon Na et al., 1990].**

Object oriented design of an expert system was presented by Xu and coworkers in 1994 through a Synergetic Expert System for Fault Diagnosis (SESFD). SESFD was composed of four sub-ordinate expert systems (SES) and a Meta expert system (MES) **[Xu et al., 1994].** Another expert system using object-oriented framework was developed by Tsang in 1994 for medical domain. This system presented a generic framework for complex medical expert system inference **[Tsang, 1994].**

There are a few formats that have been popular for knowledge representation. One of the methods preferred for representing knowledge in large knowledge-bases is a frame-based representation of facts and rules. Such systems typically connect to external databases that store facts that are loaded into knowledge-base and inference is reached by the inference engine of the expert system. In many cases, such external facts may be required several times for each inference.

Rattanaprateep and Chittayasothorn presented design and implementation of a frame-based object-relational database with a tight coupling between the expert system and the external knowledge-base **[Rattanaprateep and Chittayasothorn, 2007].**

Mendis and coworkers (2009) presented a three phase approach to the development of commonsense knowledge modeling systems for disaster management. Modeling commonsense knowledge is crucial for classifying and presenting unstructured knowledge **[Mendis et al., 2009].**

The applications of expert systems have been in diverse areas. A few assorted examples are included in what follows. Tourist Advisor system is an object oriented intelligent expert system for the tourist information centers. This system was built to recommend a suitable travel schedule that satisfies user input constraints such as time period, budget and preferences. The tourist center officials need to answer similar set of queries in their day-to-day work which has been replaced by this system **[Tsang and Woo, 1996].**

Expert System's capability to effectively present itself like an education tool was demonstrated by an expert system developed to aid the teaching of digital electronics. The techniques described in this system have been adapted to a variety of other similar applications **[Saatchi et al., 1998].** Another similar system developed was a knowledge-based tutoring system for teaching fault analysis to electrical engineering students. The aim of this project was to make teaching and learning more productive and efficient by employing modern technologies. It seeks to find new methods to teach large number of students with no prior fundamental background in the field. The system operates in an active dialog mode with the student, using examples, and providing immediate explanations and feedback to students. It also allows the students to access the learning facility at a time of their convenience. The tutoring system is based on an expert system shell. It provides a functionally interacting set of theory and problems, and supports student progress through monitoring and assessment. This tool has become an extra teaching tool for power engineering students **[Negnevitsky, 1998].**

Another general purpose expert system was a web-based, 'Class Schedule Planner' (CSP) using Java based expert system shell JESS, for the purpose of Class Schedule Planning. Making a class schedule for next semester that takes into account student's interests and meets overall graduation requirements within a time frame is not always easy. An automated tool can help identify mistakes and compare available options. CSP encapsulates class scheduling knowledge and gives intelligent scheduling advises to students. It has a set of web forms to collect inputs from the users and then translates the request into facts. The unique technical contribution of this work was that unlike most other expert systems that require static expert knowledge, this expert system allows dynamic management of knowledge in real time using web interface **[Ho and Lu, 2005].**

Salim and coworkers presented a method called Function Point Analysis (FPA) for evaluation of expert system shells for suitability in Industrial Technology pedagogy. Two types of FPA are described, a direct method in which the Expert System Shell software itself is evaluated and an indirect method in which only the specification of the software is evaluated. Both methods presented are simple and straightforward and have been used by the industrial technology educators with no specialized background in Information Technology and Software Engineering **[Salim et al., 2002].**

Expert systems have wide variety of applications such as in diagnostics and control in the Power Industry. Jain and coworkers presented this system with its GUI, Expert System Shell, and the databases developed by integrating the standardized technologies, such as C#.net, ASP.net, Ms Access Database tools and the dynamic linking library (DLL) files. The knowledge-base required for this package presents extensive data obtained from discussions with experts in different domains of electrical factory and the past historical data of fault occurrences and their clearance at the factory in the form of simple *'if…then'* rules **[Jain et al., 2009]**

Expert systems have been used for evaluating the actual state and future behavior of insulating systems of high voltage electrical machines and equipment. IZOLEX, expert system evaluates high voltage insulating systems of rotating and non-rotating machines and insulating oils. The expert system, CVEX, evaluates the discharge activity on high voltage electrical machines and equipment by means of an off-line measurement. The expert system, CVEXON is for evaluating the discharge activity by on-line measurement and the ALTONEX expert system is for on-line monitoring of rotating machines **[Zalis, 2004].**

A rule-based expert system was designed for steady-state stability analysis of a power system. The key variables, that affect steady-state stability the most, were identified through discussions with operators and engineers in Taiwan Power Company **[Hsu and Su, 1991].**

Use of expert systems has been popular in financial institutions, such as banks, and in areas of savings and loans. A rule-based expert system was designed to optimize check routing with respect to processing costs and fund availabilities. The system was developed on IBM AY400 system using IBM's Knowledge Tool. The actual knowledge elicitation had involved a number of item processing experts known as 'float managers' **[Chamberlin et al., 1990].**

Various expert system applications have been developed in Civil engineering domain. One of the knowledge representation methods in expert systems design is Case-based Reasoning. To solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation is the principle behind this representation. A system which uses case-based reasoning in selecting the best bidder for a construction job in an organization was developed by Bhattacharya and Raju (1990).

Another Expert system developed in the field of civil engineering was an interactive expert system called Structural Selection Expert System (SSE) that assists engineers and designers in the choice of the most appropriate structural system for a particular function to meet proposed criteria. It could also be used as a teaching aid for architecture, civil engineering and structural design students. **[Golabchi., 2008].**

Traditional Expert Systems are constructed using a single monolithic software program for a specific application. But when the systems are to be designed for complex and critical requirements, then there is a demand for sophisticated expert system technology. Kumar and coworkers discussed construction of an expert system shell for airborne equipment design. As the present aircrafts take in different equipments for different purposes, it is not feasible to think in terms of independently developed monolithic expert system programs for each of the equipment. To overcome these problems, a complex, competent, generic component based expert system was designed and developed for Airborne Equipment Design **[Kumar et al., 2004].**

Selecting appropriate tools for car assembly lines usually demands hours or even days of expert tool engineers consulting catalogues, examining the joint properties and studying technical guidelines or specifications. The main stream studies in this field have been limited to geometrical accessibility analysis of the joints and despite crucial effect of many other tool parameters, these are rarely taken into account. But Milani and Hamedi, (2008) developed a knowledge-based system where majority of these selection parameters have been considered that help to make the tool assignment process more realistic.

One field which has exploited the functionalities of the expert systems is that of Medical Sciences. Pazzani and Iyer (1997), developed a knowledge-based system for the management of HIV infected patients. CTSHIV (Customized Treatment

Strategies for HIV) is a rule-based expert system that recommends an individualized treatment strategy for HIV patients. Since, the HIV virus mutates rapidly, a patient can develop a resistance to particular antiretroviral agents. CTSHIV contains a knowledge-base that encodes information from the medical literature on drug-resistant mutations. It also contains additional rules that rank and weight combinations of antiretroviral agents based upon antiviral activities, redundant mechanisms of action, and overlapping toxicities **[Pazzani and Iyer., 1997].**

Crain's 'Petro-physical Handbook' has described several expert systems that were developed from 1970 onwards for use of mineral and oil prospecting. One of the expert systems, that was developed 1970s, for log analysis enables the technician to perform complex analyses which, in the past, could only be done with the assistance of a human expert. The knowledge which an analyst brings to bear on a specific problem is very specific to the region being analyzed, and therefore a considerable amount of local knowledge was required for successful analysis. This information was gathered and added to the knowledge base of the expert system. The rules can be classified in one of the three categories: Usage rules, which dictate which method is the best choice for a given data set in a given area, parameter selection rules, which indicate which parameters are to be chosen for analysis, and 'what if' or iterative rules, which help to try alternative methods or assumptions if results were not acceptable on the first attempt. The facts in this system are the known details about the rocks or fluids being analyzed. The heuristics include mathematical rules. The inference engine of the expert system applies these rules comes up with decisions and can display the reasons behind following a particular path, thus overcoming the drawback of a conventional programming system.

In the 1980s an expert system called PROSPECTOR was developed. It was provided with geological, geophysical and geochemical information as input which was supplied by a group that had just terminated exploration of site at Mt.

Tolman in Washington in 1978. PROSPECTOR analyzed these data and suggested that a previously unexplored portion of the site probably contained an ore-grade porphyry molybdenum deposit. Subsequent exploratory drilling confirmed the deposit and thus, PROSPECTOR became the first knowledge-based system to achieve a major commercial success. The weakest part of PROSPECTOR's performance was its failure to recognize the full extent of the deposit it identified **[Crain's Petro-physical handbook, 2005].**

FACIOLOG is one of the open-hole analysis expert system that is used to generate a rock facies description from the electrical log measurements. It works well where rock sample descriptions are available to aid calibration. ELAS is an expert system front end for Amoco's interactive log analysis package, which runs on an IBM mainframe-terminal configuration. The front end was written with the EXPERT tool, and is used to prompt a user through the log analysis steps of the interactive program. Both EXPERT and INLAN, Amoco's interactive log analysis packages were written in FORTRAN. MUDMAN is a program developed by NL Baroid Corp. to assist mud engineers in the field. The inputs to MUDMAN include the specifications of the type of mud needed in a particular well and the chemical and physical properties of the mud. MUDMAN compares the specifications to the actual properties, provides an analysis of drilling problems, and recommends corrective treatments. It was written in OPS5 on DEC computers. Baroid has described MUDMAN as the first expert system sold as a commercial product to the oil industry **[CRAIN's Petro-physical handbook, 2005].**

A fuzzy expert system was developed to solve lost circulation problems **[Sheremetov et al, 2005]** called Smart-Drill.

A significant development has been a dip-meter advisor system which aids interpreters and attempts to emulate human expert performance in an important and specialized oil well-log interpretation **[Davis et al., 1981, Smith and Baker, 1983].** Another expert system, Laser Drilling System Optimizer (LDSO) was developed for laser drilling which resulted in better and faster performance than the conventional rotary drilling technique. **[Ketata et al., 2005]**

AI based Fuzzy logic plays a predominant role in handling ambiguous drilling scenarios. This strategy was used in designing expert system for screening wells that could be drilled underbalanced, and for aiding in the preliminary selection of appropriate underbalanced drilling fluids for a given range of wellbore and reservoir conditions **[Ali et al., 2001].**

SEISIS is a knowledge-based expert system for the automatic segmentation of seismic sections into large regions of common textural properties **[Simaan et al., 1995].** Another system on similar lines has been a rule based system for automatic seismic discrimination **[His-Ho Liu, 1985].**

Remote sensing tools have been extensively used in exploring for various geological and mineral resources. Provided that proper imagery is selected for intended applications, valuable and cost-effective investigations can be made. But, one of the most important factors required to reach the correct interpretation is the expertise factor which is expensive or, even worse, unavailable at times. An experimental prototype expert system was developed by Al-garni and Al-sari, in Saudi Arabia. The system consists of a resident knowledge-base that can totally or partially be activated as working memory. The knowledge-base has been developed as a rule-based system using a LISP based language in a frame representation **[Al-garni and Al-sari., 1994].**

Once reasonably powerful and useful expert systems started being available, the questions about their security, validity and maintainability, started appearing **[O'Leary, 1990; O'Leary et al., 1990; Chee and Power, 1990].**

Fuzzy logic is one of the methods to represent the uncertainty of information and there exist in the literature today many contributions dealing with the incorporation of fuzzy logic in expert systems. Initially, fuzzy logic for uncertainty reasoning was common in small-scale expert systems where number of rules is in the dozens as opposed to hundreds. The more traditional (non-fuzzy) expert systems are able to cope with large numbers of rules by using Rete networks for maintaining matches of all the rules and all the facts. (A Rete network obviates the need to match the rules with the facts on every cycle of the inference engine). Pan and coworkers presented a more general Rete network that is particularly suitable for reasoning with fuzzy logic in a large scale expert system shell. The generalized Rete network consists of a cascade of three networks: the pattern network, the join network, and the evidence aggregation network. The first two layers are modified versions of similar layers for the traditional Rete networks and the last, the aggregation layer, is a new concept that allows fuzzy evidence to be aggregated when fuzzy inferences are made about the same fuzzy variable by different rules **[Pan et al., 1998].**

Artificial Neural Network models can be used to model certain highly non-linear and complex systems. The standalone neural networks have been used in many geophysical systems, but McCormach combined the neural network models with expert systems and conventional programs that take advantage of sophisticated pattern recognition capabilities **[McCormach., 1991].** Wiriyacoonkasem and Esterline presented a comprehensive work indicating the improvement in the performance of an expert system through the use of a neural network, allowing the expert system to learn from experience. Training an expert system to ask questions and reason, over repeated cycles, makes it to avoid asking irrelevant questions and proceed with enough knowledge to reason **[Wiriyacoonkasem and Esterline, 2000].**

Quah and Tan (1994) presented architecture of a hybrid neural network expert system shell. The system was structured around the concept of 'network element' and was aimed at preserving semantic structure of the expert system rules whilst incorporating learning capability of neural networks into the inferencing mechanism. Using this architecture, every rule of the knowledge-base was represented by a one or two layer neural network element. These network elements were dynamically linked up to form the rule-tree during inference drawing process. The system was also able to adjust its inference strategy according to different users and situations. A rule editor provided enabled easy maintenance of neural network rule elements.

With increasing popularity of expert systems being used in a variety of fields, researchers started thinking in terms of a common approach, a platform on which different applications in diverse disciplines could be developed. This gave rise to development of expert system shells.

Yalqinalp and Sterling presented an approach of building embedded languages in Prolog, with special attention on expert system shells. Their work presented the paradigm of meta-programming and reviewed interpreters for embedded languages **[Yalqinalp and Sterling, 1990].**

Nilsen (1990) presented some general experiences made while using expert system shell G2. This shell was used for a particular application, namely a safety assessment and post-trip guidance system intended for the control room of the Forsmark Unit 2 nuclear power plant in Sweden. The main emphasis of the presentation was on real-time aspects and matters concerning data types

AGNESS is an expert system shell developed at the University of Minnesota. It is more general than other shells in that it uses a computation network to represent expert defined rules, and can handle any well-defined inference method. The system works with non-numeric as well as numeric data and shares constructs whenever possible to achieve increased storage efficiency. AGNESS uses a menu-driven interface and has several features that make the system friendly and convenient to use. It was subsequently used to generate several expert systems in the areas of medicine, image processing and mechanical engineering **[Slagle, 1988].**

In 1997, Johnson and Carlis, examined the syntactic similarities and differences of five expert system shell production rule languages. To help knowledge-engineers manage information, they developed a composite production-rule syntax that provides a common language for defining production rules **[Johnson and Carlis, 1997].**

'Flex' (from Logic Programming Associates, UK) is a powerful and versatile expert system. It offers an open-ended knowledge-based solution to business problems. Flex is implemented in Prolog, a high-level rules-based language, and has unlimited access to the power of that underlying technology. It employs a natural language style approach to defining knowledge through the provision of a dedicated Knowledge Specification Language, KSL **[Spenser, 2004].**

As discussed in this chapter we can see that expert systems and even rule-based expert systems have been developed in several areas but none has appeared in open literature on seismic data interpretation. Although auto horizon picking programs, fault recognition programs and several other pieces of software have been developed to deal with specific problems but there appears to be no attempt to develop an overall expert system to interpret the entire seismic maps. This served as motivation to undertake the present exercise where a first step has been taken. An all encompassing prototype is perhaps a few steps away.