An Oil and Gas Decision-Making Taxonomy

Abstract
Business under-performance in the upstream oil and gas industry, and the failure of many decisions to return expected results, has led to a growing interest over the past few years in understanding the impacts of current decision-making tools and processes and their relationship with decision outcomes. Improving oil and gas decision-making is thus, increasingly, seen as reliant on an understanding of what types of decisions are involved, how they should be made in order to be optimal, and how they actually are made in the "real world".

There has been significant work carried out within the discipline of cognitive psychology, observing how people actually make decisions. However, little is known as to whether these general observations apply to decision-making in the upstream oil and gas industry. Nor has there been work on how the results might be used to improve decision-making in the industry. This paper documents the development of a theoretical Oil and Gas Decision Making Taxonomy (OGDMT) that seeks to lay a "level playing field" decision space within which to judge the processes and tools of optimal decision-making as the first step in this research.

The OGDMT builds on established ideas in the human decision-making literature, but is itself novel, and involves four different dimensions: level of investigation; task constraint; value function; and the information structure of the environment. It is concluded that decision scenarios at different places in the taxonomy will likely involve different decision-making tools, data and processes for the achievement of optimal decision-making.

The results of this work can be applied, for example, to the question of whether decisions about reserves should be made using deterministic or probabilistic tools, data and processes.

Introduction
“The last 10 years might be called ‘a decade of unprofitable growth’ for many upstream companies” [1] were the words chosen by Ed Merrow to describe the results of a study that looked at over one thousand upstream oil and gas projects undertaken during the 1990s and the early part of the new century. This conclusion is one reflection on the under-performance of the industry. Searching for ways to improve decision-making in the oil and gas industry is an area that has evolved in response to this concern [2, 3]. Within the discipline of cognitive psychology, much work has been carried out in observing how people actually make decisions [4-7]. However little is known as to how these observations can be applied within the industry, despite recent work beginning to move beyond simply pointing out the ways in which people make decisions and trying to show the applicability of these tendencies to oil and gas decisions [8, 9].

In commenting on decision research, Cooksey made the following pertinent comment: “In decision research, we should not be thinking ‘either-or’ but ‘which, when and why’ with respect to philosophical, theoretical, and methodological stances and with respect to learning from a wide range of disciplines.” [10] p 362.

Essentially, the argument is that discussions or arguments about which decision-making school of thought to follow are not helpful. The real focus should be to think about which decision-making methodology to use as well as when and why that would be the best. The primary premise is that there are optimal processes and tools (Cooksey’s “which”) to use for certain types of decision-making (Cooksey’s “when”). The secondary premise is that Cooksey’s “why” can be answered by showing, from both laboratory and real world experiments, that when decision-making tools and processes are tailored for the type of decision, optimal decision-making will result.

But in order to look at the “which, when and why” of oil and gas decision-making it is first be necessary to determine the decision type. This means there is a need to categorize or classify decisions – something not yet covered in the upstream oil and gas decision-making literature.

A previous effort, to develop a framework or classification of oil and gas decision-making, was attempted by the United Kingdom Offshore Operators Association (UKOOA). In 1999 the association published a set of industry guidelines [11], which were designed to assist operators with a more open, transparent, soundly-based and context-appropriate decision-making process as it related to offshore health, safety and environment (HSE). Called the Decision Support Framework for Major Accident Hazard Safety, it looked at decision context as the basis for making decisions, and even made some recommendations for optimal methodologies. This framework or taxonomy, however, addresses only the more surface engineering based decisions, or what may be termed...
the most downstream of the upstream oil and gas industry, and does not address many of what may be termed the more upstream of upstream decisions. This highlights the need for a more generic decision-making taxonomy that can be used at all positions within the upstream oil and gas decision-making spectrum.

Outside the upstream oil and gas industry a few taxonomies of decision-making have been published to date [12-16]. Addressing similar needs in the information systems, nursing, engineering and strategic decision-making fields, these taxonomies were constructed using empirical or other observational means and are thus specific to their industry. They are not directly transferable to the oil and gas industry. They can, however, be helpful in coming to more clearly understand what dimensions are critical to the classification of such decisions. Those taxonomies that had a minimal number of dimensions are reported as being the most useful, while those with more or more complicated dimensions have not been as successful. By observation an appropriate number of dimensions is approximately four.

This paper documents the development of an Oil and Gas Decision Making Taxonomy (OGDMT) that seeks to lay a “level playing field” decision space within which to judge the processes and tools of optimal decision-making in order to address Cooksey’s “which.” It should be remembered, however, that the aim of developing such a taxonomy has, at its heart, the desire to know how to select appropriate tools, and processes for optimal decision-making according to the type of decision – the “when” and “why”. These aims will be the topic of further research and publication.

Theoretical Background

As with all taxonomies, the root question relates to being able to place objects, or in this case decision types, in more or less homogenous groups in such a way that the relationships within and between the groups can be examined. Which elements are similar and which are dissimilar and the need to decide which dimensions are the “best” ones to use can be very subjective task, but whichever dimensions are chosen, it is critical to be able to reproduce the classification objectively. In the upstream oil and gas industry there are so many diverse decision elements, which could make up a taxonomy, that the potential to sacrifice objectivity for subjective insights or empirical evaluation is great. In order to avoid these possible prejudices a methodological approach used in mathematical psychology [17, 18] – relying on pair-wise similarity measurements – was used.

This process assumes that, by comparing typical oil and gas decisions, the generic or basic dimensions that form the underlying structure of oil and gas decision-making can be uncovered. Comparing various decisions to each other in a pair-wise comparison should, thus, reveal how tightly different decisions group together in the minds of the judges. Mathematical analysis of the clusters of decisions should then uncover what generic dimensions are common to the cluster.

Goldstone [19] indicates that there are two main representational approaches in cognitive modeling of similarity; ‘dimensional’ and ‘featural.’ In the first, dimensional representation, the stimuli are represented by locations in a multi-dimensional space. This is done in continuous values in one or more dimensions. This is done in such a way that the similarity of any stimulus represented in this space to another is related to the distance they are apart. That is, those stimuli that are similar to each other lie near one other and those that are dissimilar are separated from each other [20, 21]. This method, however, is best used to represent low-level perceptual stimuli such as changes in color and lengths of lines rather than the complex decisions that form the individual stimuli of the OGDMT.

The second method, featural representation, is more suited to high-level conceptual stimuli [22-25] because it represents data in a discrete, presences / absence or agreement / disagreement fashion. Here the similarity between two stimuli is a weighted measure of their common or distinctive features. This method, therefore, has the features necessary to assist in developing an OGDMT based on multi-featural decision tasks.

Within featural representation there are two primary approaches, the additive tree approach and the additive clustering approach [17]. In the additive tree, or tree-fitting, approach the data are modeled to represent objects associated with terminal nodes and strictly nested structures. Hence a hierarchy is imposed such that the final result looks similar to the classic Linnaean “tree structure” taxonomy. In the additive clustering approach the stimuli are not constrained to a single cluster, but each can arbitrarily overlap. The two approaches have different strengths and weaknesses. A tree model may represent a higher number of total features but a lower number of shared features. This may be appropriate in representing well know stimuli. But any taxonomy of the upstream oil and gas industry will have very imprecise elements and intuitively more overlap between those elements. Conceptually then, the additive clustering approach should be the most useful. Both, however, will be used to analyze the data in this experiment so as to see all possible solutions prior to deciding on the ultimate solution.

Method

Procedure

To uncover the generic dimensions that would make up an OGDMT using pair-wise similarity comparison a three-phase exercise was developed.

Phase one was aimed at preparing everything necessary for smooth data collection and analysis. Firstly 20 typical upstream oil and gas decision scenarios were constructed. The scenarios were designed to cover the full spectrum of the upstream oil and gas industry and came from the personal experience of the researcher, modified so as not to break confidentiality.

Next, a graphical user interface that could be used to present the scenarios to the participants in a pair-wise fashion and record their responses was developed. The interface and analysis processes were developed using the MATLAB software [26, 27] and were loaded onto a laptop computer to facilitate individual testing. MATLAB was used because the data analysis routines chosen for use had previously been written in that program [28].

Participants were solicited via an open e-mail request to those working in the oil and gas industry in Adelaide. Respondents were accepted on a “first come – first served” basis. The aim was to obtain at least 30 participants to allow...
for the collection of sufficient data to enable statistically meaningful conclusions to be drawn.

Data collection formed the second phase. Once 30 individuals had responded, appointments were made and the exercise was undertaken on an individual basis. At the commencement of the exercise the participant had the purpose explained both vocally and via an Information Sheet. When understood, consent was then obtained using a standard consent form. The participant undertook the exercise on their own but with the researcher available to clarify any misunderstandings. The goal was to have as little discussion with the researcher as possible once the exercise had begun. For each trial, subjects were shown, on the laptop monitor, two of the scenarios and asked to compare their “similarity” on a 5-point scale, using the custom designed graphical user interface (Figure 1). As they recorded their answer, via a mouse click, the next pairing was shown. This continued until they had completed 38 such comparisons at which time the exercise was concluded and their answers stored. The exercise took, on average, 50 minutes to complete.

At the conclusion of all 30 surveys, the data collected were placed in a 20 by 20 similarity matrix (Table 1). The data gathering routines were written such that there were six samples for each pair-wise comparison. The six responses were averaged and normalized to create the individual similarity measure within the similarity matrix. The higher the number in the matrix the more similar the scenarios were considered to be to each other, with a similarity score of 1 indicating that the scenarios were adjudged identical by all participants. It should be noted, however, that the similarity scores of 1 seen in Table 1 for the self-comparisons (Scenario 1 with itself, etc) were not provided by participants but rather filled in by the algorithm.

Three tests for data consistency were built into the routines. Firstly, each participant had at least one pair-wise comparison shown more than once. This facilitated analysis of the respondent’s consistency in their answers. In this exercise, over 40% over respondents chose exactly the same level of similarity the second time they were presented with the same pair-wise comparison. If this measure were expanded to allow one measure of similarity difference the level rose to 60%. Given the extremely imprecise nature of the data, this test-retest reliability was considered sufficiently high to warrant no further action.

Secondly, two scenarios were written as near duplicates of each other. This was designed to ensure that, if the respondents that were presented with the pair-wise comparison between them were answering appropriately, these two scenarios should have the highest similarity measure. This proved correct as the highest similarity measure (0.833) did occur between these two scenarios.

Finally, previous research [28] has shown that it is possible for two similarity matrices to be identical in terms of their individual entries but to have differing precision. This affects the reliability in the number of dimensions that can be placed on the final outcome. As multiple data were collected for each cell in the similarity matrix the average standard deviation of the entire matrix is used to represent the data precision. For this exercise the precision measure is 0.22. This indicates that the data is particularly imprecise – which was expected for this sort of exercise where no correlation was seen prior to the commencement of testing. The software routines used to analyze the data use this precision factor in such a way as to make sure that imprecise data, such as that collected in this exercise, are not over-fitted by an unjustifiably complex model.

Participants

As stated previously, all 30 individual participants were volunteers from within the local oil and gas industry. Table 2 summarizes the relevant data for the group. 67% were male and 33% were female. 53% of participants had less than 5 years of experience (years since undergraduate graduation), 20% had between 5 and 10 years, 7% had between 10 and 15 years and 20% had greater than 15 years of experience. The two major disciplines were split almost equally – 47% having a geosciences background and 53% having an engineering background. These statistics indicate that the volunteer group was fairly representative of the industry in general. The only difference would be that the less than 5 years experience group is more dominant in the survey than in the industry while the greater than 15 years experience group is underrepresented. This, however, is not considered critical to the results.
additive clustering techniques in order to determine which decisions were similar to each other and why. Although the theory for the analysis comes from Shepard’s work the practical algorithms used to analyze the data and display the results, together with the measures of complexity, all come from work previously published by Lee [28].

Determined which cluster best represents the data is achieved using optimization. Of course in these techniques finding the best model is a difficult combinatorial optimization problem, and the best answer cannot always be guaranteed. After each iteration a probability measure is made of the result and is compared with the previous result to determine which has the better probability measure. In the algorithms this measure occurs after each individual iteration in the search for individual similarities. Running the algorithm a second time will often result in another unique solution. In order to determine the optimized solution a simulation algorithm was written that enabled the individual routine to be run numerous times (100 in this case) and the most optimal overall answer saved as the result. Although the algorithms for the individual “runs” were those recorded by Lee [28], the multiple simulation routines were written for this research [27].

Lee [28] also discusses the use of the Variance Accounted For (VAF) and Bayesian Information Criterion (BIC) as quantitative measures of the complexity of the result in determining the optimal number of dimensions. The BIC is basically a VAF measure that has been penalized for complexity, and so, in that sense, subsumes the VAF. Therefore, in this 20-scenario case, the models can vary from the maximum complexity and highest VAF occurring when all 20 scenarios are viewed as being totally independent and the result is 20 dimensions, through to the minimum complexity (as to number of dimensions) and lowest VAF occurring when all 20 scenarios are viewed as being totally dependent and the result will be 1 dimension. Neither of these results, of course, is practical in developing the taxonomy. Rather than use an empirical route of running the model with each solution of number of dimensions (i.e., 20 then 19 then 18, etc) the BIC is used as a Bayesian statistical measure of the preferred result with the model having the minimal BIC being regarded as optimal. Following Ockham’s Razor each new model is only considered after reviewing the trade-offs between accommodating the original data and the complexity of the resultant model as measured by the BIC.

Additive Tree-Fitting
Using the additive tree-fitting algorithm, the optimal number of clusters is five at which point approximately 55% of the variance in the data is accounted for (Figure 2). The five clusters are shown on a tree-fitting structure in Figure 3.

![Figure 2 – Bayesian Information Criterion (left hand scale, solid line) and Percentage of Variance Accounted For (right hand scale, broken line) values for the similarity data using tree-fitting algorithm.](image1)

Additive Clustering
Using the additive clustering algorithm, the optimal number of clusters increases to seven at which point approximately 65% of the variance in the data is accounted for (Figure 4). Although a featural methodology, the seven clusters are best shown on a multidimensional scaling structure (a dimensional methodology construct) in Figure 5 (A – G).

![Figure 3 – Best tree-fitting result with 5 clusters](image2)

![Figure 4 – Bayesian Information Criterion (left hand scale, solid line) and Percentage of Variance Accounted For (right hand scale, broken line) values for the similarity data using additive clustering algorithm.](image3)
Discussion

The aim of using similarity analysis from pair-wise comparisons of decision scenarios was to identify the possible, generic dimensions of an OGDMT. Specifically it was believed that if certain decisions were similar to each other, that is, grouped into one cluster, they might contain a similar element that, in turn, described a dimension along which decisions could be classified.

A review of the five clusters that resulted from the tree-fitting analysis shows a basic similarity within the clusters. The decision scenarios that fall within cluster “I” all have to do with situations that have an impact on the company’s relationships outside itself. Those decisions within cluster “II” all relate to the effects of change – an old system being replaced by something new. Cluster “III” has a series of decisions that concern the need to fix or rectify some previous decision. Several of the decision scenarios were associated with various elements of obtaining new acreage and these decisions fell within cluster “IV.” Finally, one of the most often-discussed decision types characterizes cluster “V” – those relating to the creation of a ranking for capital allocation.

Although a unique conclusion was never envisioned, the tree-fitting similarity analysis yields something very usable, namely, a series of five decision types. But the true test of a taxonomy is whether its types are unique and, thus, if other decision scenarios were created would they naturally fit within the established clusters or would new clusters evolve. Several of the decision scenarios were associated with various elements of obtaining new acreage and these decisions fell within cluster “IV.” Finally, one of the most often-discussed decision types characterizes cluster “V” – those relating to the creation of a ranking for capital allocation.

The theoretical framework suggests that using the additive clustering algorithms, which allow the scenarios to overlap in arbitrary ways, should result in a more robust model. Statistically this is the case as using this modeling technique increases the level of variance accounted for by 10% - up to 65% - in yielding the optimal result. This result suggests that increasing the number of clusters from five to seven whilst also allowing the individual decision scenarios to occur in as many clusters as required better reflects the data. It is, then, critical for the various clusters developed via the clustering algorithms to be analyzed to determine if there is a unique element that groups them together. This is not as straightforward as the tree-fitting analysis.

The first thing that was noticed in the additive clustering data was that, even though the statistics indicate that seven clusters were required to optimally reflect the variety in the data, several of the clusters are, to a large extent, subgroups of other, larger clusters. For example, cluster “E” is subsumed entirely by cluster “C”. Similarly cluster “F” is nearly subsumed by cluster “A” and “G” is nearly subsumed by “C.” The data precision measure of 0.22 – the average standard deviation of the similarity matrix – very strongly controls the optimal solution for the number of clusters. Reducing the measure to 0.10, which is the equivalent of saying that the data are more precise than they are, yields 20 clusters as the optimal result. That is, each scenario is sufficiently different from each other to be considered its own cluster. Although true, this is not helpful in developing the required taxonomy. Freeing up the precision measure to, say, 0.50 reduces the number of clusters to one. Figures 6 and 7 display the relationship between number of clusters and variance in the data that is accounted for (VAF) against the precision measure obtained by reanalyzing the data at various precision measures. These data show that there is a linear relationship between the variance in the data and the precision measure.

![Figure 6 - Percentage of Variance Accounted For (VAF) versus Precision Measure](image)

![Figure 7 - Number of Clusters versus Precision Measure](image)

It was therefore decided to experiment with the resolution at which the scenarios are represented in the hopes of finding a taxonomically usable characterization. Knowing that using a precision measure of 0.22 yielded an optimum of 7 clusters and although accounting for 65% of the variance in the data, was practically unusable and that using a precision measure of 0.5 yielded 1 cluster and accounted for just under 20% of the
variance in the data but equally unusable, it was decided to
reanalysis the data assuming a VAF of 50% which would yield
a precision measure of 0.30989. This reduced the optimal
number of clusters to down to four as shown in Figure 8.

The optimal four clusters would then be “A” (with no
change in make up), “B” (with a very slight change in make
up), “C” (with no change in make up) and “D” (with a slight
change in make up) as shown in Figure 9.

The search for the unique dimensions now becomes much
more straightforward. The element that ties the decision
scenarios of Cluster “A” together can best be expressed in
terms of the UKOOA decision framework [11] and Russo and
Schoemaker’s “pyramid of choice approaches” [29]. Both
systems argue that the lowest level of decision type is the
intuitive or off-repeated decision – done so many times that no
“thinking” is required. There are no decisions of this type in
the scenarios listed. The next level up, are those decisions that
can be reached by straightforward or heuristic procedures.
Cluster “A” decisions all require this level of investigation in
order to achieve successful outcomes whilst all the other
decisions require much more investigation.

Cluster “B” consists of decisions which all have a
singular constraint. Whatever type of decision is being
undertaken, there will be factors that constrain the choices
available to the decision maker. These interact with one
another to determine which decisions are possible and feasible.
The primary constraints that are ubiquitous within
the oil and gas industry are time and capital. Cluster “B”
consists of scenarios in which the only constraint is capital.
All decisions that fall outside cluster “B” have multiple
constraints.

In order to make a choice between two or more options the
decision maker will require some value function that measures
the relative worth of the options against one another. In all of
the decisions that make up Cluster “C” multiple, conflicting
value functions that must be weighed against one another are
required to determine the ‘right’ choice. No, one, single
function can be used. By comparison, all the decisions that
fall outside cluster “C” can be solved using singular value
functions.

Finally, all “real world” decision-making involves a
process of acquiring information, often sought to resolve
conflicts between existing information and uncertainty. This
usually requires time, and may expend other resources. The
usefulness of such searches, then, depends critically on the
availability of information, and the patterns or relationships
between the information items. All of the decisions within
Cluster “D” can be viewed as requiring complex searches
because they are “one offs,” i.e., the situation will only ever
arise once and so the decision to be reached will be unique.
All the decisions outside cluster “D” can be considered
repeatable. That is, the decision situation is not unique and the
acquisition of information to make the decision can take the
same form each time.

In summary, the four generic dimensions that define the
custers of decision scenarios are:

- Level of Investigation,
- Task Constraints,
- Value Functions, and
- Environment Information Structure

Conclusion
An innovative component of the theoretical framework of this
research involves developing an OGDMT for characterizing
decision-making situations in the upstream oil and gas
industry. This taxonomy, although building on established
ideas in the human decision-making literature, is itself novel,
and involves four different components, which are now
reviewed and expanded.

1. Level of Investigation: Humans routinely make
decisions that require different levels of investigation. This
dimension can be thought of in terms of what Russo and
Schoemaker [29] call their “pyramid of choice approaches.” In
describing why they use a pyramid they state:

“We have placed these choices in a “pyramid” to indicate
that higher approaches are used less frequently than lower
ones [and for more important decisions than are lower ones].
The techniques at the lower levels of the pyramid are rapid
and often executed automatically with little attempt to follow a
deliberate process. The higher ones are more time-consuming
and costly, but yield greater accuracy and reliability in
complex environments.” [29] p 134.

Similarly in the oil and gas industry, this dimension covers
the entire spectrum from some types of decisions, which will
require little investigation through to others, which will
require high levels of investigation.

2. Task Constraints: Whatever type of decision is being
made, in the “real world” it is almost always subject to
multiple constraints. These include, most particularly, time
and resource constraints, but there are other constraints that
make various decisions uniquely different from each other.
This dimension is therefore a series of discrete entities. At the
simplest level the constraints impact decisions on an
individual basis but as decisions become more complex it is
likely that there are multiple constraints coming into play. It
is, however, critical that arbitrary constraints are not taken as
real constraints. These may include the age-old “capital
constraint” argument – arguing that there is not enough money to do a project when in reality it is available but simply means someone else (outside the regular decision-making stream) has to approve allocating it. Possible constraints, all discrete entities, could include:

**Time** – Time constraints can impact decisions in differing ways. For example, there may be a cut-off, after which certain choices are no longer available. Alternately, time can interact with other constraints such that the passage of time alters the value of alternatives.

**Capital** – Money, or other resources, can limit which choices, of those potentially available, can actually be afforded. For example, a small company may know of a field with great potential but have insufficient funds to go-ahead by itself, even though that would result in the greatest benefit to the company.

**Availability** – In a world of limited resources, some options may not be made available to some people – simply due to tyrannies of distance or politics. These limitations can reduce the options available to a decision maker just as a lack of money or time can, and can interact with these limitations.

**Complexity** – This constraint determines the amount of calculation required to adequately consider the different options available to the decision maker. This will interact with the other constraints to determine which options can feasibly be explored.

**Technology** – Related to the above constraint of complexity, this refers to the limits on what technology can do in terms of the outcomes of the decision. Some problems may actually be insoluble with current technology.

**Size** – Some decisions could be constrained by the size of the decision. This could be related to complexity but it could also be independent. Some decisions may be very large but still remain rather simple.

**Impact** – Some decisions are only taken if they are judged to have small impacts (instrumentalism). Or the opposite – where only a decision expected to have a large impact and “be seen” is made.

**Staff** – Certain levels of staff numbers are required in order to make and implement some decisions

**Skill** – The company may have the staff numbers but some decisions cannot be made unless the staff has a certain level of skill.

**Political** – This refers to the State being a constraint on decision-making. Native title curbing access to some onshore land in Australia is an example of a political constraint.

3. **Value Function:** “real world” decisions can usually succeed or fail in numbers of different ways, with different penalties and rewards for different outcomes. Value functions define the various costs and benefits that relate a decision to the environment in which the decision is made. In order to make a choice between two or more options, as is required of a decision maker; they require some value function that measures the relative worth of the options against one another. In fact, a single decision maker will often have multiple, conflicting value functions that must be weighed against one another to determine the ‘right’ choice. These various functions are all discrete entities. Some of the value functions that are common include:

**Utility** – The most commonly used type of value function is utility, where the economic value of a project is calculated using estimates of the various parameters that affect such and compared with its cost and discounting measures. This is the primary, normative standard against which decisions are measured.

**Environmental** – Companies have reconciled their understanding of the fact that their ongoing operations do not exist in isolation from their surrounding environments, and that negative impacts and inefficiencies arise from thinking of the environment as a pure “cost” versus a competitive “profit” centre. In response, many upstream oil and gas companies have implemented, or are in the process of adopting, innovative approaches to maximizing environmental sources of value, such as environmental impact assessment (EIA), and environmental management systems (EMS).

**Social** – This function involves being clear about the company’s as well as society’s purpose and taking into consideration the needs of all the company’s stakeholders – shareholders, customers, employees, business partners, governments, local communities and the public. There is a moral or ethical dimension to this function as well.

**Personal** – Personal value functions are those of the people involved in the decision process. In addition to the assumed goal of maximizing utility, people are often engaged in politicking to better their own standing in the company. Thus, decisions are also made according to which outcome will most benefit the decision maker, not just the company.

4. **Environment Information Structure:** A key dimension of any complete decision-making taxonomy, but one that is often overlooked, involves the information structure of the environment in which the decision is made. All “real world” decision-making involves a process of acquiring information, often sought to resolve conflicts between existing information and uncertainty. This usually requires time, and may expend other resources. The usefulness of such a search, then, depends critically on the structure of the availability of information, and the patterns or relationships between the information items. For example, if each new piece of information is novel and useful, then further search is useful whereas finding more and more data that supports the same conclusion (i.e., where high dependencies exist) is less useful and dictates a different optimal search procedure. These observations apply even if a decision is not subject to time or resource constraints or has a value function with large rewards and penalties for successful and unsuccessful outcomes. For this reason, characterizing the information structure of a decision-making environment plays a central role in understanding how decisions should be made. An added complexity is that although, in general, the information structure may relate to the decision type this is not necessarily the case.

The OGDMT, then, has four dimensions – two continuums (level of investigation and environment information structure) and two discrete (task constraint and value function). In order to display the taxonomy as a template upon which varying decision types can be displayed it is necessary to display the two discrete dimensions as the increasing number of either constraints or value functions. The proposed taxonomy template is shown as Figure 10. This taxonomy sets up a
“level playing field” against which “real world” decision-making can be compared with theoretical decision-making. Any new decision-making scenario can thus be considered in terms of their properties along each of these four dimensions in order to be characterized as belonging in a particular area of the OGDTM.

Ongoing Research

It was concluded that decision scenarios at different places in the taxonomy or, different shapes on the taxonomy template, will likely involve different decision-making tools, data and processes for the achievement of optimal decision-making [30]. Each of the dimensions within the taxonomy, or on the template, can be analyzed in the psychology laboratory in order to determine the optimal tools and processes associated with it.

Hence the next stage of the research will be to analyze the laboratory results for key decision types and see how they relate to the “real world.” For example, the decision to go ahead and develop an oil and gas discovery may be subject to a long, rigorous, high-level investigation process involving many value functions, the investment of billions of dollars as well as many other task constraints, but be similar to other developments undertaken by the company. This may be characterized on the template as a block shape, or decision type, as shown in Figure 11. On the other hand, decisions around optimizing the production from an existing oil well may be repetitively made on a daily basis, at low cost and have relatively small consequences. These may be described as boot type decisions on the taxonomy template (Figure 12). Finally, the results of this work may be applied to the question of reserves, which may be characterized as crescent type decisions (Figure 13). Further research into the theoretically best tools and processes for this shape, or decision type, on the taxonomy will add to the discussion on whether decisions about reserves should be made using deterministic or probabilistic tools, data and processes.

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