Reservoir Characterization III

Proceedings
Third International
Reservoir Characterization Technical Conference
Tulsa, Oklahoma
November 3-5, 1991

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PennWell Books
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Tulsa, Oklahoma

SCREENING ENHANCED OIL RECOVERY METHODS WITH FUZZY LOGIC

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ABSTRACT

Three reasons many potential users argue against using expert systems for solving problems are (1) because of the relatively high cost of specialized LISP Machines and the large expert system shells written for them; (2) because some expert systems are used for jobs that the average professional could do with a relatively short literature search, a few hours of reading, and a few calculations; and (3) because some classical "crisp" rule-based expert systems are limited by their inflexible representation of human decision making, which is sometimes needed in problem solving. This paper demonstrates how a

small, but useful expert system can be written with inexpensive shells that will run on inexpensive personal computers.

Rule-based expert assistants have been developed to help petroleum engineers screen possible enhanced oil recovery (EOR) candidate processes. Though the final candidate process is selected on the basis of an economic evaluation, the expert assistant greatly reduces the amount of work involved. Rather than having to do exhaustive economic calculations for all possible processes, the work is reduced to an economic comparison between two ar three candidates.

This manuscript describes how a classical expert system is used to solve some sample EOR screening problems. The expert system approach is compared with standard hand calculations that were performed using various graphs and charts. The manuscript also shows the advantages of the expert system method, solves several EOR screening problems using both the crisp expert system and the more flexible "fuzzy" expert system, and compares the two approaches.

I. INTRODUCTION

Reasons for studying enhanced oil recovery (EOR) techniques are summarized in a 1986 paper by Stosur (1). When his paper was published, only 27% of all the oil discovered in the United States had been produced. Under current economic conditions, only about 6% more will be produced using existing technology. The remaining 67% is a target for EOR. Currently, about 6% of our daily oil production comes from EOR. Even in these times of reduced concern of an energy crisis, these numbers indicate that the study of EOR processes can be rewarding because of the potentially high payoffs.

Because, in general, EOR processes are expensive, it is necessary for engineers to pick the best recovery method for the reservoir in question to optimize profits or to make any profits at all. The screening methods are expensive and typically involve many steps, one of which is to consult the technical screening guide; this screening step is the subject of this paper. Screening guides consist of tables or charts that list the rules of thumb for picking a proper EOR technique as a function of reservoir and crude oil properties. Once a candidate EOR techniques is determined, further laboratory flow studies are often required. Data obtained from these studies are then used to demonstrate the viability of the selected technique. Throughout the screening process, economic evaluations are carried out .

In this paper, we present two expert systems for screening of EOR processes. In the first, we developed a crisp, rule-based assistant, which replaces the previously published screening guides. It provides essentially the same information as the table and graph method, but is more comprehensive and easier to use than the screening guides. The second, fuzzy expert assistant was then developed to eliminate some of the weaknesses observed in the first expert system. At the end of the test session, both of these expert assistants provide users with a ranked list of potential techniques. This is difficult to do using the tables. With both expert systems, the user must enter oil gravity, viscosity, composition, formation salinity, type, oil saturation, thickness, permeability, depth, temperature, and porosity. Although the final choice of technique will be based upon economics, the first screening step is quite important because the screening process is expensive and because of the absolute necessity of choosing the most economically optimum EOR technique.

II. THE EOR SCREENING PROBLEM

For this study, EOR is defined as any technique that increases production beyond water flooding or gas recycling. This usually involves the injection of an EOR fluid. Both of the expert systems discussed here are rule based and both rely mainly on the work of Taber and Martin (2) and Goodlet et al. (3,4) for their rules.

EOR techniques can be divided into four general categories: thermal, gas injection, chemical flooding, and microbial. Thermal techniques are then subdivided into *in situ* combustion and steam flooding, which require reservoirs with fairly high permeability. Steam flooding has, traditionally, been the most used EOR method. It was previously applied only to relatively shallow reservoirs containing viscous oils. In this application, screening criteria are changing because the improved equipment allows economic operations on deeper formations. New studies show that, in addition to their effect on viscosity and density, steam temperatures also affect other reservoir rock and fluid properties. Thus, reservoirs previously not considered as candidates for steam flooding are being reevaluated. The expert system format is a good one to use here because we can easily change the program as the knowledge of a technology changes. Gas injection techniques, however, are at the opposite extreme from steam flooding. They are divided into hydrocarbon, nitrogen and flue gas, and carbon dioxide. These techniques tend to work best in deep reservoirs containing light oils. Chemical flooding techniques are divided into polymer, surfactant-polymer, and alkaline recovery techniques. Microbial techniques are new, and primarily experimental, at this time. The microbial category is not subdivided. Figure 1 shows all four of these categories and their associated EOR methods as the search tree for both expert assistants.

We often hear the comment, "We have excellent papers on this subject with graphs and tables and information to help us solve the problem. Why do we need an expert system"? Our response is that an expert system is not absolutely necessary, but the problem can be solved more quickly, and often better, with the expert system. Table I, taken directly from Ref. 2, is a matrix of eight EOR techniques and nine EOR criteria.

Theoretically, if the values of the EOR criteria for the reservoir in question are known, engineers can pick some candidate processes from Table I, even without having much

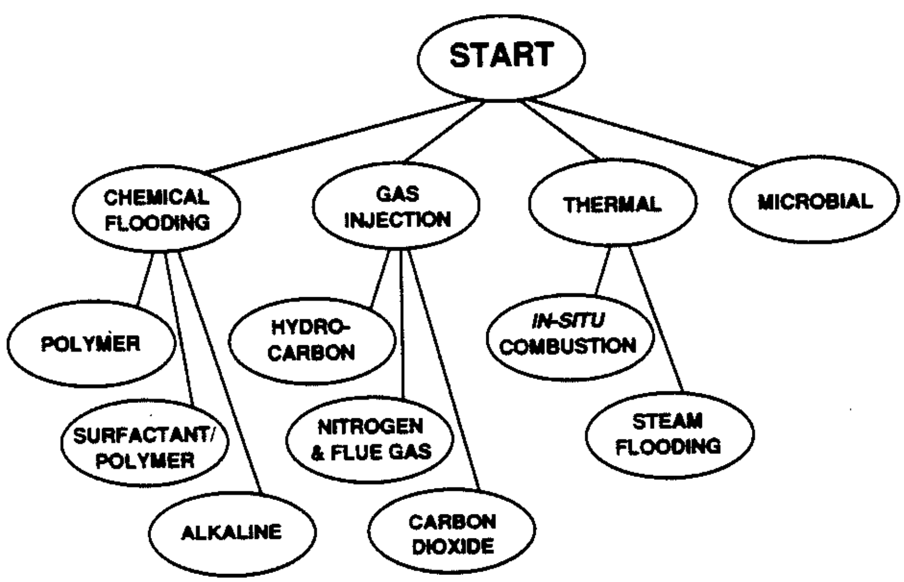


Fig. 1. Search tree for the expert assistants.

TABLE I. Summary for screening criteria for enhanced recovery methods[c]

	Oil Properties			Reservoir Characteristics					
	Gravity °API	Viscosity (cp)	Composition	Oil Saturation	Formation Type	Net Thickness (ft)	Average Permeability (md)	Depth (ft)	Temperature (°F)
Gas Injection Methods									
Hydrocarbon	>35	<10	High % of $C_2 - C_7$	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC NC	<2000 (LPG) to <5000 HP gas	NC
Nitrogen & Flue Gas	>24 >35 for N	<10	High % of $C_1 - C_7$	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC	>4500	NC
Carbon Dioxide	>26	<15	High % of $C_5 - C_{12}$	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC	>2000	NC
Chemical Flooding									
Surfactant/Polymer	>25	<30	Light Intermediates desired	>30% PV	Sandstone preferred	>10	>20	<8000	<175
Polymer	>25	<150	NC	>10% PV Mobile oil	Sandstone preferred Carbonate possible	NC	>10 (normally)	<9000	<200
Alkaline	13–35	<200	Some organic Acids	Agove waterflood residual	Sandstone preferred	NC	>20	<9000	<200
Thermal									
Combustion	<40 (10–25 normally)	<1000	Some asphaltic components	>40–50%PV	Sand or Sandstone with high porosity	>10	>100[a]	>150 preferred	>150 preferred
Steam Flooding	<25	>20	NC	>40–50%PV	Sand or Sandstone with high porosity	>20	>200[b]	300–5000	NC

NC = not critical
[a]Transmissibility >20 md ft/cp
[b]Transmissibility >100 md ft/cp
[c]From reference 2.

knowledge about EOR. The following simple examples show some of the problems with this argument. For Example 1, the following EOR criteria are used with Table I:

Example 1

(1) Gravity = 18 degrees API
(2) Viscosity = 500 cp
(3) Composition = high percent of $C_4 - C_7$
(4) Oil saturation = 50%
(5) Formation type = sandstone
(6) Payzone thickness = 35 ft
(7) Average permeability = 1000 md.
(8) Well depth = 2000 ft
(9) Temperature = 110°F.

If we search the table, starting at the top, and move left-to-right before moving down a row, we are using backward-chaining or a goal-driven method. That is, we first assume a solution (e.g. hydrocarbon gas-injection), then check the data either to verify or to disprove that assumption. On the other hand, a data-driven or forward-chaining approach would begin the search in the upper left-hand corner of the table and would move down, row by row, to the bottom before moving to the next column. That is, the search would start with the datum value for the oil gravity and would check that value against every EOR method before moving on to the other data. In this example, we use backward-chaining to find that steamflooding is the only good method to use for this example. The results of this search are shown in Fig. 2. *In situ* combustion techniques might also work. In Table I the meaning of the statement "greater than 150°F preferred" for the reservoir temperature is not perfectly clear. This is one example of how fuzzy logic can be useful, but we will discuss fuzzy logic further in a later paragraph.

The preceding situation, is not ideal because there is only one candidate for the next screening step, and this candidate could be eliminated, for other reasons, in a later screening step; then there would be no candidate recovery methods for this case. Having a property that is not recommended for EOR is certainly legitimate, but we shouldn't eliminate the possibility of EOR because of too little knowledge. By changing the previous example just a little, we can have the opposite problem, as

Gas Injection Methods	Gravity	Viscosity	Composition	Oil Saturation	Formation Type	Net Thickness	Average Permeability	Depth	Temperature
Hydrocarbon	no								
Nitrogen & Flue Gas	no								
Carbon Dioxide	no								
Chemical Flooding									
Surfactant/Polymer	no								
Polymer	no								
Alkaline	yes	no							
Thermal									
Combustion	yes	yes	yes	yes	yes	yes	yes	yes	no
Steam Flooding	yes	yes	NC	yes	yes	yes	yes	yes	NC

NC = not critical

Fig. 2. Solution to Example Problem 1.

shown in the Example 2, which has the following values for the EOR criteria:

Example 2

(1) Gravity = 35 API
(2) Viscosity = 5 cp
(3) Composition = high percent of $C_4 - C_7$ and some organic acids
(4) Oil saturation = 50%
(5) Formation type = sandstone
(6) Payzone thickness = 10 ft
(7) Average permeability = 1000 md.
(8) Well depth = 5000 ft
(9) Temperature = 150°F.

By searching Table I, again with a backward-chaining technique, we obtain the results shown in Fig. 3. This time only the steamflooding EOR method has been eliminated. This leads us to the second step with, possibly, too many candidates.

This is not a criticism of Ref. 2 or of tables like Table I. In fact, for every case like those in the examples above, there are several cases that will fall in between these extremes. This is merely an effort to point out that in order to do a good first screening step, we will often need more information than is available in these tables. Much of this needed information is available in Refs. 2–4. References 3 and 4 include a tables similar to Table I. Table II contains all of the material from Table I, as well as some of the information from the table in Ref. 4, including the microbial drive EOR method. The additional information improves the results of our search, but is still insufficient. We need information that will tell us what the impact of a reservoir temperature of 110°F will be when a temperature of greater than 150°F is preferred. We also need information that will help us rank two or more methods when the methods fall within the acceptable range. In other words we need a ranked list of methods. A nonexpert can obtain a ranked list by reading the papers, and, possibly, by undertaking a short literature search, in addition to using Table I or II. But the time required for this screening step may be far greater than the few minutes required for searching the tables. If the exercise has to be repeated several times or by several different nonexperts, then a small PC-based expert system can be easily justified for the job.

Gas Injection Methods	Gravity	Viscosity	Composition	Oil Saturation	Formation Type	Net Thickness	Average Permeability	Depth	Temperature
Hydrocarbon	yes	yes	ok	yes	yes	ok	NC	yes	NC
Nitrogen & Flue Gas	yes	yes	ok	yes	yes	ok	NC	yes	NC
Carbon Dioxide	yes	yes	ok	yes	yes	ok	NC	yes	NC
Chemical Flooding									
Surfactant/Polymer	yes	yes	ok	yes	yes	yes	yes	yes	yes
Polymer	yes	yes	NC	yes	yes	NC	yes	yes	yes
Alkaline	yes	yes	ok	yes	yes	NC	yes	yes	yes
Thermal									
Combustion	yes	yes	ok	yes	yes	yes	yes	yes	NC
Steam Flooding	no								

NC = not critical

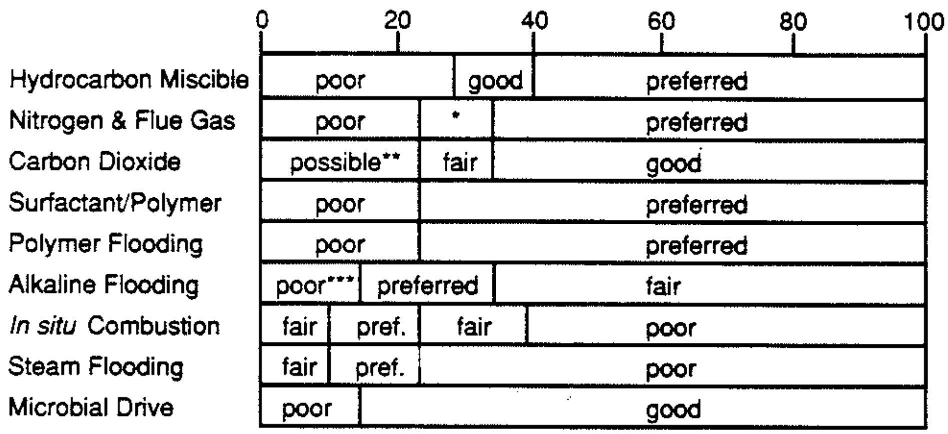
Fig. 3. Solution to Example Problem 2.

TABLE II. Summary for screening criteria for enhanced recovery methods[e]

	Oil Properties				Reservoir Characteristics						
	Gravity °API	Viscosity (cp)	Composition	Salinity (ppm)	Oil Saturation	Formation Type	Net Thickness (ft)	Average Permeability (md)	Depth (ft)	Temperature (°F)	Porosity %
Gas Injection Methods											
Hydrocarbon	>35	<10	High % of $C_2 - C_7$	NC	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC	>2000 (LPG) to >5000 HP gas	NC	NC
Nitrogen & Flue Gas	>24 >35 for N_2	<10	High % of $C_1 - C_7$	NC	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC	>4500	NC	NC
Carbon Dioxide	>26	<15	High % of $C_5 - C_{12}$	NC	>30% PV	Sandstone or Carbonate	Thin unless dipping	NC	>2000	NC	NC
Chemical Flooding											
Surfactant/Polymer	>25	<30	Light Intermediates desired	<140,000	>30% PV	Sandstone Preferred	>10	>20	<8000	<175	>20
Polymer	>25	<150	NC	<100,000	>10% PV Mobile oil	Sandstone Preferred Carbonate possible	NC	>10 (normally)	<9000	<200	≥20
Alkaline	13–35	<200	Some organic Acids	<100,000	Above water-flood residual	Sandstone preferred	NC	>20	<9000	<200	≤20
Thermal											
Combustion	<40 (10–25 normally)	<1000	Some asphaltic components	NC	>40–50%PV	Sand or Sandstone with high porosity	>10	>100[a]	>500	>150 preferred	≥20[c]
Steam Flooding	<25	>20	NC	NC	>40–50%PV	Sand or Sandstone with high porosity	>20	>200[b]	300–5000	NC	≥20[d]
Microbial											
Microbial drive	>15	*	Absence of toxic cone, of metals, No biocides present	<100,000	NC	Sandstone or Carbonate	NC	>150	<8000	<140	—

NC = not critical
[a]Transmissibility >20 md ft/cp
[b]Transmissibility >100 md ft/cp
[c]Ignore if saturation times porosity >0.08
[d]Ignore if saturation times porosity >0.1
[e]Modified from Refs. 2 and 4

Figures 4–14 demonstrate the basis of a scoring system for the various EOR criteria and for the EOR methods used in a first attempt to solve this problem using a crisp rule-based expert system [see reference (5)]. Figures 5, 11, and 12 were taken from Ref. 2 and modified. The others were created by studying Ref. 2 through 4 and 6 through 8. Figures 4–14 are bar graphs showing the relative influence each EOR criterion on each EOR method. The scoring system is empirical and was designed to add some judgement or expertise to the expert system. A great deal of work went into developing this scoring system.



* Minimum preferred, 24 for flue gas and 35 for nitrogen.
** Possible imMiscible gas displacement.
*** No organic acids are present at this gravity.

Fig. 4. Oil gravity screening data (°API).

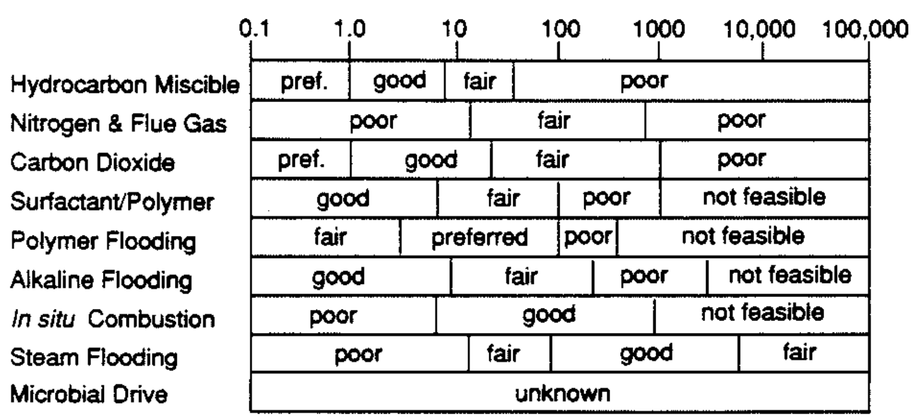
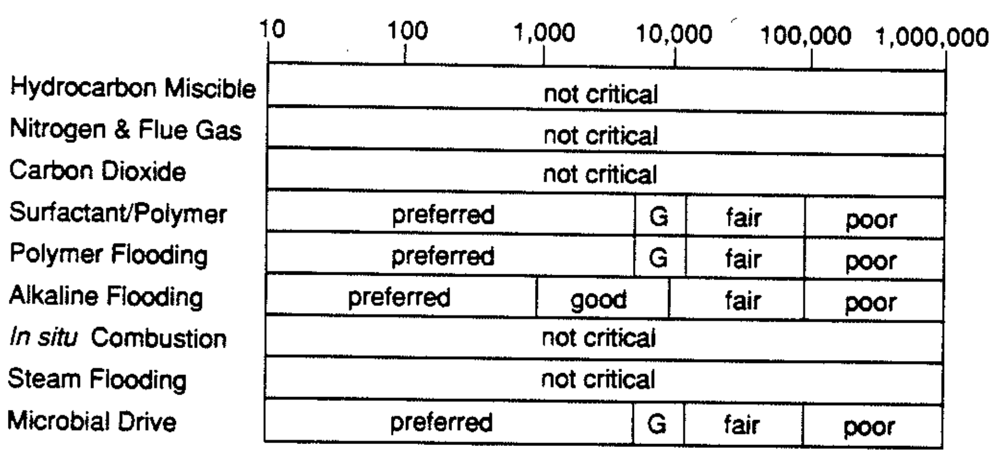


Fig. 5. Oil viscosity screening data (cp).

	High % $C_2 - C_7$	High % $C_1 - C_7$	High % $C_5 - C_{12}$	Organic Acids	Asphaltic Components
Hydrocarbon Miscible	preferred	good	fair	NC	NC
Nitrogen & Flue Gas	good	preferred	fair	NC	NC
Carbon Dioxide	fair	fair	preferred	NC	NC
Surfactant/Polymer	fair	fair	preferred	NC	NC
Polymer Flooding	NC	NC	NC	NC	NC
Alkaline Flooding	NC	NC	NC	preferred	NC
In situ Combustion	NC	NC	NC	NC	preferred
Steam Flooding	NC	NC	NC	NC	NC
Microbial Drive	NC	NC	NC	NC	NC

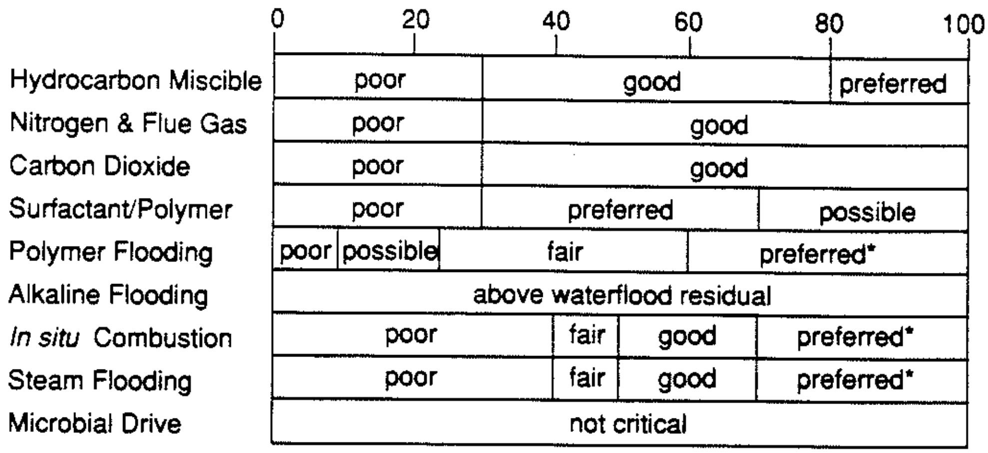
NC = not critical

Fig. 6. Oil composition screening data.



G = good

Fig. 7. Formation salinity screening data (ppm)



*Preferred status is based on the starting residual oil saturations of successfully producing wells as documented by Ref. 8.

Fig. 8. Oil saturation screening data (% PV).

	Sand	Homogeneous Sandstone	Homogeneous Sandstone	Homogeneous Sandstone	Homogeneous Sandstone
Hydrocarbon Miscible	good	good	poor	good	poor
Nitrogen & Flue Gas	good	good	poor	good	poor
Carbon Dioxide	good	good	poor	good	poor
Surfactant/Polymer	preferred	preferred	poor	good	poor
Polymer Flooding	preferred	preferred	good	fair	poor
Alkaline Flooding	poor	preferred	fair	not feasible	not feasible
In situ Combustion	good	good	good	good	fair
Steam Flooding	good	good	fair	good	fair
Microbial Drive	good	good	good	good	poor

Fig. 9. Formation type screening data.

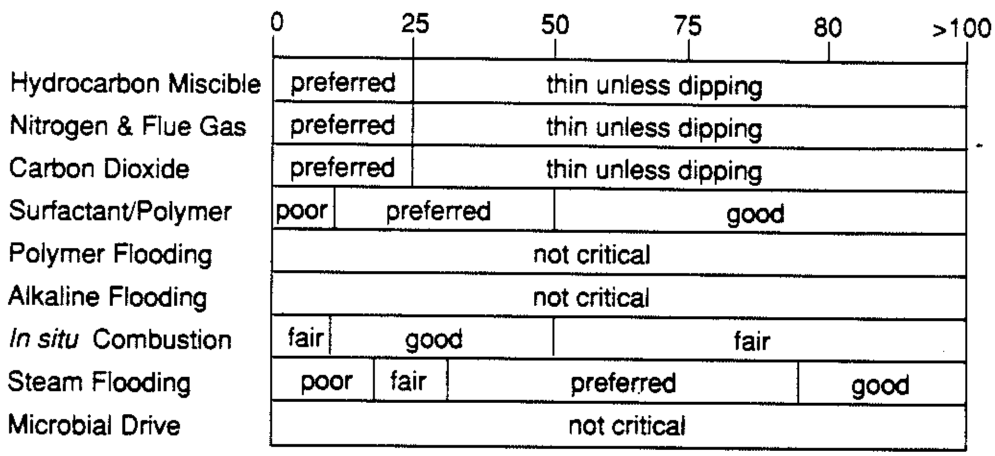


Fig. 10. Net thickness screening data (feet).

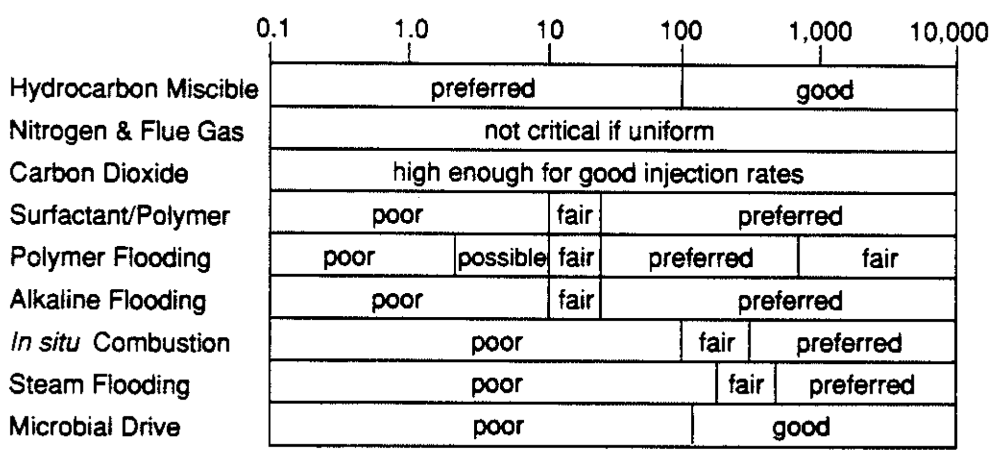


Fig. 11. Permeability screening data (md).

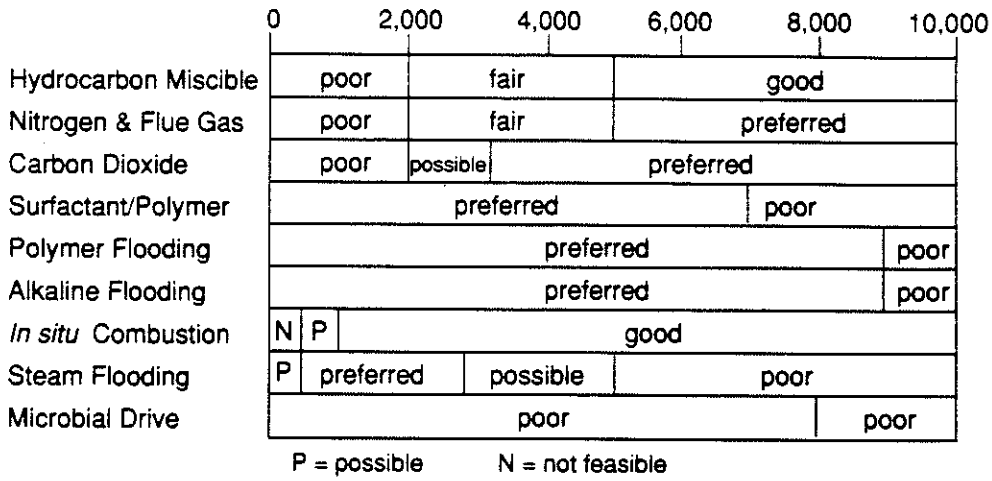


Fig. 12. Well-depth screening data (feet).

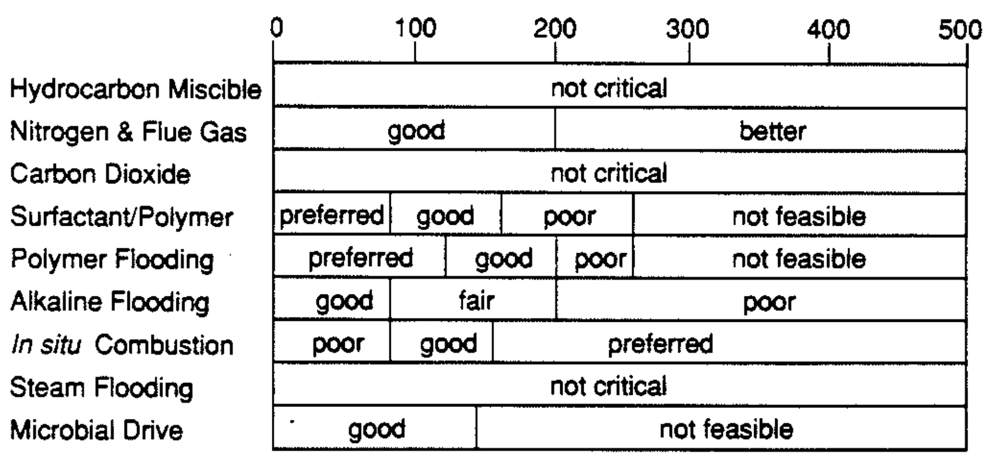


Fig. 13. Formation temperature screening data (°F).

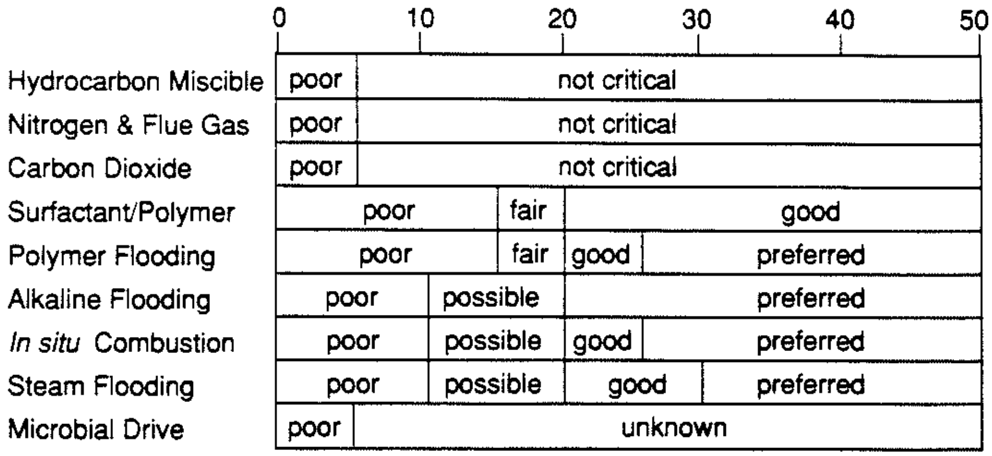


Fig. 14. Formation porosity screening data (%).

The system is a significant improvement over the tables because each category is broken into many increments or sets. However, this system is still not adequate because the sets are crisp and they have a membership of either 0 or 1. This works fine for many problems but not for others. Look, for example, at Fig. 13. The influence of the formation temperature on the microbial drive method is tremendous. With a change of one degree, the choice can go from "Good" to "Not Feasible." This is a change of 60 points. Although there is a temperature above which the bugs die, the demarcation is not that sharp. The crisp scoring system is based on the key words in Figs. 4–14, and works like this:

Not feasible	-50	Fair	6
Very poor	-20	Good	10
Poor	0	Not critical	12
Possible	4	Preferred	15

Note that "Not Critical" is a very good situation to have.

For the microbial drive method, the affect of viscosity, and, to a large extent, porosity, is unknown. Until more information is obtained, they are assigned a grade of 6 for an "Unknown," which is the same score as a "Fair."

For an example of the scoring system, turn to Fig. 5 and consider an oil with a viscosity of about 500 centipoise. The hydrocarbon gas injection, surfactant-polymer, and alkaline chemical flood techniques are all "Poor," with scores of zero.

The other two gas injection techniques, nitrogen and flue gas and carbon dioxide, are both "Fair," with scores of 6. The polymer flooding technique cannot be used with a viscosity this high, so it gets a score of –50. Each of the thermal techniques is "Good," and each gets a score of 10. The microbial drive method has an "Unknown," so it gets a score of 6.

Some EOR criteria carry more weight than others, and, in some cases, a given criteria may affect one method more than another, which explains why the maximum and minimum scores for each method vary within a given criteria (see Fig. 4). The variation in oil gravity allows the score of the hydrocarbon miscible gas injection method to range from "Poor" to "Preferred," a point spread of 0 to 15. The same gravity variation allows the score of the carbon dioxide gas injection method to range from "Possible" to "Good," a point spread of 4 to 10. This indicates that oil gravity has a larger influence on the hydrocarbon miscible method than on the carbon dioxide method. Much of the information in Figs. 4–14 is based on experience and judgement, and it is influenced by the study of the more than 200 EOR projects listed in Ref. 8. The scoring system used in either expert system can easily be changed by someone with different experience or with new information.

Although scoring system described does quite well in most cases, there are some notable exceptions. These are described in the next two examples. Example 3 has the following values for the EOR criteria for two similar scenarios:

Example 3 - Scenario One

(1) Gravity = 23 degrees API
(2) Viscosity = 30 cp
(3) Composition = high percent $C_5 - C_{12}$
(4) Salinity = 101,000 ppm
(5) Oil saturation = 29%
(6) Formation type = sandstone (homogeneous)
(7) Payzone thickness = 26 ft
(8) Average permeability = 24 md
(9) Well depth = 1999 ft
(10) Temperature = 91°F
(11) Porosity = 19%

Scenario Two

(1) Gravity = 24 degrees API
(2) Viscosity = 22 cp
(3) Composition = high percent of $C_5 - C_{12}$
(4) Salinity = 99,000 ppm
(5) Oil Saturation = 31%
(6) Formation type = sandstone (homogeneous)
(7) Payzone thickness = 24 ft
(8) Average permeability = 26 md
(9) Well depth = 2001 ft
(10) Temperature = 89°F
(11) Porosity = 21%

The differences between these two scenarios are hardly measurable. Yet The crisp expert system gives them following rankings and raw scores:

Scenario One (Rankings)

1-	Polymer flooding	102 points
2-	Alkaline flooding	97 points
3-	*In situ* combustion	93 points
4-	Steam flooding	92 points
5-(tie)	Microbial drive	88 points
6-(tie)	Surfactant/polymer	88 points
7-	Carbon dioxide	85 points
8-	Hydrocarbon miscible	77 points
9-	Nitrogen and flue gas	72 points

Scenario Two (Rankings)

1-	Surfactant/polymer	142 points
2-	Polymer flooding	136 points
3-	Alkaline flooding	127 points
4-	Carbon dioxide	116 points
5-	Nitrogen and flue gas	114 points
6-	Hydrocarbon miscible	104 points
7-	Microbial drive	94 points
8-	Steam flooding	83 points
9-	*In situ* combustion	80 points

As you can see, the rankings of these scenarios are completely different. The scores for the second scenario, except for *in situ* combustion and steam flooding, are much higher than those for the first scenario. (The relevance of the magnitude of these scores is discussed at the end of this section.) A verification of these scores and the reason for the differences are shown in Figs. 4–14. These figures show that the scores for many of the EOR methods fall on one side of a crisp boundary in the first scenario and on the other side in the second scenario. The differences are increased because this occurs several times for each method as the expert system searches through the EOR criteria. This example is a worst case. It was set up so that the differences in scores would propagate, rather than cancel, from one criteria to another. But it is realistic in that most measurement techniques are not accurate enough to determine which side of a crisp boundary the data should really be on. The problem is exacerbated by the fact that a small change in the state of an EOR criterion can dramatically influence some EOR methods. For example, Fig. 4 shows that a small change in the API gravity of an oil can change the potential for surfactant/polymer and polymer flooding from "Poor" to "Preferred." Another example is the affect of viscosity on *in situ* combustion (see Fig. 5). A sharp change occurs, from "Poor" to "Good," as the viscosity increases. Another sharp change occurs, from "Good" to "Not Feasible," as the viscosity increases further. Even though these changes are relatively sharp, they are not as crisp as those shown in Figs. 4–14 or as used as those in the crisp expert system.

The scenarios in Example 4 demonstrate yet another related problem. If we add information about salinity and porosity to Example 1 so that we can use all of Figs. 4–14, and if we change the viscosity and the gravity and composition to be consistent with the heavier oil viscosity, we can demonstrate the *in situ* combustion and surfactant/polymer viscosity problems and their related problems.

Example 4 — Scenario One

(1) Gravity = 15 degrees API
(2) Viscosity = 999 cp
(3) Composition = high percent of $C_5 - C_{12}$
(4) Salinity = 50,000 ppm
(5) Oil saturation = 50%
(6) Formation type = sandstone (homogeneous)
(7) Payzone thickness = 35 ft
(8) Average permeability = 1000 md
(9) Well depth = 2000 ft
(10) Temperature = 110°F
(11) Porosity = 28%

Scenario Two

(1) Gravity = 15 degrees API
(2) Viscosity = 1001 cp
(3) Composition = high percent of $C_5 - C_{12}$
(4) Salinity = 50,000 ppm
(5) Oil saturation = 50%
(6) Formation type = sandstone (homogeneous)
(7) Payzone thickness = 35 ft
(8) Average permeability = 1000 md
(9) Well depth = 2000 ft
(10) Temperature = 110°F
(11) Porosity = 28%

The difference between these two scenarios is only 2 centipoise or 0.2% in viscosity. If we list the rankings of the top four methods computed from Scenario One, we find *in situ* combustion ranked second and surfactant/polymer ranked fourth.

Scenario One (Rankings)

1-	Steam flooding	132 points
2-	*In situ* combustion	125 points
3-	Alkaline flooding	117 points
4-	Surfactant/polymer	116 points

Scenario Two (Rankings)

1-	Steam flooding	132 points	
*-	*In situ* combustion	65 points	(Not Feasible)
2-	Alkaline flooding	117 points	
*-	Surfactant/polymer	66 points	(Not Feasible)

With only the small change in viscosity (2 centipoise), the *in situ* combustion and surfactant/polymer techniques drop from the second and fourth ranked methods to ones that are Not Feasible. Even though a rather sharp drop in feasibility occurs, it isn't that sharp if you consider the viscosity increase.

Examples Three and Four demonstrate the kinds of problems experienced by some expert systems decision boundaries. Although there are several ways to reduce these problems, the problem of screening of EOR methods is ideally suited to fuzzy logic. Fuzzy logic is like human logic at those boundaries. Instead of deciding which side to be on, we must weight the average of each side. This makes the transition from one side of the boundary to the other much smoother. The fuzzy logic approach is discussed in the next section.

An important task of the expert system is to give the user meaningful advice about the individual EOR methods on the basis of the raw scores computed by the program. For these expert systems, the raw scores were normalized on the basis of a maximum possible best score of 100% for the best possible process, which is steam flooding. That is, if all methods were to receive the best possible score, steam flooding would get the highest score, with 148 points. It also has the largest number of "Preferred" ratings in Figs. 4–14. The other EOR methods (except the microbial drive) are all rated quite close to the steam flooding method. The raw score of 148 corresponds to 100%. All raw scores are divided by 148 to produce a normalized score relative to the best score possible.

At the end of a session, the scores are tallied, providing the user with a ranked list of candidates to take to the next screening step and an idea of how good the candidates are relative to the best possible score. So far in these examples,both expert systems have given realistic results, except in those cases where the fuzzy decision was important. These expert systems have been run using much of the information given in Ref. 8 for actual EOR projects. In about 60% of the cases run, the method ranked highest by the expert system was the method that was actually selected for and used in that project. In most of the other cases, the actual method used was ranked in the top three by the expert system. This is not too unusual because the actual test data influenced the scores used by the expert system.

Expert systems are often built by comparing the results of the expert system with the results given by the experts, then modifying the system until it is as good as the experts. This approach gives us confidence in the accuracy of the results predicted by the expert systems.

III. EXPERT SYSTEMS AND FUZZY LOGIC

Good texts on artificial intelligence and expert systems (9,10) point out that most real expert systems have to deal with some kind of uncertainty. On the first (crisp) expert system, considerable effort was expended examining the literature and working with raw data to reduce the uncertainty. If, for example, an EOR method gets a "Good" rating for an EOR criterion, that rating is assumed with 100% confidence, to be worth 10 points. Considerable effort went into defining the boundaries of the various ratings within each EOR criteria. For the crisp expert system, each rating block is considered to be a crisp set, that is, either the EOR method gets a particular rating or it doesn't. For instance (see Fig. 4), if the API gravity of the oil is greater than 40, the hydrocarbon miscible method gets a "Preferred" rating. If the gravity is not greater than 40, the method gets some other rating. This works fine as long as the gravity is not near the boundary (in this case 40). But if it is, then some uncertainty arises. For example, what if the gravity is 27, right about the boundary between "Good" and "Poor," for the hydrocarbon miscible method? Should the score be 0 for "Poor" or 10 for "Good"? The crisp expert system makes a decision and assigns a membership, to either "Poor" or "Good," for the hydrocarbon miscible gravity, and the score for the hydrocarbon miscible method is incremented appropriately.

The fuzzy expert system reduces the uncertainty caused by set boundaries by replacing the crisp sets with fuzzy sets. Fuzzy logic is conventional logic, or inference rules, that is applied to fuzzy sets rather than crisp sets. Fuzzy sets are represented by membership functions. Unlike the crisp sets, the value for an EOR criterion for an EOR method can have membership in more than one set. Figures 15–23 are the membership functions, or fuzzy sets, that correspond to the crisp sets in Figs. 4–14.

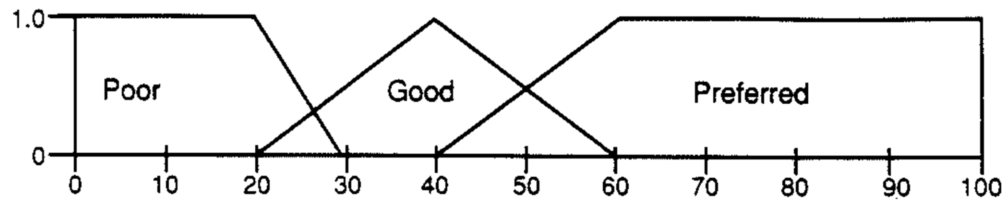


Fig. 15a. Membership functions for gravity for the Hydrocarbon Miscible Method.

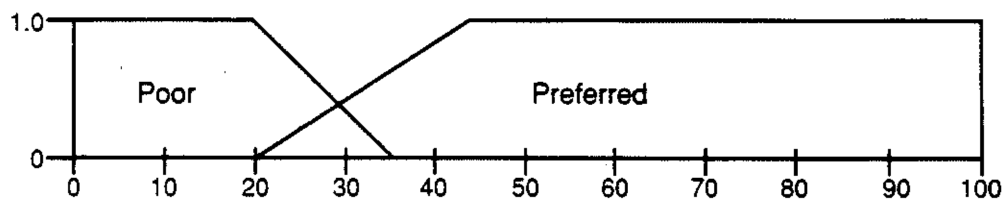


Fig. 15b. Membership functions for gravity for the Nitrogen and Flue Gas Methods.

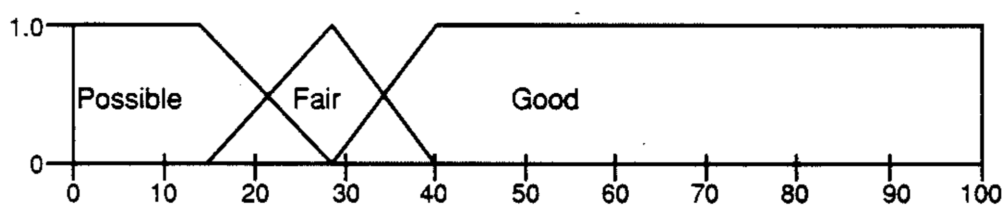


Fig. 15c. Membership functions for gravity for the Carbon Dioxide Method.

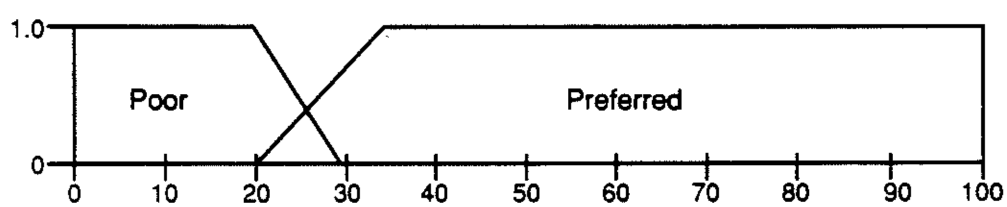


Fig. 15d. Membership functions for gravity for the Surfactant/Polymer and Polymer Flooding Methods.

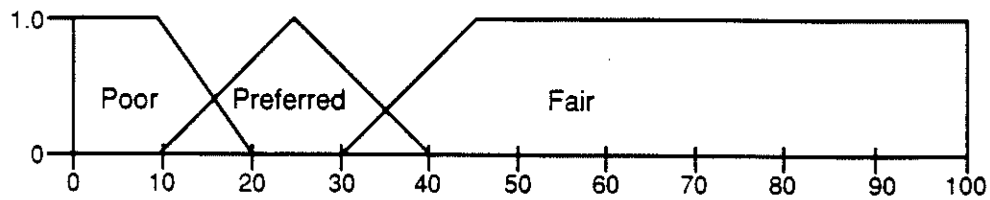


Fig. 15e. Membership functions for the gravity for the Alkaline Flooding Method.

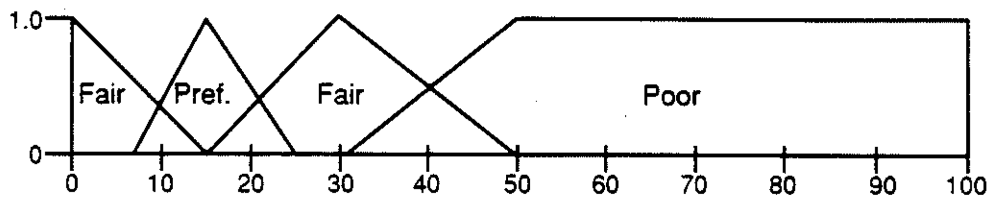


Fig. 15f. Membership functions for the gravity for the *In situ* Combustion Methods.

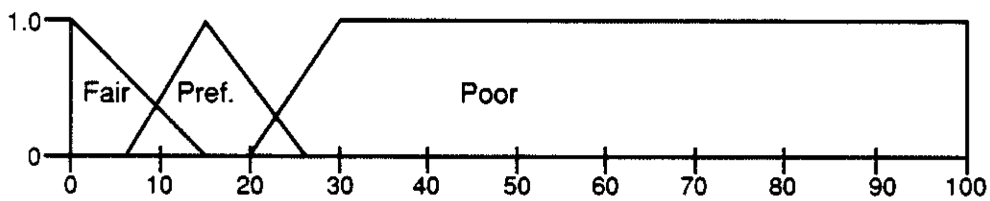


Fig. 15g. Membership functions for the gravity for the Steam Flooding Method.

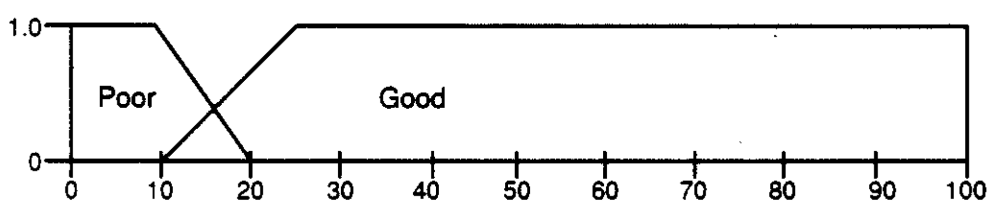


Fig. 15h. Membership functions for the gravity for the Microbial Drive

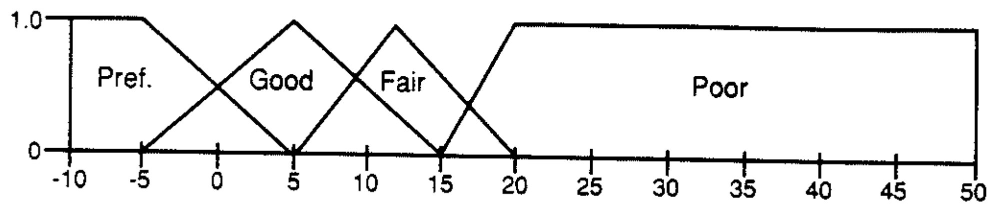


Fig. 16a. Membership functions for viscosity for the Hydrocarbon Miscible Method.

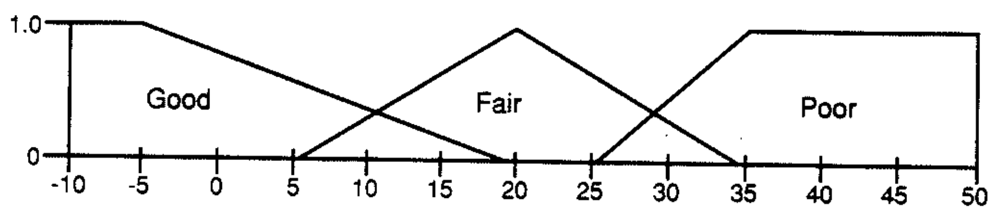


Fig. 16b. Membership functions for viscosity for the Nitrogen and Flue Gas Methods.

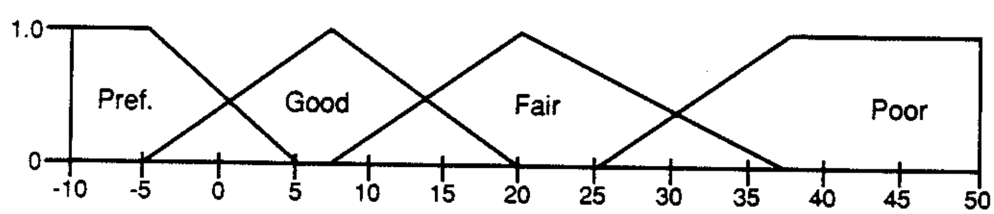


Fig. 16c. Membership functions for viscosity for the Carbon Dioxide Method.

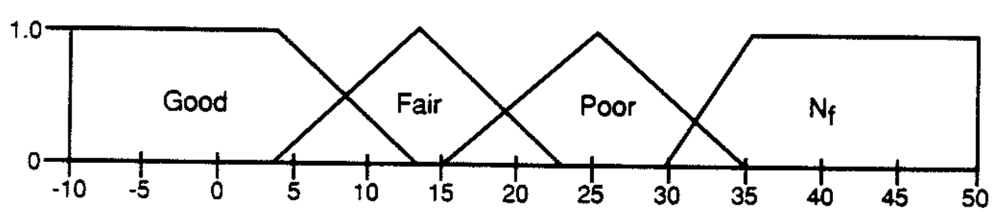


Fig. 16d. Membership functions for viscosity for the Surfactant/Polymer Method.

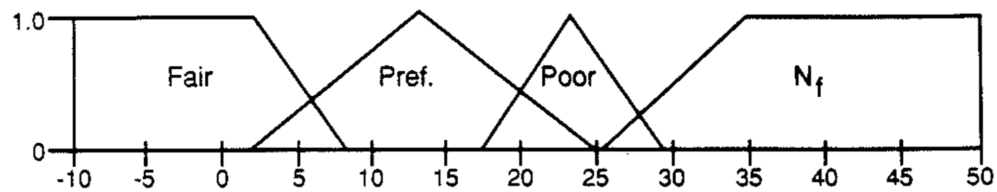


Fig. 16e. Membership functions for the viscosity for the Polymer Flooding Method.

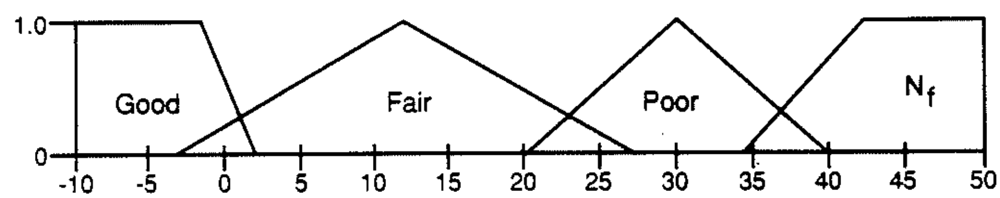


Fig. 16f. Membership functions for viscosity for the Alkaline Flooding Method.

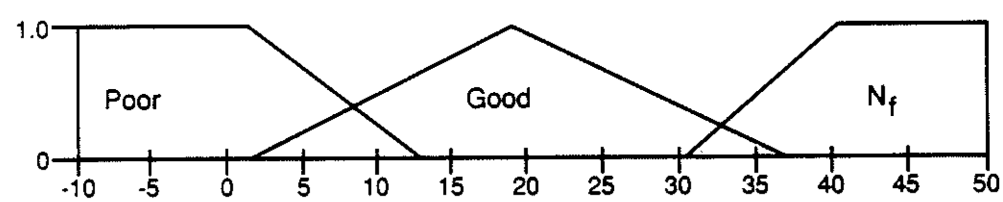


Fig. 16g. Membership functions for the viscosity for the *In Situ* Combustion Method.

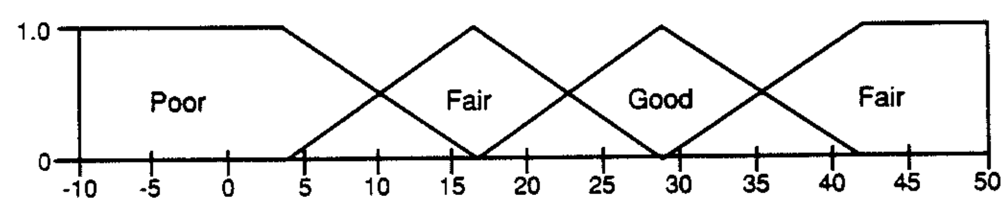


Fig. 16h. Membership functions for the viscosity for the Steam Flooding Method.

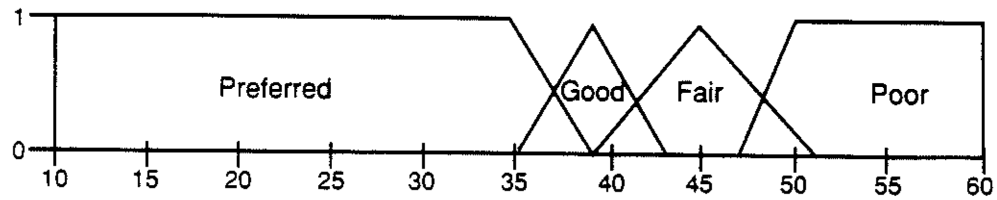


Fig. 17a. Membership functions for salinity for the Surfactant/Polymer Method.

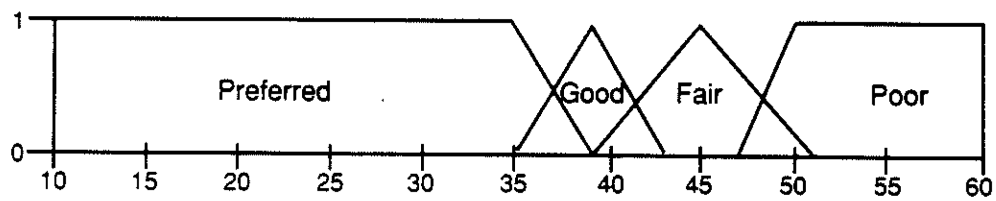


Fig. 17b. Membership functions for salinity for the Polymer Flooding Method.

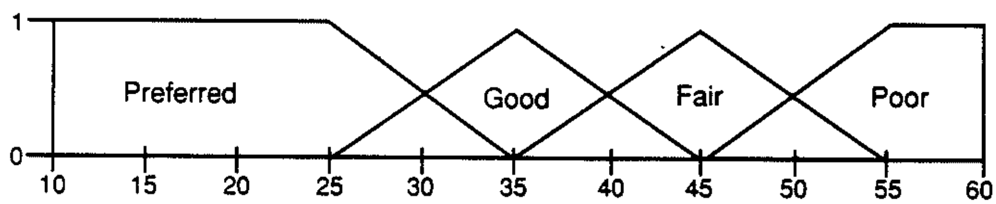


Fig. 17c. Membership functions for salinity for the Alkaline Flooding Method.

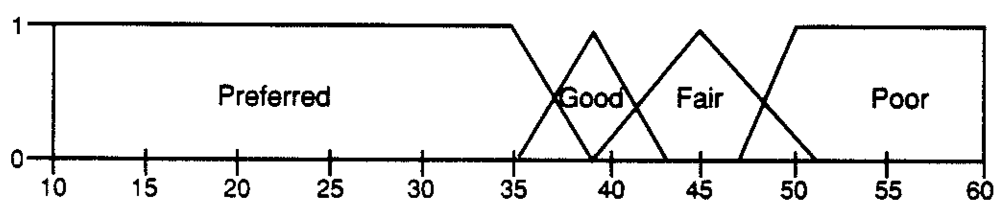


Fig. 17d. Membership functions for salinity for the Microbial Drive Method.

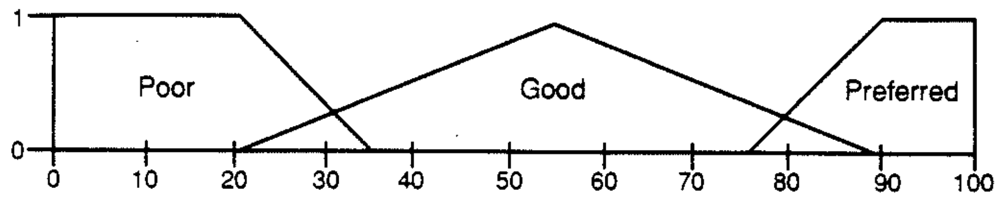


Fig. 18a. Membership functions for oil saturation for the Hydrocarbon Miscible Method.

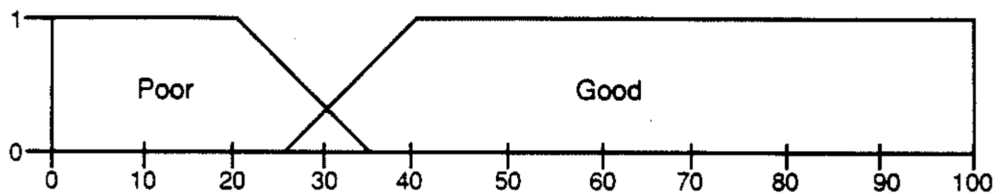


Fig. 18b. Membership functions for oil saturation for the Nitrogen and Flue Gas Method.

Fig. 18c. Membership functions for oil saturation for the Carbon Dioxide Method.

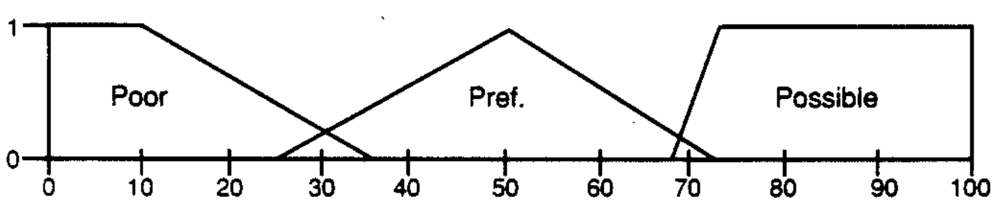


Fig. 18d. Membership functions for oil saturation for the Surfactant/ Polymer Method.

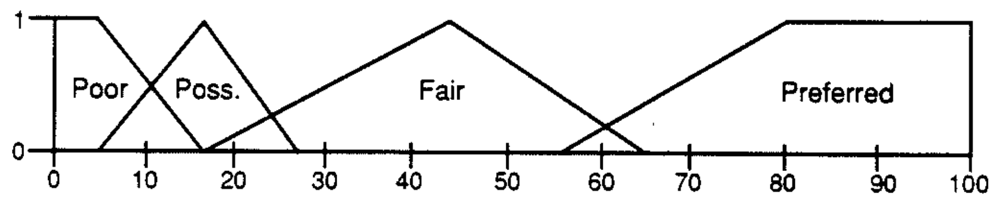


Fig. 18e. Membership functions for oil saturation for the Polymer Flooding Method.

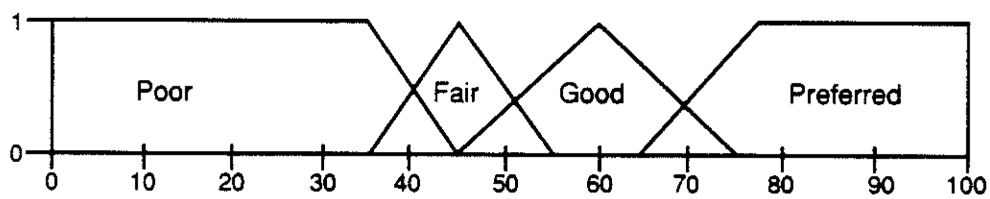


Fig. 18f. Membership functions for oil saturation for the *In situ* Combustion Method.

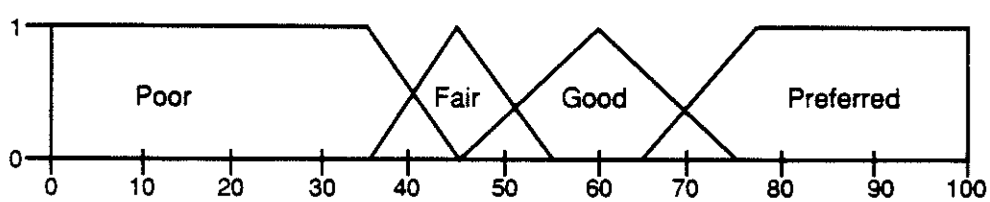


Fig. 18g. Membership functions for oil saturation for the Steam Flooding Method.

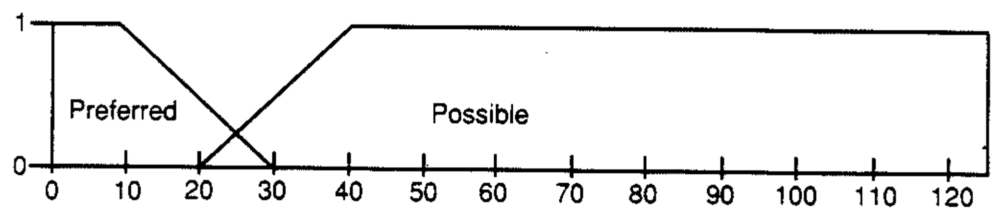


Fig. 19a. Membership functions for thickness for the Hydrocarbon Miscible Method.

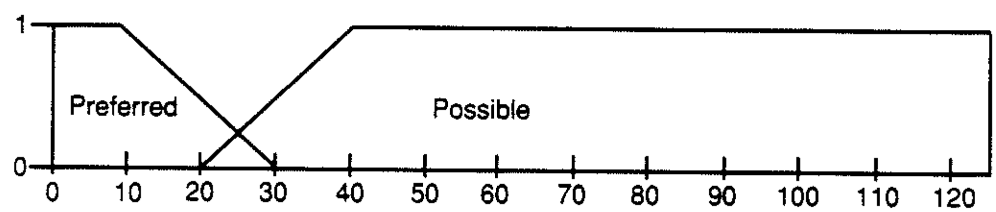


Fig. 19b. Membership functions for thickness for the Nitrogen and Flue Gas Method.

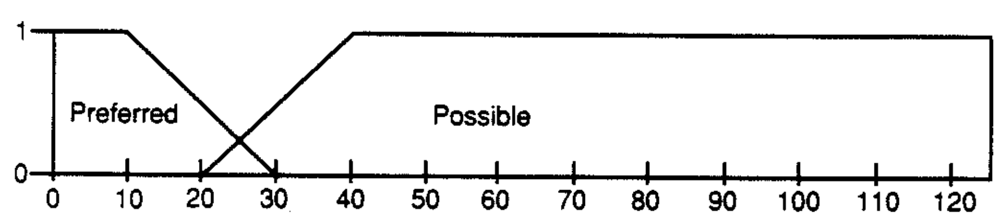


Fig. 19c. Membership functions for thickness for the Carbon Dioxide Method.

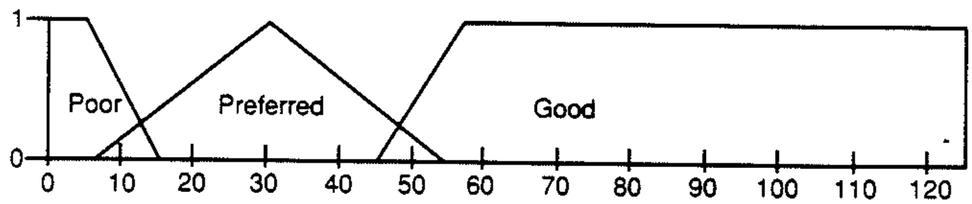


Fig. 19d. Membership functions for thickness for the Surfactant/Polymer Method.

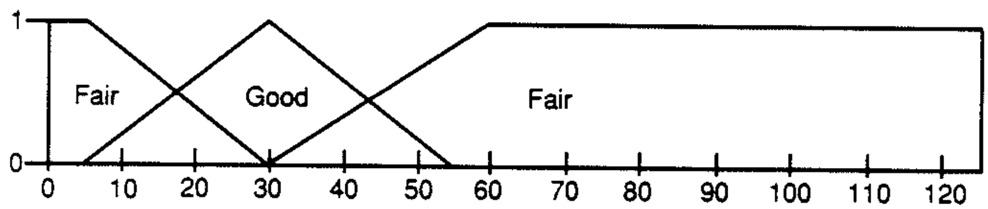


Fig. 19e. Membership functions for thickness for the *In situ* Combustion Method.

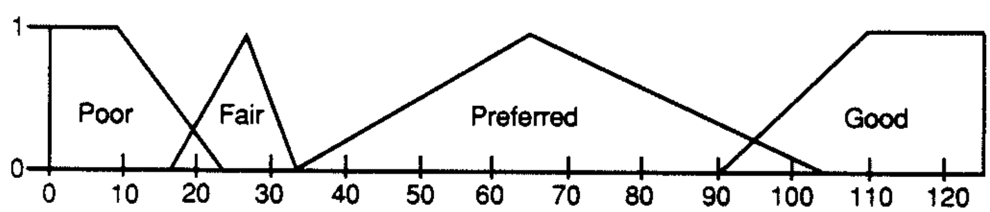


Fig. 19f. Membership functions for thickness for the Steam Flooding Method.

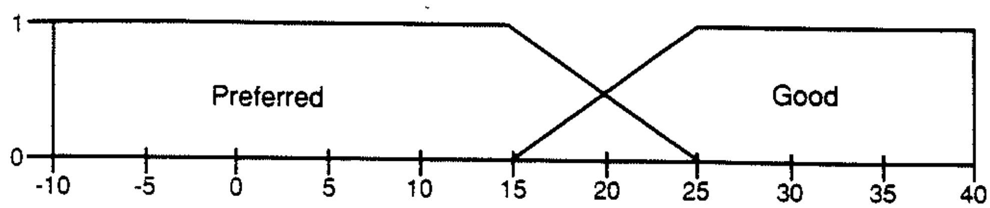


Fig. 20a. Membership functions for permeability for the Hydrocarbon Miscible Method.

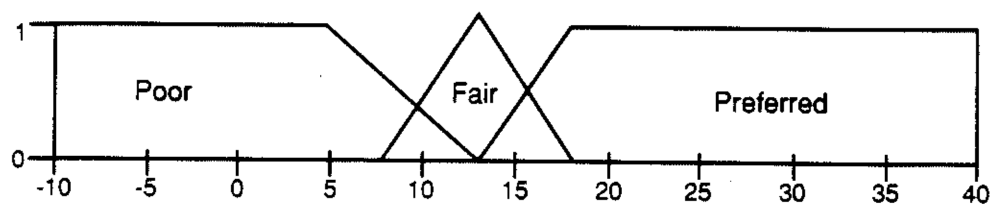


Fig. 20b. Membership functions for permeability for the Surfactant/ Polymer Method.

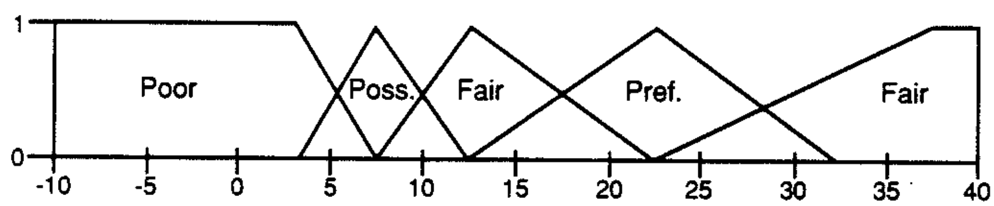


Fig. 20c. Membership functions for permeability for the Polymer Flooding Method.

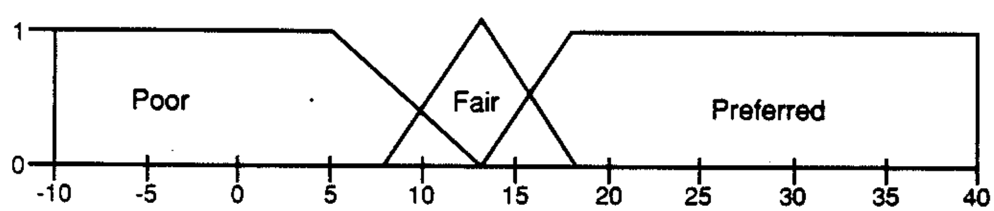


Fig. 20d. Membership functions for permeability for the Alkaline Flooding Method.

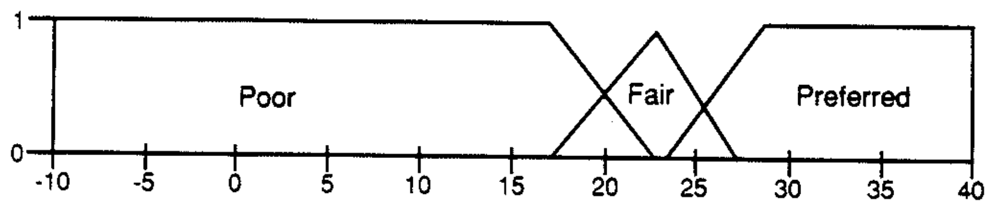


Fig. 20e. Membership functions for permeability for the *In situ* Combustion Method.

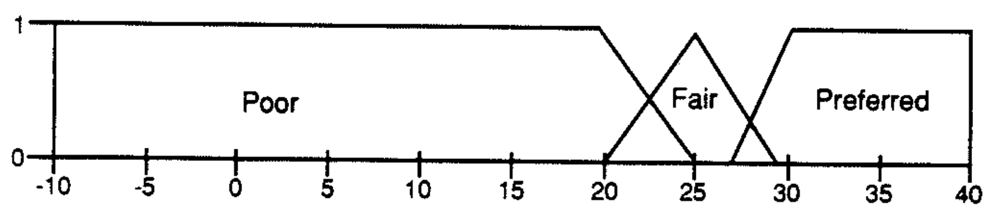


Fig. 20f. Membership functions for permeability for the Steam Flooding Method.

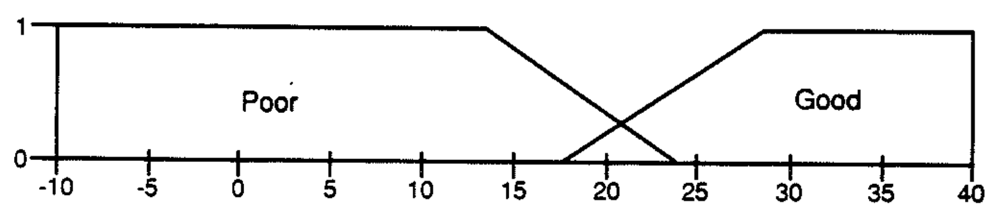


Fig. 20g. Membership functions for permeability for the Microbial Drive Method.

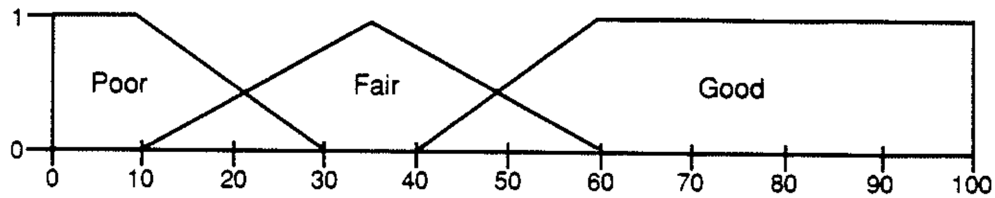


Fig. 21a. Membership functions for depth for the Hydrocarbon Miscible Method.

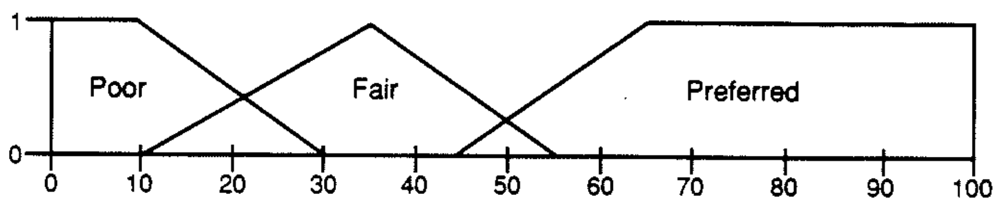


Fig. 21b. Membership functions for depth for the Nitrogen and Flue Gas Method.

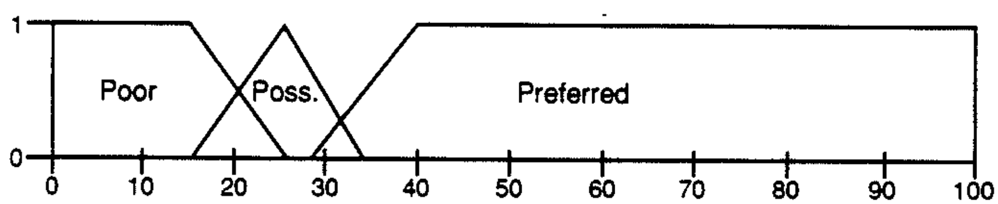


Fig. 21c. Membership functions for depth for the Carbon Dioxide Method.

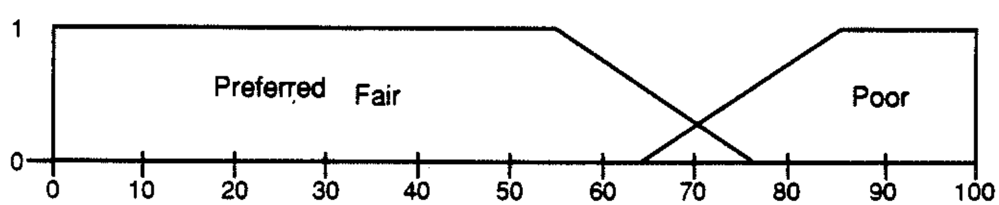


Fig.21d. Membership functions for depth for the Surfactant/Polymer Method.

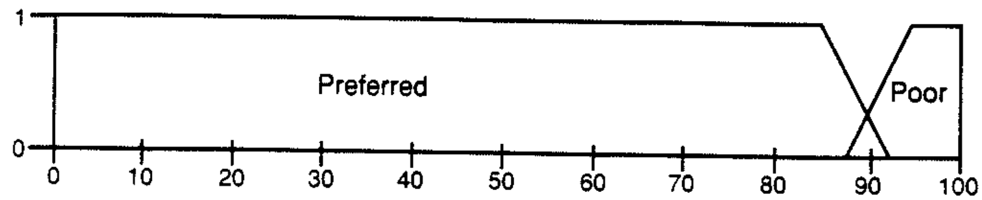


Fig.21e. Membership functions for depth for the Polymer Flooding Method.

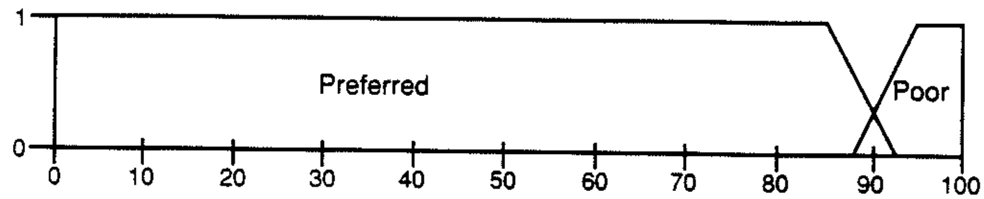


Fig. 21f. Membership functions for depth for the Alkaline Flooding Method.

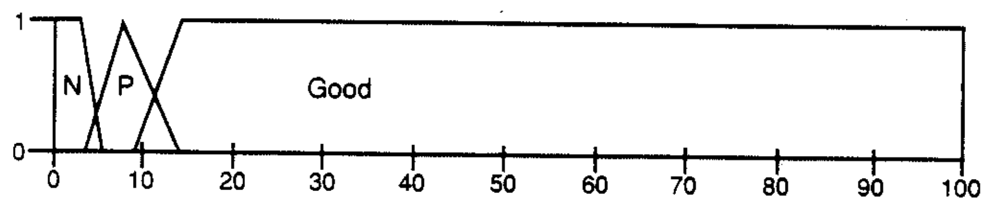


Fig.21g. Membership functions for depth for the In situ Combustion Method.

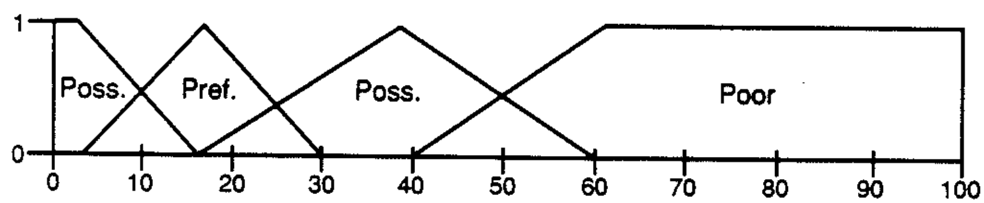


Fig. 21h. Membership functions for depth for the Surfactant/Polymer Method.

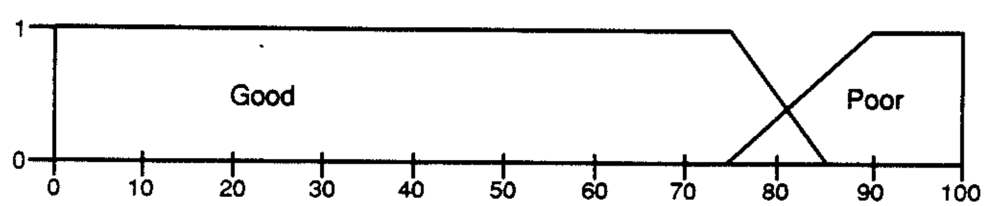


Fig. 21i. Membership functions for depth for the Microbial Drive Method.

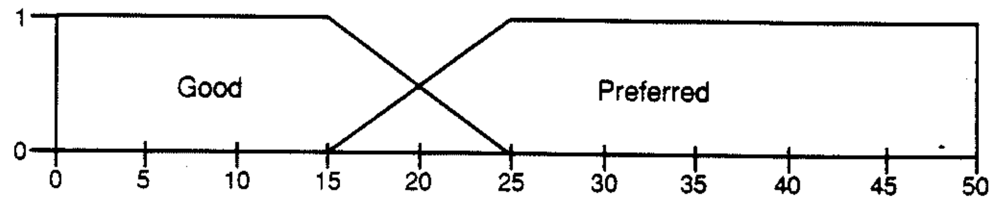


Fig. 22a. Membership functions for temperature for the Nitrogen and Flue Gas Method.

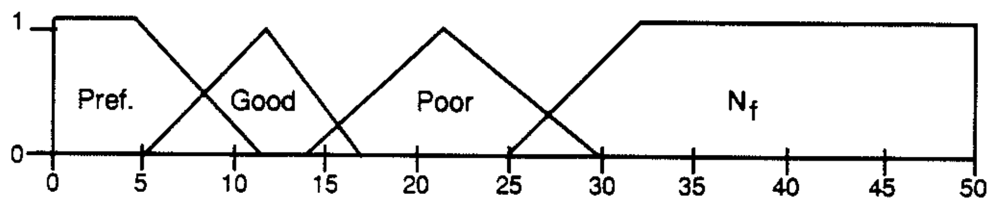


Fig. 22b. Membership functions for temperature for the Surfactant/ Polymer Method.

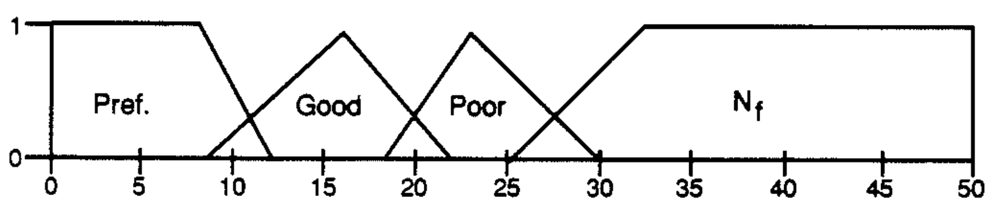


Fig. 22c. Membership functions for temperature for the Polymer Flooding Method.

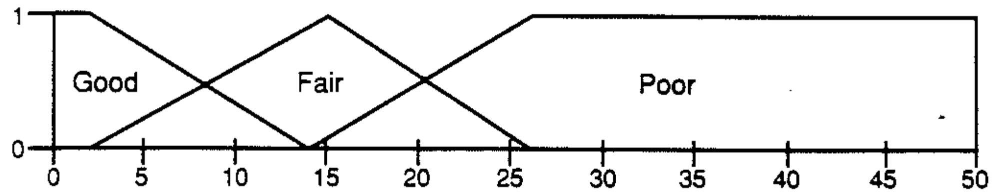


Fig. 22d. Membership functions for temperature for the Alkaline Flooding Method.

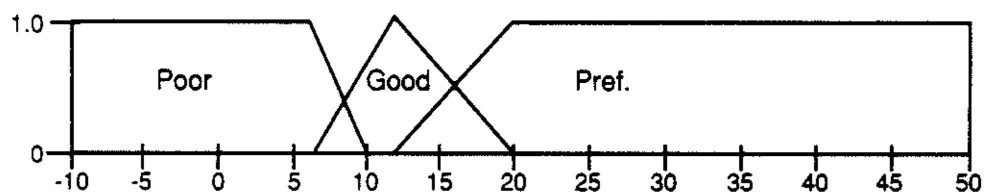


Fig. 22e. Membership functions for temperature for the *In situ* Combustion Method.

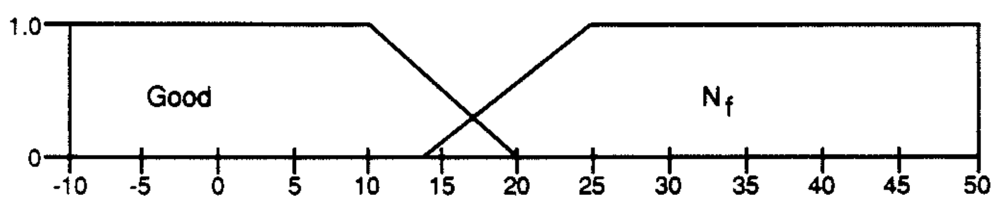


Fig. 22f. Membership functions for temperature for the Microbial Drive Method.

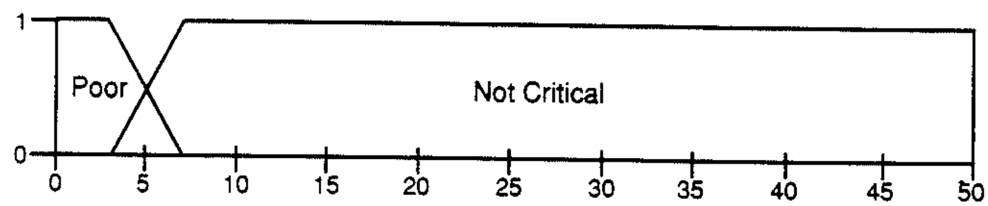


Fig. 23a. Membership functions for porosity for the Hydrocarbon Miscible Method.

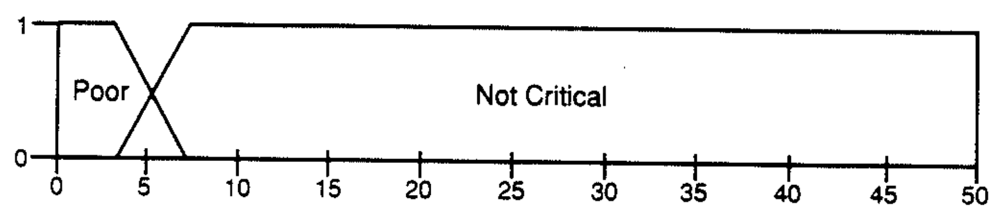


Fig. 23b. Membership functions for porosity for the Nitrogen and Flue Gas Method.

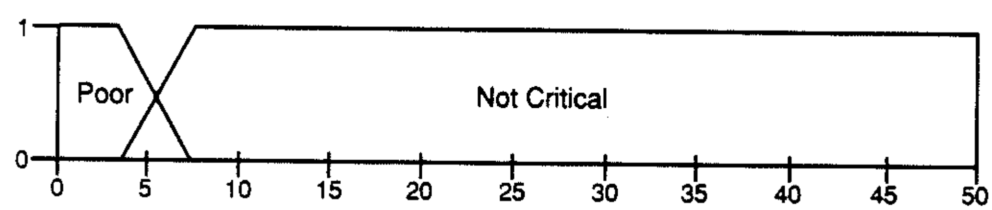


Fig. 23c. Membership functions for porosity for the Carbon Dioxide Method.

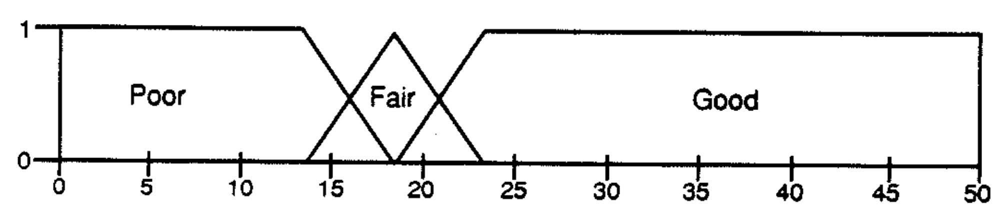


Fig. 23d. Membership functions for porosity for the Surfactant/Polymer Method.

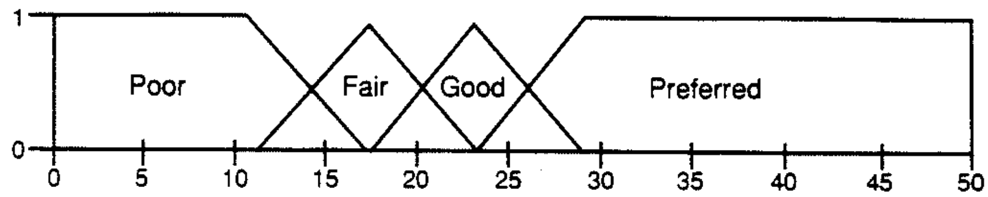


Fig. 23e. Membership functions for porosity for the Polymer Flooding Method.

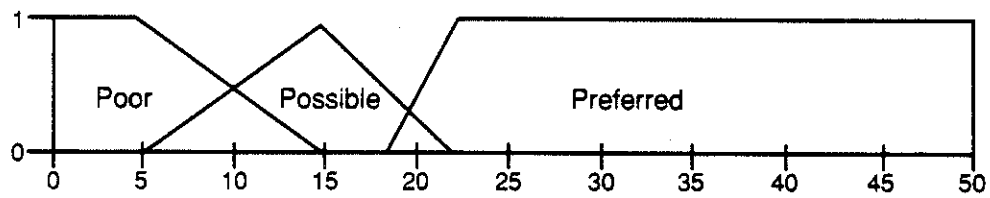


Fig. 23f. Membership functions for porosity for the Alkaline Flooding Method.

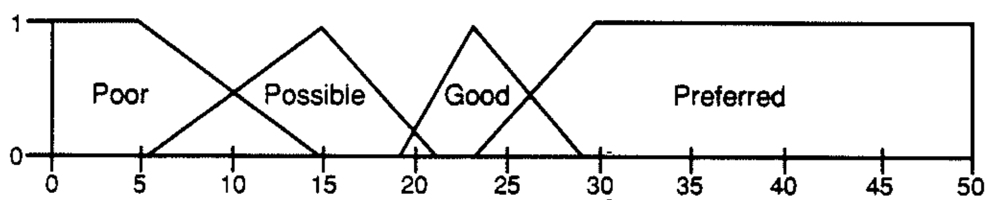


Fig. 23-g. Membership functions for porosity for the *In situ* Combustion Method.

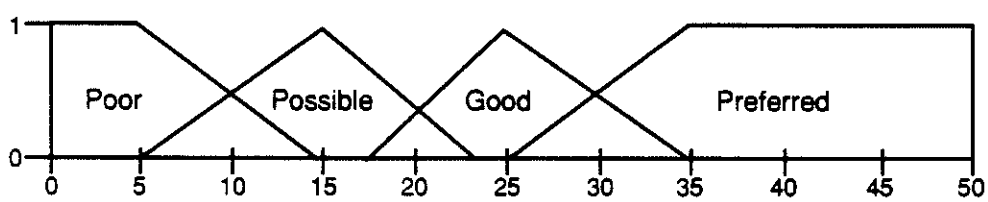


Fig. 23-h. Membership functions for porosity for the Steam Flooding Method.

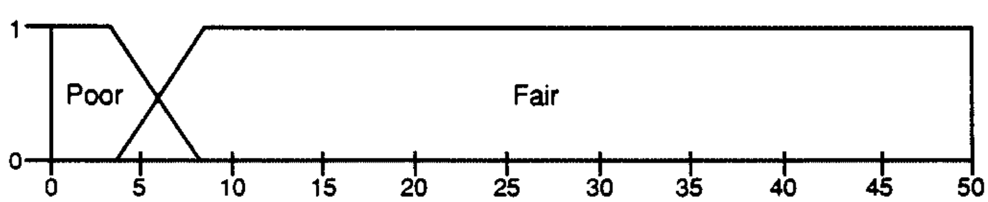


Fig. 23-i. Membership functions for porosity for the Microbial Drive Method.

There are no corresponding fuzzy sets for Fig. 6 (oil composition), or Fig. 9 (formation type). These two EOR criteria remained crisp for this study. Note that some of the abscissae of the fuzzy sets are different from those shown for the corresponding crisp sets. In these cases, simple transformations were used on the EOR criteria variable to better fit them to the fuzzy expert system shell.

As can be seen by observing Figs. 15–23, each of the values for each of the EOR criteria, for each EOR method has a membership in more than one fuzzy set. If we continue our example with the API gravity and observe Fig. 15a for the hydrocarbon miscible method, we see that for a gravity of 27 the hydrocarbon miscible method has a membership of about 0.3 in "Poor" and a membership of about 0.3 in "Good". These memberships are combined to produce a crisp score. Our example demonstrates how memberships are combined to produce a crisp score.

Since a gravity of 27 for the hydrocarbon miscible method has membership in two sets, two rules are fired, each with a "strength" relative to the set membership value (in this case 0.3 for each rule). The two rules are:

1. If gravity_Hydrocarbon_Miscible is Poor
   Then Score = Poor
2. If gravity_Hydrocarbon_Miscible is Good
   Then Score = Good.

Figure 24 shows the membership functions for the output or the Score. From the rules above we can see that the Score should be part "Good" and part "Poor," resulting in a crisp value somewhere between 0 and 10. There are several methods for combining memberships. The one used by our fuzzy expert system is called the Max-Min Inference Method. This method combines the "Good" and "Poor" Scores by clipping the outpout membership function triangles at the height of the membership function value. (In this case the height is 0.3 for both "Good" and "Poor".) The crisp value for the Score is the centroid of the combination of these two truncated triangles. In our case it is the integer value 4. Figure 25 is a composite drawing of a portion of Fig. 15a and a portion of Fig. 24. It shows how the input and output membership functions are connected by the rules and how the crisp output Score is computed based on the number of rules fired and the value of the membership function for the rule

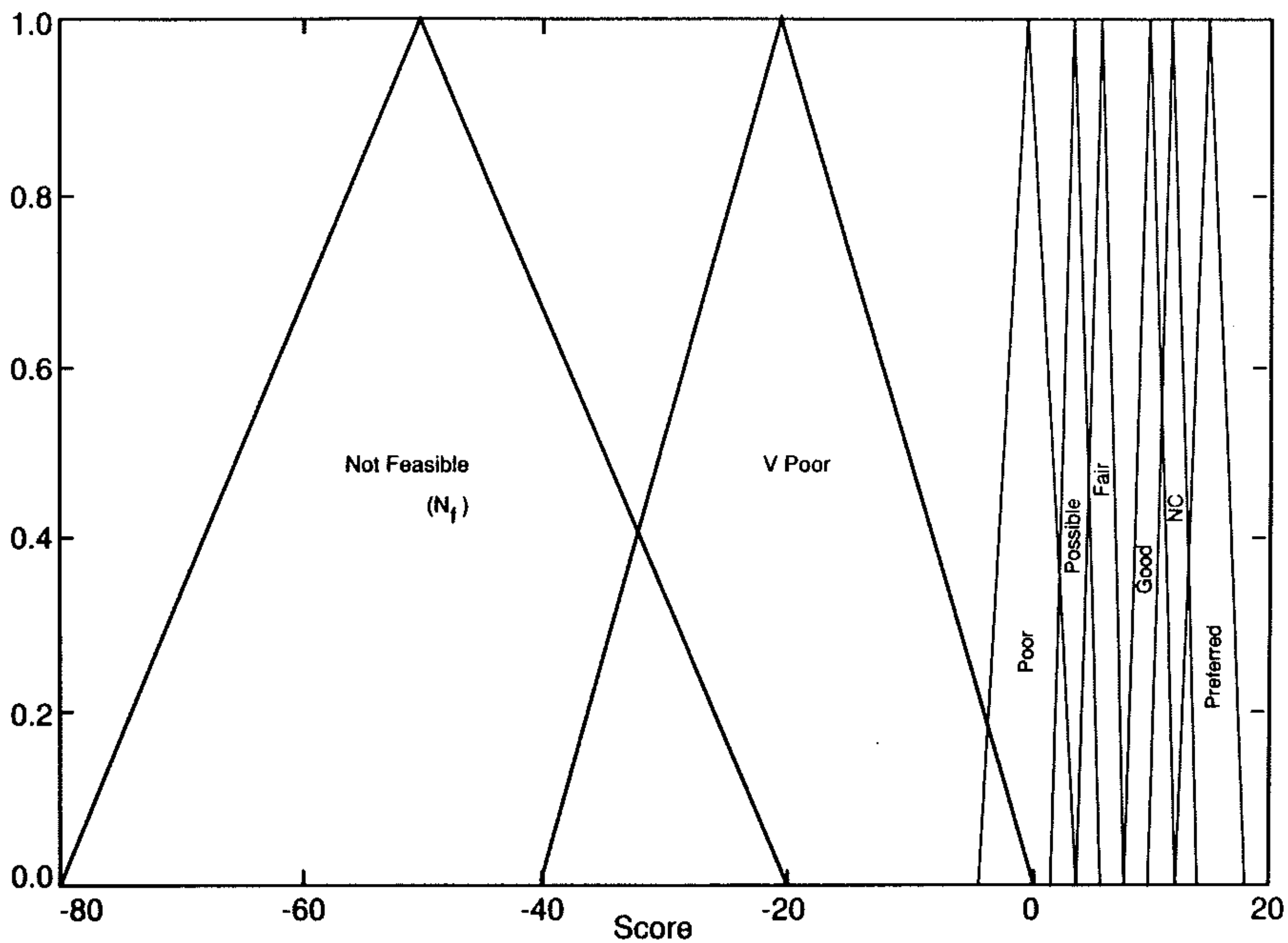


Fig. 24. Output membership functions for the score.

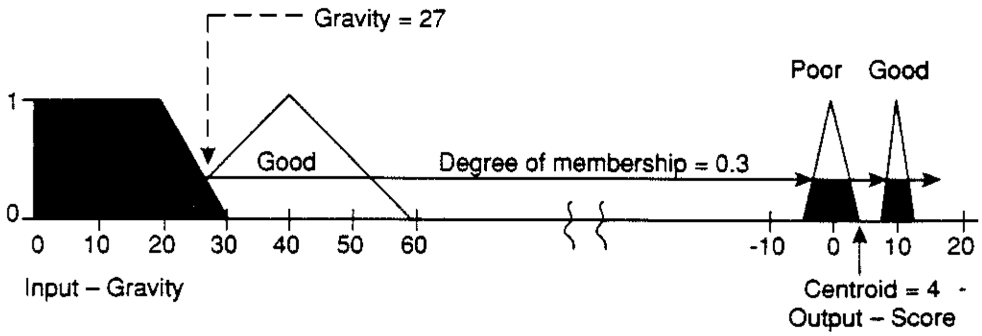


Fig. 25. Demonstration of the max-min interference method.

premises. (e.g., in this case the membership function value for each premise for each rule was 0.3.)

IV. HOW THE EXPERT SYSTEMS WORK

If an engineer were solving the EOR screening problem by hand, using the backward-chaining or goal-driven method, he would first pick a goal (for example, the hydrocarbon gas injection method from the left-hand side of Tables I and II). The engineer would then pick the subgoals that would have to be met before the original goal could be satisfied (for example, the gas injection category.) This process of picking subgoals would continue as long as necessary, but in our case, it would stop here. The engineer would ask only those questions necessary to determine whether gas injection would be a feasible category. If the feasibility of the gas injection category were established, the engineer would ask only those questions necessary to determine whether the hydrocarbon method would be feasible. If not, another goal would be picked. If yes, the problem would be solved, unless more than one solution were desired, in which case, another goal would be picked and the process continued.

With the forward-chaining, or data-driven, approach, the engineer lets the data help search through the search tree (the system keeps asking questions until it is clear which node to move to next).

The crisp expert system, the first one assembled, uses backward-chaining. With this system, the approach is to first assume that hydrocarbon injection is going to work. In order for hydrocarbon injection to work, the category of gas injection must be applicable. In order for gas injection to be applicable both the oil property data and the reservoir data shown in Figs. 4–14 must have scores greater than preprogrammed threshold values.

The program begins by trying to verify these subgoals by asking questions about gravity, viscosity, oil composition, etc. It continues until a final goal is met or until an assumption is rejected at some level. When an assumption is rejected, that branch of the search tree is pruned. The program then moves to the next unpruned branch to the right and picks that EOR process as a goal, then continues until a solution is found. Since we want a ranked list of candidate EOR methods, the program searches the tree until all possible solutions are found. When the search is finished, the solutions are printed, with a score for each qualifying method.

Figure 26 is a portion of an *and/or* graph for a portion of the search space for the crisp version of the expert assistant. It is called an *and/or* graph because the branches connected by an arc are *and* branches (all of the leaves must be true, and in this case, must have a preprogrammed minimal score, before the branch is resolved). The unarced branches are *or* branches. They require only a single truth (minimal score) for resolution.

The fuzzy expert system was written next. It uses forward-chaining and, essentially, an exhaustive search. It starts with the API gravity of the oil in the reservoir (Fig. 15) and assigns a score to each EOR method. It then moves on to viscosity (Fig. 16) and repeats the procedure. The procedure is repeated until all 11 EOR categories are checked. The fuzzy expert system actually uses some crisp rules, combined with the fuzzy rules. Figure 6 shows oil composition screening data. This is probably an area that would fuzzify very well if enough data were available. The only data we have are for those compositions listed. We have no data for composition mixtures. Therefore, the rules for oil composition remain crisp. Figure 9 shows the screening data for the reservoir rock formation type. One could probably force some fuzziness on these EOR criteria if enough data were available, but it probably is not worth the effort. These EOR criteria will probably always remain crisp.

Another area where the rules remain crisp is one in which an EOR criterion offers no options for an EOR method. Figure 7 shows screening data for formation salinity. For five of the nine EOR methods formation salinity is not critical. This gives rise to five crisp rules.

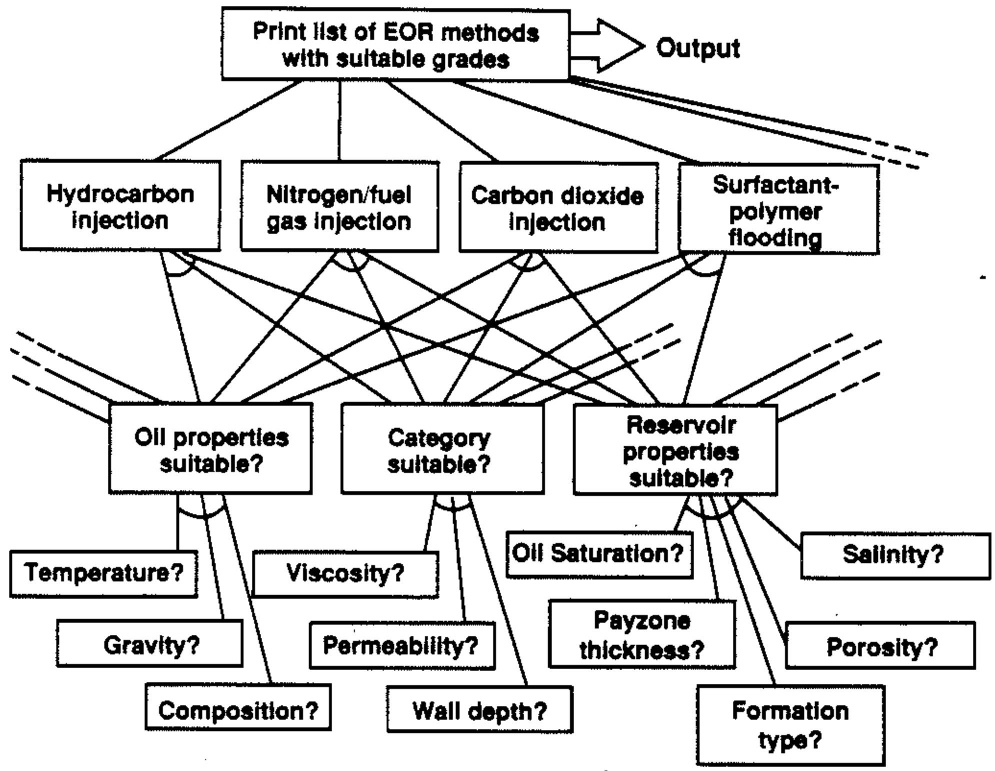


Fig. 26. *And/or* graph for a portion of the search space for the CLIPS backward-chaining version of the problem.

The fuzzy expert system was forced to fit the design basis for the crisp expert system, which is its scoring system. We believe the fuzzy expert system could be improved by using a basis that is specifically designed for it. One large difference between the two expert systems are the tools, or expert system shells, used. Each system uses a different shell, as is discussed in the next section.

V. PROGRAM COMPARISONS AND SUMMARY

The crisp expert system was written with the expert system shell, CLIPS (11), developed by NASA. CLIPS is a forward-chaining shell written in the C programming language. It is a very versatile and flexible shell, which can even be used to write expert systems in the backward-chaining mode, as was done for the crisp expert system (backward-chaining was used because it is more intuitive and, therefore, easier to prune search trees).

The crisp expert system is a great improvement over the hand calculation method that utilizes graphs and charts. Considerable information has been added to the expert system, as can be seen in Figs. 4–14. A final example of this is the first example problem in this paper in which two conditions have been added from Table II. The salinity is 50,000 ppm and the porosity is 28%. Using this information with Table II one would get the same solution we obtained in our sample session, as shown in Fig. 2 and described in the text. This example, again, shows that the only method that can be used is steam flooding. The expert assistant, however, produces a ranked list of five different candidate processes. They are, in order, as follows:

	Score (%)
(1) Steam flooding	89
(2) *In situ* combustion	85
(3) Alkaline flooding	76
(4) Polymer flooding	73
(5) Microbial drive	72

The expert system has provided the solutions to the two problems we had earlier, when using only Table I. It has given us a ranked list, instead of just one candidate or a large unranked list of candidates. Methods such as *in situ* combustion can be ranked because it can also weigh problems such as "What does it mean to have a temperature of 110°F when the table says greater than 150°F preferred"? and it gives the method a relative score. This weighting is possible because of all the additional information provided in Figs. 4–14. As pointed out earlier, this expert system works very well on most real world cases. Examples 3 and 4 point out, however, that there is a definite potential for serious errors because of the sharp boundaries of the crisp sets shown in Figs. 4–14.

The fuzzy expert system was written to eliminate this potential problem and to add some human-like fuzzy reasoning to the otherwise rigid crisp expert system. This expert system was written with the Togai Fuzzy C development system (12). This system does a lot of work for the programmer; it makes it easy to enter membership functions, such as those shown in

Figs. 15–23, and it computes the necessary centroids, as demonstrated in Fig. 25. This system shell is harder to use than CLIPS because the programmer must write a C language program to drive the Fuzzy C program. This means that the programmer has to write the search routines and other peripheral management software that is typically already supplied with shells like CLIPS. Although this allows more flexibility, a great deal of time is required to write search routines with the sophistication of those found in CLIPS. Because it was easiest to write, a forward-chaining exhaustive search was used on this expert system. Still, extensive coding was required.

This expert system does a much better job on problems such as those discussed in Examples 3 and 4. In Example 3, the crisp expert system causes dramatic changes between the two Scenarios, even though the input data for the two scenarios are very similar. The results shown in the ranked list above are from the crisp expert system. The following results are from the fuzzy expert system.

Scenario One (Rankings)

1-	Alkaline flooding	109 points
2-	Polymer flooding	107 points
3-	Surfactant/polymer	101 points
4-	Carbon dioxide	97 points
5-	Microbial drive	89 points
6-	Hydrocarbon miscible	86 points
7-	*In situ* combustion	83 points
8-	Nitrogen and flue gas	82 points
9-	Steam flooding	81 points

Scenario Two

1-	Alkaline flooding	112 points
2- (tie)	Polymer flooding	109 points
3- (tie)	Surfactant/polymer	109 points
4-	Carbon dioxide	102 points
5- (tie)	Microbial drive	89 points
6-(tie)	Hydrocarbon miscible	89 points
7-(tie)	*In situ* combustion	87 points
8-(tie)	Nitrogen and flue gas	87 points
9-	Steam flooding	78 points

Only small changes occur between Scenarios One and Two when the fuzzy expert system is used. In fact the only changes are small changes in the total points awarded. The relative rankings are not really changed.

Example 3 is intended to be a realistic problem, but it is a worst case. The overall raw scores or points produced in the fuzzy version of Example 3 show little increase from Scenario One to Scenario Two. This means that the predicted viability of the EOR methods will not be unduly enhanced by small changes in the input data by the fuzzy expert system.

In Example 4 (Scenario One) the crisp expert system ranked *in situ* combustion as the second best method and surfactant/polymer as fourth best. In Scenario Two, the only change in the input data was an increase of 0.2% in the oil viscosity, hardly a measurable change. This change caused the *in situ* combustion and surfactant/polymer methods to be discarded. They were "Not Feasible." The fuzzy expert system keeps *in situ* combustion as the second best method and surfactant/polymer as the fourth best method in both scenarios, partly because the abscissae shown in Fig. 5 and used in the crisp expert system were converted to a logarithmic scale and plotted linearly in Fig. 16. This is how they are used in the fuzzy expert system. The transformation equation is as follows: transformed-viscosity = (integer) $(10^{*}\log_{10}(\text{viscosity}) + .5)$. (The scale shown in Fig. 6 is linear data plotted on a logarithmic graph.) The transformation itself tends to fuzzify the set boundaries. The transformation was made because the fuzzy expert system shell doesn't handle very large numbers or long scales very well. The fuzzy membership functions also help fuzzify the set boundaries. But when any other output membership function is combined with the "Not Feasible" output membership function, with its centroid at –50, it's hard to make the result of the boundary change very gradual. The –50 score was designed to dramatically reduce the raw score of an EOR method that was thought to be "Not Feasible." This is a good idea if the criterion value is not near the set boundary. Even though a change in feasibility may be quite dramatic as the criterion value changes, it most likely is not a step function. Complete resolution of this problem will require a little more work.

The fuzzy expert system is much better at solving problems, such as those in Examples 3 and 4, than the crisp expert system is. Although these "worst case" problems do not represent the majority of EOR screening problems, they are real, and some degree of the crisp set boundary problem is present in almost every EOR screening problem. Our crisp expert system works more like a classical expert system than the fuzzy expert system does. The crisp system works interactively with the user. It tries to prune the search tree and it offers a simple explanation facility. On the other hand, with the fuzzy expert system, users enter the data and wait for all of the scores to be computed. If the users want some explanation, they can request a dump and watch the progress of the score calculation.

Some of the differences between the two expert systems occur because fuzzy expert systems are designed to fire all the rules that apply to the problem, even those that have only a minor influence on the outcome. A conventional expert system, like the crisp expert assistant does just the opposite, that is, it tries to prune the search tree by eliminating any consideration of rules that have little or no influence on the problem outcome. Much of the difference between the two systems is a function of the difference between the two expert system shells used. A future project should combine the best features of both shells to produce one very good expert system.

The final issue we will discuss is the development of the membership functions for the fuzzy sets shown in Figs. 15–24. Reference (12) states that, "Determining the number, range, and shape of membership functions to be used for a particular variable is somewhat of a black art." It further states that trapezoids and triangles, such as those shown in Figs. 15–24, are a good starting point for membership functions. Trapezoids and triangles served as a starting point for membership functions for this project. The membership functions in Figs. 15–24 are still trapezoids and triangles but many of them are different from those used as the starting points. Some effort was spent polishing the membership functions and several changes were made. In many cases the changes made little difference in the final scores, but in some cases they made a great deal of difference. Ideally, we would expect the triangular membership functions to resemble bell-shaped curves and the trapezoids to resemble S-shaped curves. References (10 and 13–15) suggest methods for determining better membership functions. Example 4 shows that, in at least some cases, there is a need for improved membership functions. Improving the membership functions will require taking a harder look at the available data and will be the subject of another study. The idea of using neural nets, fuzzy pattern recognition, or genetic algorithms (15) to "teach" the membership functions to improve their shape is intriguing and should be considered for a future project.

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