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USING AN EXPERT SYSTEM TO EXPLORE ENHANCED OIL RECOVERY METHODS

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Abstract—This paper describes the use of an expert system, written with inexpensive shells (CLIPS and EXSHELL) for running on personal computers (PCs), to assist in selecting complex petroleum recovery processes. CLIPS is a forward-chaining rule-based system written in C, with rules entered in a LISP-like format. EXSHELL is a backward-chaining rule-based system written in PROLOG. These shells were used to write a system, an expert assistant, for use by petroleum engineers to screen candidate processes for enhanced oil recovery (EOR). The final choice is always made on the basis of economic evaluations. Testing has shown that the expert assistant greatly reduces the amount of work involved in making this choice.

Rather than doing exhaustive economic calculations for all possible processes, the work is reduced to an economic comparison between the two or three most promising candidates. Rather than having to glean information and data from graphs or charts in technical papers, the user and the system work interactively to obtain the needed information. The system automatically selects the optimal paths to the solutions and is easily updated as new data on recovery processes become available. This paper also demonstrates the utility and power of these inexpensive shells, compares the approach used by each, and demonstrates the relative advantages of data-driven vs goal-driven search for this screening problem.

Key words: Expert systems, Enhanced oil recovery.

INTRODUCTION

Reasons for studying enhanced oil recovery (EOR) are listed in a 1986 paper by Stosur [1]. When he wrote his paper, only 27% of the oil ever discovered in the US had been produced. About 6% more will be produced using existing technology under current economic conditions. This leaves the remaining 67% as a target for EOR. Currently, only about 6% of our daily oil production comes from EOR. These numbers indicate, even in times of reduced awareness of energy crisis, that the study of EOR methods is rewarding because of the high potential pay off.

Because EOR can be very costly, engineers must pick the best EOR recovery method for the reservoir in question to optimize profit, or indeed, to make any profit at all. The entire screening method is expensive and involves many steps. The first step in the traditional approach is to consult the technical guides. Screening guides consist of a table or several charts that list the rules of thumb for picking the proper EOR technique. These techniques are usually a function of reservoir and crude oil properties. The candidate techniques are often subjected to laboratory flow studies. Data from these studies are then used to demonstrate the viability of the selected technique. Economic evaluations are carried out throughout the screening process.

Our expert assistant was developed to automate this screening process. It provides the same information as the old table and graph method, but it is more comprehensive than the tables and easier to use than the graphs. It provides the user with a weighted list of potential techniques at the end of the session. This is often quite difficult to do with the traditional table method. The expert assistant is easy to use in that it asks all the questions and leads the user through the first stages of the screening process. It is always understood that the final choice of technique will be based upon economics; therefore the first screening steps are quite important, both because of the high cost of the entire screening process as well as the absolute necessity of choosing the most economical EOR technique.

Since an important prerequisite for our expert assistant was to make it easily available to several users, we employed inexpensive expert system shells designed to run in a PC environment. It was then a simple matter for users to request a floppy disc containing the shell and the expert system. With a few instructions, they can be "in business" interacting with our expert advisor.

THE PC-BASED EXPERT SYSTEM SHELLS

We found two inexpensive PC-based shells that were adequate for our expert assistant: CLIPS [2] and EXSHELL [3].

CLIPS, developed by NASA, is a forward-chaining, rule-based shell written in the C programming language; it emulates in many ways the LISP language. To program with the CLIPS shell, it is helpful, though not essential, to know both C and LISP. EXSHELL was developed by the University of New Mexico Computer Science Department [3]. It is a backward-chaining, rule-based shell written in the PROLOG programming language. One must know some PROLOG in order to program with EXSHELL. Using either expert assistant, however, requires no programming skills and only a few instructions.

Both of these shells are valuable tools, even though they have different features. Because our comparisons of the shells and the programs may be useful to other investigators in the future, we have included a section on program comparisons.

Even though our expert assistant is small compared with some, it does use over 300 rules. Both shells handle this expert system application easily, and it appears that they will continue to do so as new rules are added in the future.

THE EOR SCREENING PROBLEM

For this study we define EOR as any technique that goes beyond water flooding or gas recycling to increase oil well production. We include the injection of material not usually found in the reservoir. The program we have developed relies mainly on the work of Taber and Martin [4] and Goodlet *et al.* [5,6] for its rules.

Enhanced oil recovery techniques can be divided into four general categories: thermal, gas injection, chemical flooding and microbial. Thermal techniques are subdivided into *in situ* combustion and steam flooding. To be technically and economically feasible, thermal techniques usually require reservoirs with fairly high permeability. Steam flooding is traditionally the most used EOR method in the US, and is most often applied to relatively shallow reservoirs containing viscous oils. Recently, however, studies and field tests indicate that steam injection methods are attractive in deeper reservoirs containing lighter, less viscous oils. New studies also point out that steam temperatures affect other reservoir and oil properties, in addition to viscosity. The expert system technology, with its traditional modularity of rules, is excellent for use in this situation because we can easily change the program and add new rules to reflect new changes in the oil recovery technology.

Miscible gas injection techniques are, in a sense, the opposite extreme to steam flooding. To be feasible, the reservoirs must have considerable depth so that the process pressure is adequate for achieving miscibility between a displacing fluid and the displaced fluid. Miscible gas injection techniques are divided into hydrocarbon, nitrogen and flue gas and carbon dioxide. As with steam flooding, there have been a number of recent developments in the technology for immiscible gas flooding. As these developments become available it is easy to change our rule base to reflect the new knowledge.

Chemical flooding has a much less restricted set of conditions for use and is divided into polymer, surfactant-polymer and alkaline recovery techniques. Reservoir permeability poses some restrictions on chemical flooding, but more often, characteristics affecting chemical stability, such as temperature, formation brine and rock composition are the limiting parameters.

Microbial techniques, which are relatively new and primarily experimental, are included for completeness. The microbial category is not subdivided. Figure 1 presents these categories and their associated EOR methods; these choices make up the search tree for the expert assistant.

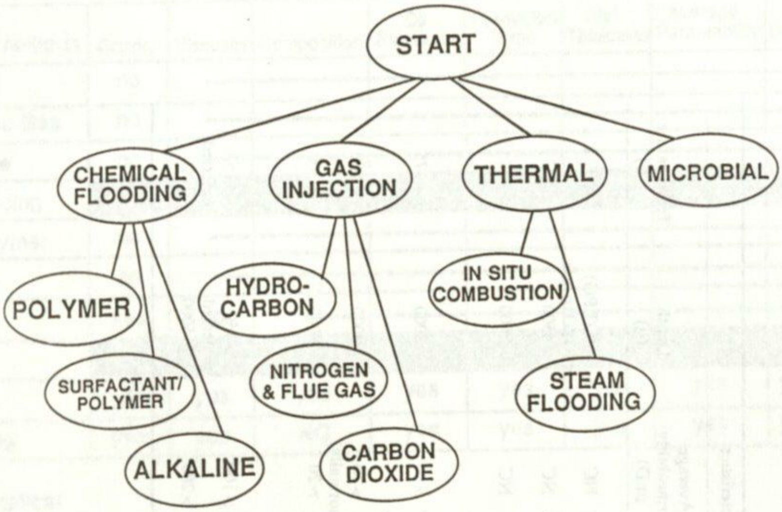


Fig. 1. Search tree for the expert assistant.

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?". The answer is that you can solve the problem more quickly, and often better, with the expert system. Table 1 is taken directly from Ref. [4]. This table presents a matrix of eight EOR techniques and nine EOR criteria.

Theoretically, engineers who know the values of these EOR criteria for the reservoir in question should be able to pick some candidate processes by just using Table 1; thus, it might seem that they do not need to know very much about EOR techniques themselves. We now present several examples that show some of the problems with this argument and approach to the problem. For the first example we use the following EOR criteria with Table 1:

(1) gravity = 18° API,
(2) viscosity = 500 cP,
(3) composition = high-percentage 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 the backward-chaining or goal-driven method. That is, we are first assuming a solution, e.g. hydrocarbon gas-injection, and then checking the data either to verify or disprove that assumption. 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 value of the oil gravity and check it against every EOR method before moving on to the other data.

In our first example, we use backward-chaining to find that steam flooding is the only good method to use for this situation. The results of this search are shown in Fig. 2. Although *in situ* combustion techniques might also work, it is not perfectly clear what is meant, in Table 1, by "greater than 150° F preferred." This situation is not ideal because we have only one candidate for the next screeing step. Furthermore, if this one candidate were eliminated for other reasons in later screening, we would have no candidate recovery methods for this case. Having a well that is not recommended for EOR is certainly legitimate, but we shouldn't eliminate the possibility because of too little knowledge.

Table 1. 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	>2000 (LPG) to <5000 Hp gas	NC
Nitrogen and flue gas	>24 >35 for N_2	<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	Above water-flood 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 300–5000	>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 Ref. [4]. *Copyright © 1983, Society of Petroleum Engineers.*

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.

If we change our example just a little, we can produce the opposite problem. Our second example has the following values for the EOR criteria:

(1) gravity = 35° API,
(2) viscosity = 10 cP,
(3) composition = high percentages 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.

If we search Table 1 again with a backward-chaining technique, we obtain the results shown in Fig. 3. This time only one potential EOR method is eliminated, that is, steam flooding. In this example, we might go to our second step with too many candidates.

This is not a criticism of Ref. [4] or tables similar to Table 1. In fact, for every case like the examples above, there are several that will fall in between these extremes. It is merely an effort to

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 2. Summary of 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 and 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 concentration 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 [4] and [6].

point out that we will often need more information than is available in these tables to do adequate screening.

Much of this needed information is available in Refs [4–6]. References [5] and [6] also have tables similar to Table 1. Table 2 contains all of the material from Table 1 and some information from the table in Ref. [6]. It also includes another EOR method, microbial drive. Although this helps improve the results of our search, we still do not have enough information. We need information that will tell us the impact of using a well temperature of 110° F when a temperature "greater than 150°F is preferred." We need information that will help us rank two or more methods when they all fall within the acceptable range. What we need from this screening step is a ranked list of methods.

A ranked list can be obtained by a nonexpert simply by reading the papers and perhaps making a short literature search, in addition to using Tables 1 or 2. When such work is necessary, the time invested by the nonexpert is not just the few minutes required to search the tables. If the exercise has to be repeated several times or by several different nonexperts, a small PC-based expert system can be easily justified to guarantee that the search process is both comprehensive and easy.

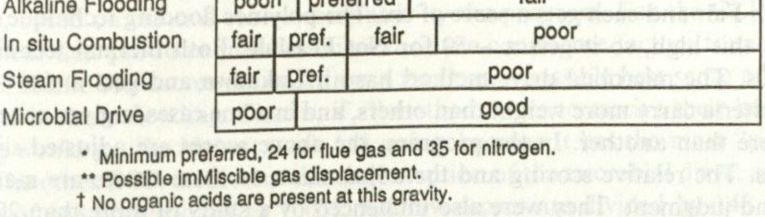
Figures 4–14 demonstrate the basis of our scoring system for the various EOR criteria and EOR methods. Figures 5, 11 and 12 were taken from Ref. [4] and modified. The others were created by studying Refs [4–9]. Figures 4–14 are bar graphs showing the relative influence of each EOR criterion on each EOR method. Our scoring system is empirical and is designed to add some of our own judgment or expertise to the expert system. The system is based on the key words in Figs 4–14 and works as follows:

Not Feasible = −50, Fair = 6,
Very Poor = −20, Good = 10,
Poor = 0, Not critical = 12,
Possible = 4, Preferred = 15.

As can be noted, our scoring is *ad hoc*, but designed to implement our own experience in EOR method selection. Our range of possible usable methods is from −20, **Very Poor**, to +20. No recommendation is absolutely perfect, and **Preferred** is our highest recommendation at 15. At the other extreme, for some situations a method may simply be **Not Feasible** and given a rank of −50. In this situation we wanted no combination of other features to bring it into an acceptable range. Note also that in our metric, **Not Critical** is a very good situation to have.

With the microbial drive method the effects of viscosity and, to a large extent porosity, are unknown. Until we have more information we are assigning a grade of 6 for an **Unknown**, the same as that assigned to **Fair**.

As an example of the scoring system, consider Fig. 5, an oil with a viscosity of about 500 cP. The hydrocarbon gas injection, surfactant-polymer and alkaline chemical flood techniques are all



* 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).

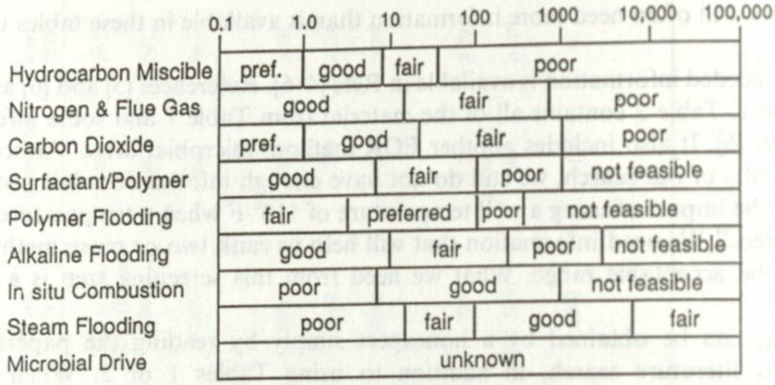


Fig. 5. Oil viscosity screening data (cP).

	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.

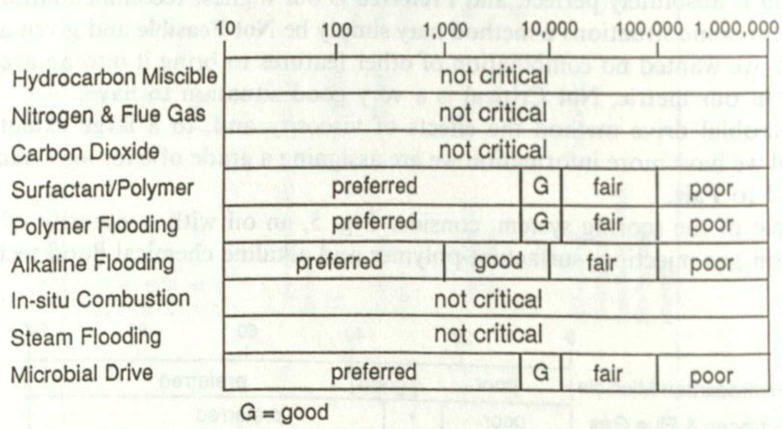
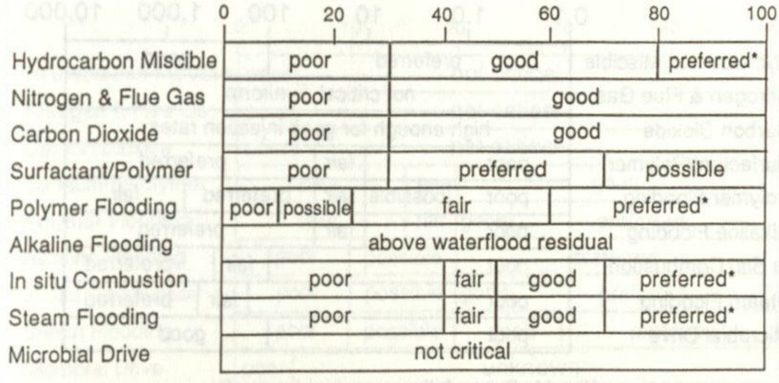


Fig. 7. Formation salinity screening data (ppm).

Poor and all score zeros. The other two gas injection techniques, nitrogen/flue gas and carbon dioxide, are both **Fair** and each gets a score of six. The polymer flooding technique cannot be used with a viscosity this high, so it gets a -50 for **Not Feasible**. Both thermal techniques are **Good** and both get 10s. The microbial drive method has an **Unknown** and gets a six.

Some EOR criteria carry more weight than others, and in some cases, a given criterion may affect one method more than another. In the program, the above scores are adjusted slightly to reflect these differences. The relative scoring and the adjustments to these scores are made on the basis of experience and judgment. They were also influenced by a study of more than 200 enhanced oil recovery projects listed in Ref. [9]. These scores are explicitly listed in the computer program and



* Preferred status is based on the starting residual oil saturations of successfully producing wells as documented by Ref. 9.

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

	Sand	Homogeneous Sandstone	Heterogeneous Sandstone	Homogeneous Carbonate	Heterogeneous Carbonate
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	poor	good	poor

Fig. 9. Formation type screening data.

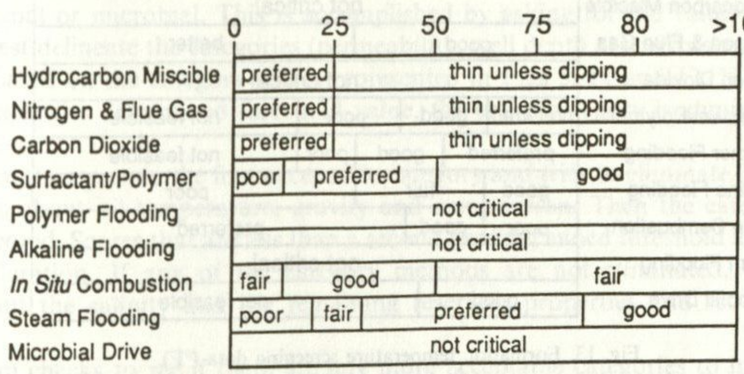


Fig. 10. Net thickness screening data (ft).

thus may easily be changed by someone whose experiences differ from ours or who might have new information.

An important task of the expert system is to give the user meaningful advice about the individual EOR methods, based on the raw scores computed by the program. For the CLIPS programs, we designed a system that produces numbers similar to the confidence factors found in many shells, including EXSHELL. The scores are based on a maximum possible best score of 100%. The best possible process is steam flooding. That is, if all methods were to receive their best possible score, steam flooding would get the highest, with 148 points because it has the most "preferred" ratings in Figs 4–14. The other EOR methods, with the exception of the microbial drive, are all quite close. The raw score of 148 corresponds to 100%. All raw scores are divided by 148 to produce their relative confidence factors.

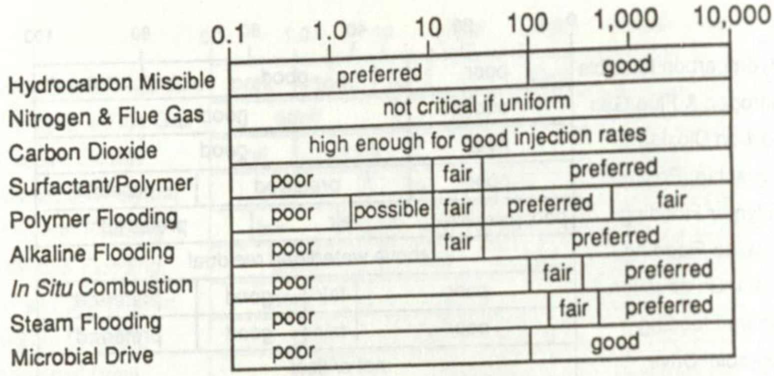


Fig. 11. Permeability screening data (mD).

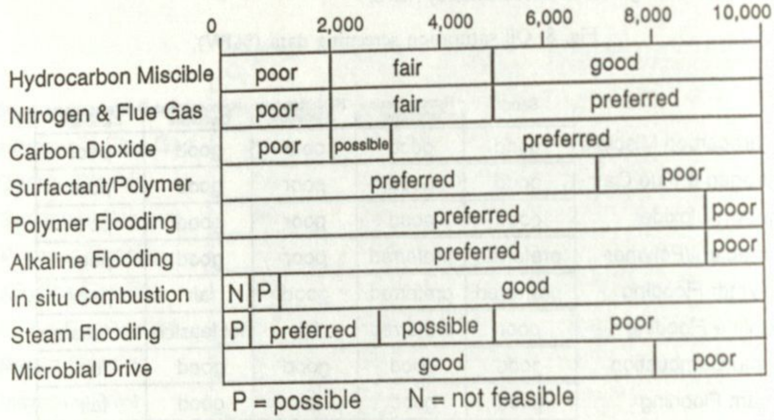


Fig. 12. Well depth screening data (ft).

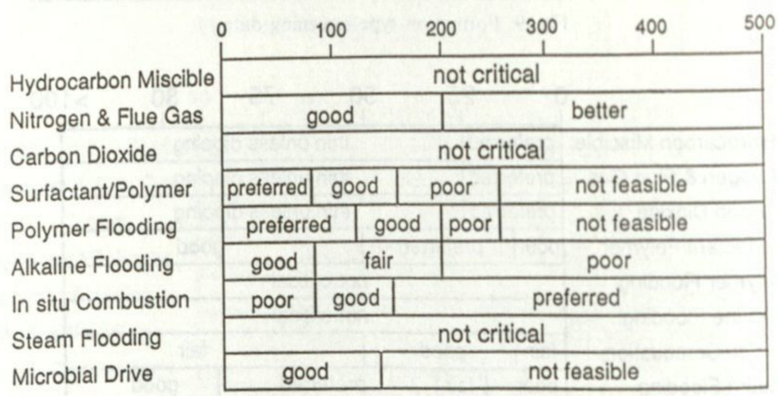


Fig. 13. Formation temperature screening data (°F).

At the end of a session, the scores are tallied, and the user has a ranked list of candidates to take to the next screening step. So far, this approach has given realistic results. We have run these expert systems with much of the information given in Ref. [9] for actual EOR projects. In about 60% of the cases run, the method ranked highest by the expert system agreed with the actual method used for that project. In nearly all of the rest of the cases, the actual method used was ranked in the top three by the expert system. In no case was the method used significantly better than ours, i.e. the top recommended methods were roughly equivalent.

Our success is not surprising because these data did influence the scores used by the expert system. An important aspect of the expert system's design methodology is to keep comparing the results of the expert system with the results given by the human experts and continue modifying the system until it reflects the same skill level as that of the human experts. This development process of continued refinement gives us confidence in the results predicted by our expert system.

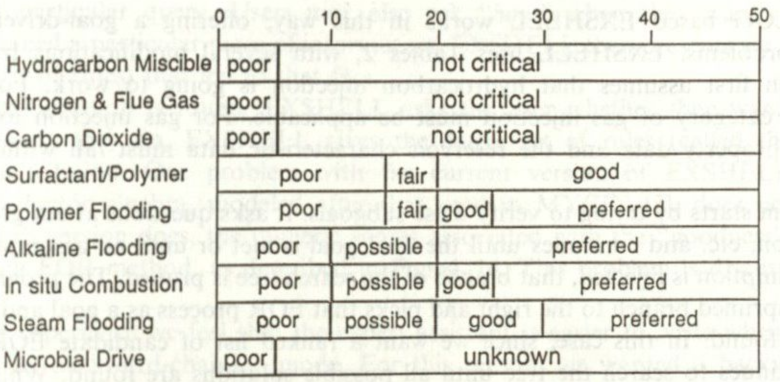


Fig. 14. Formation porosity screening data (%).

Our first program CLIPS is data-driven or forward-chaining. The backward-chaining technique works well when using the data given in Tables 1 and 2. For this reason we developed the second expert assistant in backward-chaining mode with EXSHELL. These techniques are discussed in the next section.

THE EXPERT ASSISTANTS: HOW THEY WORK

Our first EOR expert assistant, written with CLIPS, is forward-chaining. In the forward-chaining or data-driven approach, the engineer lets the data help guide the way through the search space. The system asks questions until it determines which node in the search tree to move to next. The CLIPS search, described in the previous section, works in this manner. The CLIPS software can also be programmed to back-chain, but this we found more difficult; our final example takes this approach.

Data-driven search first finds an acceptable EOR category from the list: chemical flooding, gas injection, thermal or microbial. This is accomplished by asking for the values of the three EOR criteria that best delineate the categories (permeability, well depth and viscosity). A category score is computed based on the category scores represented in Figs 5, 11 and 12. If the category score is less than an earlier determined threshold value, the entire category is eliminated from further consideration.

The program then goes to the first acceptable category and tries to eliminate individual methods with questions about oil temperature, gravity and composition. Then the category methods are individually scored. Scores that are less than a second predetermined threshold are eliminated from further consideration. If any of the category methods are not eliminated, the program asks questions about the salinity and the remaining reservoir properties and scores these methods further.

The program checks to see if there are any more acceptable categories to investigate. If there are, it repeats the process just described. If there are not, it stops and prints the scores of the remaining candidate methods. A flow diagram for this version of the expert assistant is given in Fig. 15.

The backward-chaining expert assistant was written with EXSHELL. If an engineer is solving the EOR screening problem by hand using the backward-chaining or goal-driven method, he or she first picks a goal, for example the hydrocarbon gas injection method, from the left-hand side of Tables 1 and 2. The engineer then picks a subgoal that must be met before the original goal can be satisfied, for example the gas injection category. The engineer continues to pick subgoals as long as necessary, but in our example, would stop at this point.

In goal-driven reasoning the engineer asks only those questions necessary to determine whether gas injection is a feasible category. If it is feasible, he or she then asks only those questions necessary to determine whether the subgoal, the hydrocarbon method is feasible; if it is not feasible, another goal is picked. If it is feasible, the problem is solved, unless more than one solution is desired. In this case, another goal is picked and the process continues.

The PROLOG based EXSHELL works in this way, offering a goal-driven approach to solving the problems. EXSHELL uses Tables 2, with several modifications from Figs 4–14. This approach first assumes that hydrocarbon injection is going to work. For hydrocarbon injection, the category of gas injection must be applicable. For gas injection to be applicable, both the oil property data and the reservoir characteristic data must fall within the limits of Table 2.

The program starts by trying to verify these subgoals. It asks questions about gravity, viscosity, oil composition, etc. and continues until the final goal is met or until an assumption is rejected. 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 and continues until a solution is found. In this case, since we want a ranked list of candidate EOR methods, the program continues to search the tree until all possible solutions are found. When the search is finished, the solutions are printed with a confidence factor for each process. The confidence factors give a ranking to each candidate. These rankings are similar, but not identical to, the rankings in the first program.

Figure 16 presents the *and /or* graph searched by the EXSHELL version of the expert assistant. It is called an *and/or* graph because the options or branches connected by an arc are *and* branches, that is, all of them must be true before the branch is resolved. The other branches (not connected by an arc) are *or* branches; these require the solution of only a single option or branch for resolution.

An important feature of EXSHELL is that it has an explanation facility [3]. Users may ask "*why*" to any query and EXSHELL responds by presenting the rule it is currently using to try

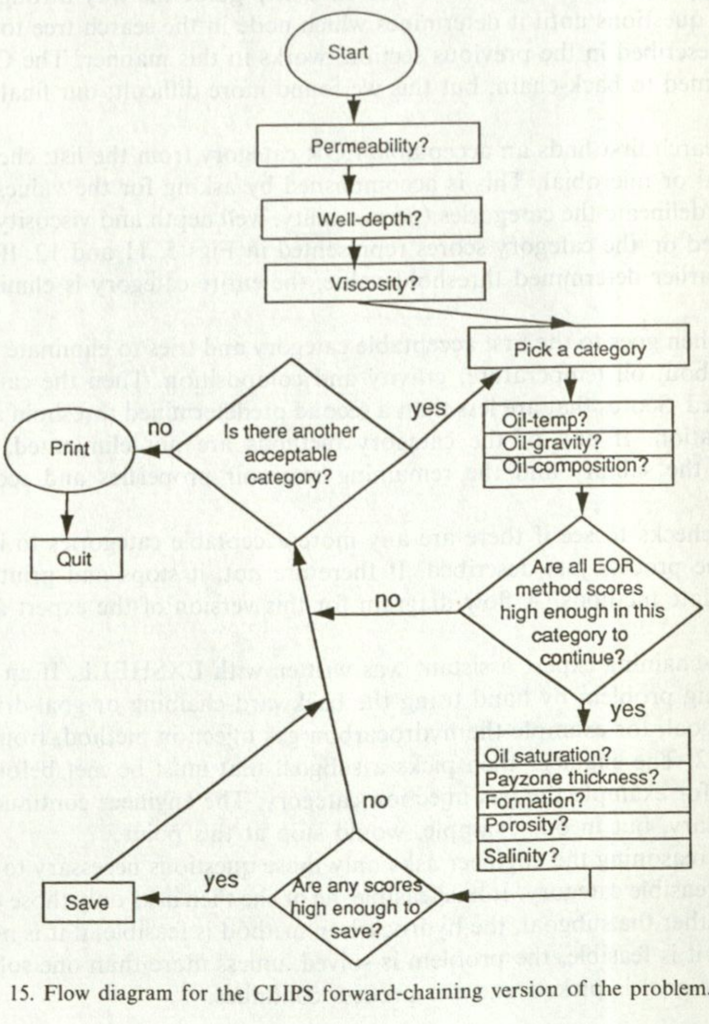


Fig. 15. Flow diagram for the CLIPS forward-chaining version of the problem.

to resolve that particular query. Users may also ask "*how*" when they want to know how EXSHELL obtained a particular piece of information. EXSHELL then presents the branch of the tree (with the list of rules) that led to that fact.

When the final solution is found, EXSHELL asks the user whether they want to trace the solution process. If they do, EXSHELL gives the entire set of rules (called the proof tree) that led to the solution. One problem with the current version of EXSHELL is that it's simple certainty factor algebra, modeled after that used in MYCIN [3], does not capture, as well as the CLIPS version does, the numeric scores associated with the "goodness" of the EOR criterion for each EOR method, as described in Figs 4–14. This problem is discussed further in the next section.

Based on our experience we feel that the expert assistant is easier to write when it is done in the goal-driven or backward-chaining mode. For this reason, we wanted a backward-chaining method that handled the relative scores as well as the first CLIPS version did. We had the choice of working more with EXSHELL or continuing with CLIPS. We chose to work with CLIPS and forced it into the backward-chaining mode; we also used the minimal scores, obtained from Figs 4–14, to eliminate the unlikely candidate methods.

This final version of our expert assistant works much like the EXSHELL version, except for the scoring. Figure 17 is a portion of the search space for the problem, presented in *and/or* graph form. We have also added a simple explanation facility. At the end of the session, the user can ask *why* a given EOR method was eliminated from consideration, and the program explains which set of EOR criteria values caused the score to drop below the threshold, and therefore caused that candidate method to be eliminated. An example session with this program is presented in the Appendix.

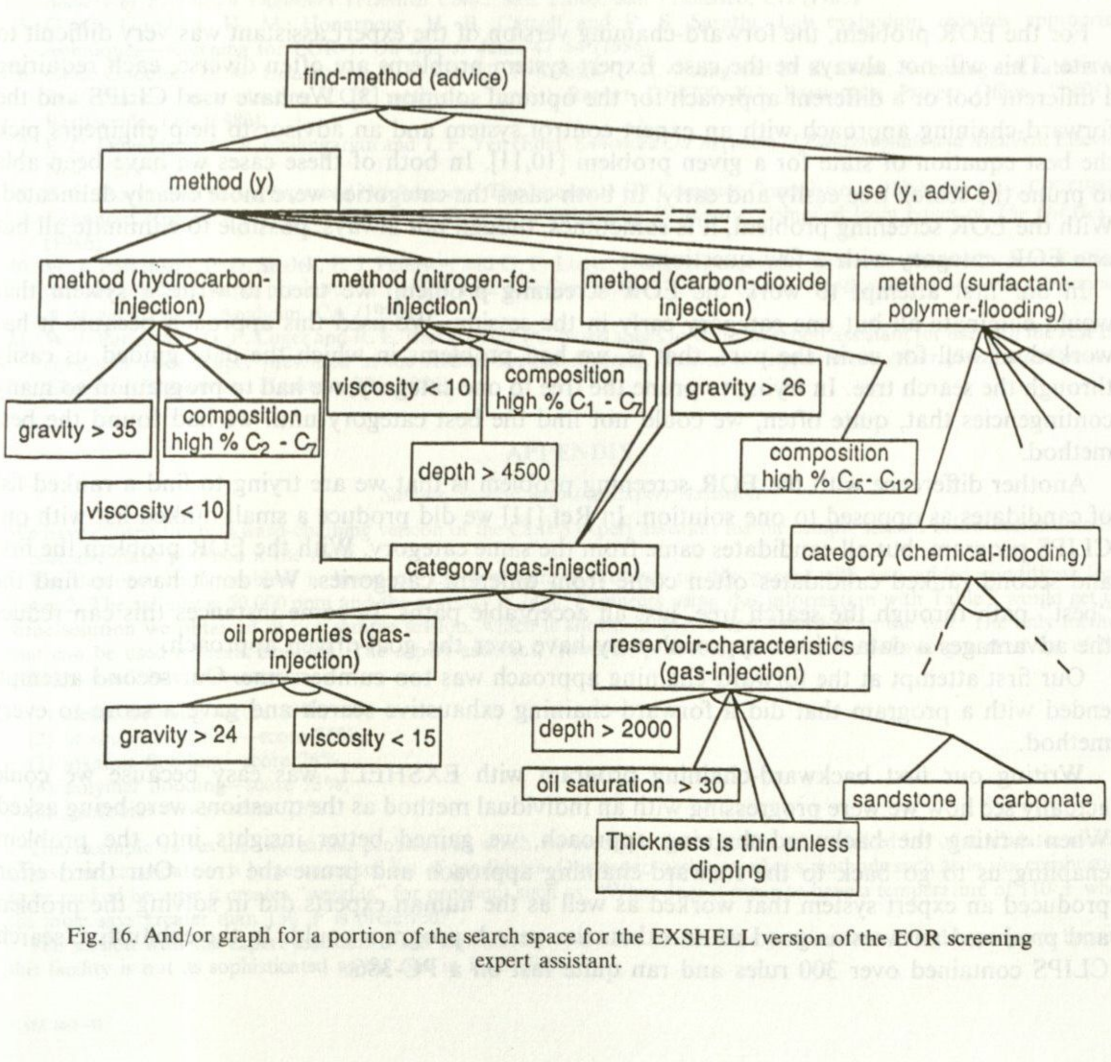


Fig. 16. And/or graph for a portion of the search space for the EXSHELL version of the EOR screening expert assistant.

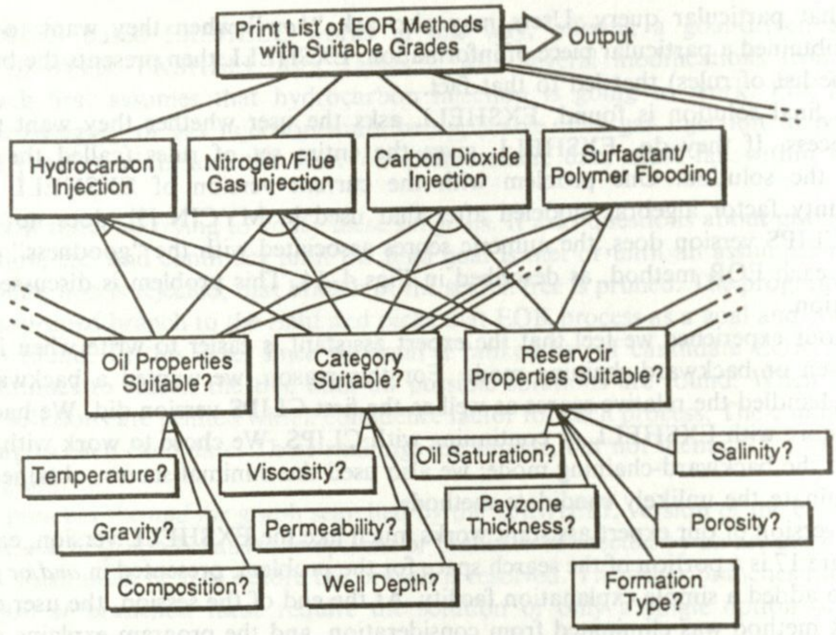


Fig. 17. And/or graph for a portion of the search space for the CLIPS backward chaining version of the problem.

PROGRAM COMPARISONS AND SUMMARY

For the EOR problem, the forward-chaining version of the expert assistant was very difficult to write. This will not always be the case. Expert system problems are often diverse, each requiring a different tool or a different approach for the optimal solution [3]. We have used CLIPS and the forward-chaining approach with an expert control system and an advisor to help engineers pick the best equation of state for a given problem [10,11]. In both of these cases we have been able to prune the search tree easily and early. In both cases the categories were more clearly delineated. With the EOR screening problem, it is sometimes, though not always, possible to eliminate all but one EOR category with a few questions.

In our first attempt to work the EOR screening problem, we tried to write a system that would eliminate all but one category early in the session. We used this approach because it has worked so well for us in the past, that is, we had problems in which the data guided us easily through the search tree. In trying to prune the tree to one category, we had to program in so many contingencies that, quite often, we could not find the best category until we had found the best method.

Another difference with the EOR screening problem is that we are trying to find a ranked list of candidates as opposed to one solution. In Ref [11] we did produce a small ranked list with our CLIPS program, but all candidates came from the same category. With the EOR problem the first and second ranked candidates often come from different categories. We don't have to find the "best" path through the search tree, just all acceptable paths. In some instances this can reduce the advantages a data-driven approach may have over the goal-driven approach.

Our first attempt at the forward-chaining approach was too cumbersome. Our second attempt, ended with a program that did a forward-chaining exhaustive search and gave a score to every method.

Writing our first backward-chaining program with EXSHELL was easy because we could actually see how we were progressing with an individual method as the questions were being asked. When writing the backward-chaining approach, we gained better insights into the problem, enabling us to go back to the forward-chaining approach and prune the tree. Our third effort produced an expert system that worked as well as the human experts did in solving the problem and produced answers as good as an exhaustive search program could. In the exhaustive search, CLIPS contained over 300 rules and ran quite fast on a PC-386.

Our EXSHELL version of this program was not without it's problems. For example, it deals very well with questions such as "Is the formation thin and dipping? Yes or no." But it has more problems with questions such as "What is the viscosity?". In our program users may need to answer a question like "Is the viscosity less than 15?" then later answer the question, "Is the viscosity less than 10?". This makes the program a little awkward. Another problem is the scoring method. It is easy for EXSHELL to handle probabilities or confidence factors but much more difficult for it to handle a scoring system similar to the one described for the CLIPS versions. For this reason we can lose some of the information in Figs 4–14. On the plus side, EXSHELL has an excellent explanation facility that is built into the system.

EXSHELL is easier to program than CLIPS. CLIPS, on the other hand, is more flexible, putting more program control in the user's hands. For this reason we were able to force CLIPS to do backward-chaining. We were also able to write a simple explanation facility, but we did have to program this in ourselves.

We have written three expert assistants that all help a user perform the first screening steps in the selection of an EOR process. Each of these expert assistants is slightly different, but each gives nearly the same results. We have tested them against data available from human experts and they have performed well.

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APPENDIX

Sample Session with the Expert Assistant

We have chosen the backward-chaining version of the CLIPS expert assistant for the sample session below because we like it best and have polished it the most.

The demonstration problem is based on the first sample problem in this paper, with two added conditions from Table 2. The salinity is 50,000 ppm and the porosity is 28%. Engineers using this information with Table 2 would get the same solution we obtained in our sample session, which is shown in Fig. 2 and described in the text. The only method that can be used is steam flooding. The expert assistant, however, produces, in order, the following ranked list of five different candidate processes:

(1) steam flooding—score 89%,
(2) *in situ* combustion—score 85%,
(3) alkaline flooding—score 76%,
(4) polymer flooding—score 73%,
(5) microbial drive—score 72%.

This example solves the two earlier problems in which we used just Table 1. We get a ranked list of candidates instead of just one candidate or a large unranked list of candidates. Our expert assistant allows methods such as *in situ* combustion to be ranked because it creates "weights" for problems such as: "What does it mean to have a temperature of 110° F when the table says greater than 150° F is preferred?".

The session with the expert assistant is self-explanatory. We built some of the justifications into this program because this facility is not as sophisticated as the one in EXSHELL.

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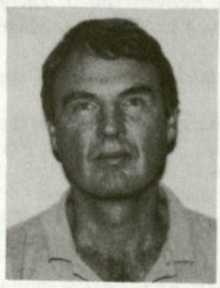
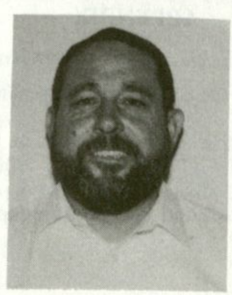


George F. Luger—Dr Luger has over 20 yr experience as a computer scientist. He has served in a variety of technical and teaching positions with the University of Edinburgh, the Medical Research Council, the University of New Mexico, and as a private consultant. He is an internationally recognized expert in the field of artificial intelligence and has written and published numerous professional articles and books in that subject area. He has been involved in the design and implementation of a number of practical software systems that are capable of simulating the problem solving abilities of a human expert. Dr Luger has also served as a consultant, designing expert systems for universities, industry, and government laboratories.



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