Automatic Injection Profile Prediction by Soft Computing Methods

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Abstract—*Soft computing methods are well known for their applications in the petroleum industry. Injection profile is one of the most important factors that need be taken into consideration in major oilfield development or related decision making. Injection profile is affected by multiple geological and developmental factors, which form complicated nonlinear relationships that are difficult to model by using conventional approaches. In this paper, an intelligent system is presented to construct fuzzy inference systems (FIS) automatically by integrating the fuzzy subtractive clustering and the Adaptive-Network-based Fuzzy Inference System (ANFIS). The method was tested by injection profile prediction in the Daqing Oilfield in China. A data cleaning strategy, the TANE algorithm, was applied to identify and to remove inconsistency in the raw data set collected from the oilfields. Results demonstrated that cleaned data produced more robust FIS and achieved higher prediction accuracies. The same approach can be applied in intelligent systems in resolving complicated Internet problems.*

Index Terms—*soft computing, ANFIS, fuzzy subtractive clustering, approximate dependency mining, conflicting data patterns*

1. INTRODUCTION

Soft computing techniques have been applied in many areas of the petroleum industry, such as reservoir characterization [1,2,3], well log interpretation [4,5,6], production prediction [7] and treatment optimization [8].

Injection profile of injection wells in water flooding oilfields is one of the most important factors in oilfield development. In water-flooding oilfields, injected water drives petroleum fluid (oil, gas and water) to move towards the wellbore by pushing the oil/gas/water in the porous media underground. Understanding injection profiles significantly aids in analyzing key petroleum production problems, such as residual oil distribution, residual reserve estimation, water flooding efficiency, water injection balancing and so on.

Many methods can be applied to obtain injection profiles in oilfields [9, 10], such as sealed coring, sidewall coring, logging data interpretation, C/O spectral logging, numerical simulation and comprehensive analysis of static and dynamic data from the oilfield development. Most of those methods, except for numeric simulation, are for obtaining injection profiles by in place measurement and interpretation. They are expensive and time-consuming. In addition, it is impossible to obtain injection profiles whenever and wherever they are needed for improving oil recovery (IOR) purposes. Reservoir numeric simulation models the oil/gas production by combining petroleum fluid flow and other models. By properly modeling reservoir and matching the history production data, reservoir simulation produces injection profiles in the production history and predicts injection profiles in the given future. However, reservoir simulation has its own inherent problems, including that: 1) modeling multiple parameters and the integration of sub-models are difficult; 2) history matching is actually a trial-and-error and time-consuming process which depends on reservoir simulation expertise intensively; and 3) reservoir simulation sometimes encounters difficulties in modeling actual reservoir features due to built-in limitations in models. In addition, time-consuming post-processing is required to obtain injection profile data from reservoir simulation results. Considering that injection profiles are required in many different IOR projects, it would be nice to have handy data available when it is required.

Injection profile prediction using soft computing methods was reported in [11]. The paper integrated the subtractive clustering and the ANFIS methods to construct optimized FIS automatically using available data from the Daqing Oilfield. In this paper, we briefly introduce the profile injection problem in water flooding oilfields and describe the problem modeling considerations in more detail. In order to enhance the performance of soft computing methods, the TANE algorithm was applied to identify implicitly conflict data patterns in the raw data. The similar problem modeling procedure and same data were used. Compared with results presented in [11], improved injection profile prediction accuracy was achieved. It shows the importance of data quality in problem modeling using soft

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computing methods, especially when the available training data set is small. The same method can be applied in other complicated problems in the petroleum industry, such as production predict and reserve evaluation.

The rest of this paper is organized as follows. Section 2 presents considerations in soft computing method selection and the problem of injection profile prediction; Section 3 presents the methodology used in injection profile modeling and prediction; Section 4 summarizes the experimental results and Section 5 concludes the paper.

2. PROBLEM STATEMENT

In water flooding oilfields, the distribution of injected water along the producing strata, the injection profile, is tightly related to oil/gas production from producing wells. Water injectivity in active producing strata is affected by many parameters, such as permeability of formations, the communication of injection and producing wells, injection pressure differences, well patterns, and so on. Because the fluid flow in the porous media in reservoir follows the non-linear Darcy's Law and these factors interact complicatedly, it is difficult to model their relationships with the injection profile data by conventional approaches. To improve the injection profile prediction efficiency and accuracy, soft computing methods are applied.

2.1 Parameter Selection

In problem modeling using soft computing methods, problem formulation and decomposition are equally important. Parameter selection determines how the problem is modeled and resolved. In the influential parameter selection, following points should be considered:

- Selected parameters affect the target problem and the target parameter. Strong relationships, linear or non-linear, must exist among selected parameters and target variables;
- Selected parameters must be well-populated and corresponding data must be as clean as possible. Since the soft computing methods model problems based on available data, the data availability and quality are essential for successful modeling.

In order to model and predict injection profiles, above mentioned factors, formation permeability, communication of injection and producing wells, well patterns and production setups, should be considered. In order to filter proper influential parameters, injection profile data from 25 wells, totally 218 active strata, was analyzed. Following parameters were selected:

- Gross sand thickness near the wellbore of injection wells, denoted as h_{gross1};
- Net sand thickness near the wellbore of injection wells, denoted as h_{net1};
- Gross sand thickness near the wellbore of nearby producing wells, denoted as h_{gross2};
- Net sand thickness near the wellbore of nearby producing wells, denoted as h_{net2};
- Spacing distance between injection wells and surrounding producing wells, denoted as d.

The first four parameters reflect the communication between injection and producing wells. Well spacing distance reflects the effect of well pattern and production criteria, the larger the well spacing, the smaller the injection capability.

Formation permeability of active strata is another key factor that affects the water injectivity and the injection profiles. Injected water moves faster in the direction of higher permeability, and breaks through in producing wells in high-permeability zones. Studies on available data show that absolute permeability of active strata is positively related to the sand type in the Daqing Oilfield. Sand types are embodied by the thickness of sand and communication of injection and producing wells, as shown in Table 1. In addition, permeability is not widely available in our tested area. Therefore, permeability is not considered in problem modeling.

Thickness of sand-body (m)	<0.5 gross	≥0.5 gross	0.2-0.5 net	0.5-1.0 net	1.0-1.5 net	1.0-1.5 net
Average permeability (um^2)	0.037	0.123	0.264	0.802	1.064	2.181

Table 1: Relationship of permeability and sand thickness in the active producing strata

2.2 Problem Formulation

The relationship of injection profile and selected parameters is not obvious. Injection profile is calculated by summing up relative water intakes of producing wells perforated in each active stratum, formulated as follows:

$$ri_i = RI \times ratio_i / \sum_i ratio_i \quad (1)$$

$$ratio_i = h_{net2_i} + (h_{gross2_i} - h_{net2_i}) / 3.3 \quad (2)$$

where i=1,2,…, refers to one of surrounding producing wells of injection wells. Hence in the problem modeling, the input is h_{gross1}, h_{net1}, h_{gross2}, h_{net2}, d and the output is ri_i. The resulting FIS models the relationships of input and output data.

The injection of an active stratum is calculated as follows:

$$RI_k = \sum_i ri_{ki} \quad (3)$$

where k is the index of a producing stratum of an injection well, and i is the index of surrounding producing wells of the injection well in the producing stratum.

Predicted injection rates are compared with corresponding measured rates. If two rates have small difference, as in

$|RI_k^{predicted} - RI_k^{measured}| \le threshold$, where *threshold* is defined based on requirement in the petroleum industry, it is correctly predicted. Prediction accuracy is evaluated by percentage of correctly predicted injection rate using following formula:

$$accuracy = \frac{\#\ of\ \ |RI^{predicted} - RI^{measured}| \le threshold}{\|predicted\ \ set\|} \times 100 \quad (4)$$

In injection profile prediction, a bias of 2% to injection rate meets the precision requirements. Therefore, 2% is taken as a threshold to calculate the prediction accuracy.

3. THE METHODOLOGY

3.1 Soft Computing Method Selection

Fuzzy logic (FL) was introduced by Zadeh in 1965 [12], which processes data using partial set membership rather than crisp set membership. Similar to neural networks, FL is able to generate definite conclusions based on vague, ambiguous, imprecise and missing input information. One essential task in constructing proper FIS is to provide correct fuzzy membership functions and fuzzy rules. It is a time-consuming task, and requires profound expertise for a given problem. In addition, it is oftentimes difficult to convert domain knowledge into if-then fuzzy rules, even for domain experts.

Some methods [13,14] have been proposed to learn fuzzy membership functions and fuzzy rules and further FIS automatically by analyzing available input-output data. ANFIS [15] is a sophisticated neuro-fuzzy system and is able to model complicated fuzzy relationships. It learns the Sugeno-Takagi (or ST) FIS [16] using forward and backward passes, as shown in Fig. 1. The ST FIS is formatted as equations (5) and (6). ANFIS is an efficient approach to construct FIS for a given problem using available data for training.

$$R^1 : if\ \ x_1\ is\ A_1^1\ and\ \ x_2\ is\ A_2^1, then\ \ f_1 = p_1 x_1 + q_1 x_2 + r_1 \quad (5)$$

$$R^2 : if\ \ x_1\ is\ A_1^2\ and\ \ x_2\ is\ A_2^2, then\ \ f_2 = p_2 x_1 + q_2 x_2 + r_2 \quad (6)$$

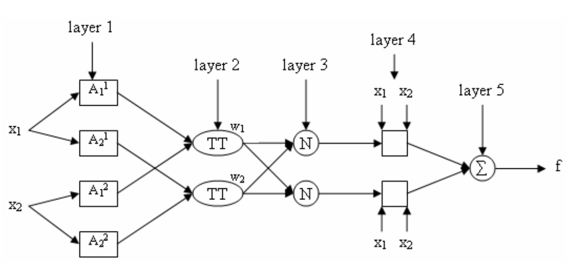

Fig. 1. The equivalent ANFIS architecture of the first order ST fuzzy inference system in equations (5) and (6).

To aid the construction of ANFIS, a clustering approach, the fuzzy subtractive clustering [17], is employed to cluster available data into fuzzy clusters. After fuzzy clusters are generated, an FIS can be generated based on the clustering results. Fuzzy subtractive clustering works better than other clustering methods for FIS. The resulting FIS can be refined further by the ANFIS.

In using the fuzzy subtractive clustering method to a given problem, main parameters that are required to adjust are the influential radii of a cluster center in the multiple dimensional data space. The method assumes that all data falls within a unit hyper-box. Smaller influential radii generate more clusters for further process, and larger radii generate fewer clusters. Different radius combinations generate different FIS. Hence it is important to select proper influential radii for a given problem.

In our method, the fuzzy subtractive clustering and ANFIS are integrated to model complicated real-world problems. This combination has been applied in automation control [18]. In order to save the trial-and-error radius adjustment, an automatic optimization process was employed to obtain the best combination of influential radius in our approach. Given injection profile prediction problem, a range of influential radius of 0.3~0.7 was used based on the precision requirement. Optimized radius combination was selected according to the root mean square errors (RMSE) from the training and validating data sets.

3.2 Conflict Data Pattern Identification

To identify conflict data patterns in the raw data, the TANE algorithm [19] was applied. The TANE algorithm analyzes the functional or approximate dependencies of different attributes in given data source. The results tell whether the key (e.g. primary key or compound key) is properly selected or data patterns are properly associated. Interesting results were observed, as reported in Section 4.

The TANE algorithm requires partition of continuous values for interesting domains. Data should be pre-processed before being put into the TANE algorithm. Based on the precision requirement for the injection profile prediction, the gross thickness and net thickness of strata near the wellbore of injection and producing wells are kept in its original representation. Well spacing is processed into discrete numbers using following rules:

$$d' = \begin{cases} 150 & 125 \le d < 175 \\ 200 & 175 \le d < 225 \\ 250 & 225 \le d < 275 \\ 300 & 275 \le d < 325 \end{cases} \quad (7)$$

The relative injection was kept in precision of 1%, which meets the precision requirement in the petroleum industry.

After all these processing, the TANE algorithm was run in APPROXIMATE mode. By running the TANE algorithm, four approximate dependencies are discovered using given error threshold. To identify exceptional tuples, it is required to investigate the equivalence partitions of both left-hand and right-hand sides of approximate dependency. Results are shown in Section 4.

3.3 Injection Profile Modeling & Prediction

In modeling the injection profile problem, the fuzzy subtractive clustering and the ANFIS were integrated, and a parameter optimization strategy was applied to achieve best performance FIS for training and validating data. Problem modeling follows steps in Fig. 2.

Main data set used in this paper is from the South V District and the South II District in the Daqing Oilfield. It covers 10 injection wells, 53 active producing strata, and 45 producing wells. In problem modeling, totally 363 data points were sampled from the raw data. After data cleaning, 356 data points were left for analysis. In problem modeling, sampled data points were separated based on injection wells. Data from nine injection wells were used to construct the FIS; the left data were used to validate the resulting FIS. Average validation accuracy is calculated based on different training and validating data sets. In injection profile prediction, un-involved profile data from the same development district was used to calculate the prediction accuracy.

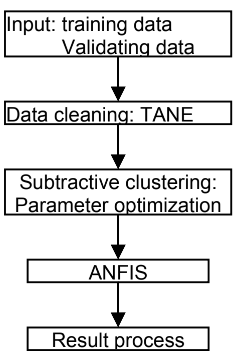

Fig.2. Flowchart of injection profile modeling using the fuzzy subtractive clustering and ANFIS methods.

4. EXPERIMENTAL RESULTS

4.1 Sample Data Set

Fig. 3 shows the complicated relationships of five selected parameters with relative injection.

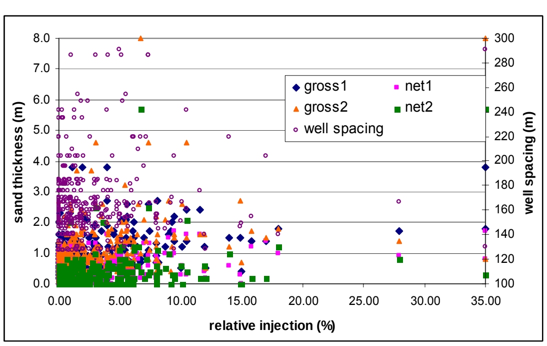

Fig.3. Relationships of selected parameters to relative injection of producing oil strata, where gross1 stands for h_{gross1}, net1 for h_{net1}, gross2 for h_{gross2}, net2 for h_{net2}, and well spacing for d.

4.2 Conflict Data Patterns in the Raw Data

Using the TANE algorithm in the APPROXIMATE mood and error threshold of 0.07, following approximate dependencies are identified, as shown in Table 2. Some other approximate dependencies can be discovered by using other error thresholds. The first dependency is the most important one because it shows that selected five parameters have consistent association relationship with the water intake per active layer except a few data tuples. To simplify and ensure the correct approximate dependency analysis, only the first dependency was analyzed for identifying conflict data patterns.

By analyzing the first dependency, following conflict tuples were identified out, as listed in Table 3. Highlighted pairs have large pattern conflicts, and bolded highlighted patterns were removed from the data set to study the effect of conflict patterns on the prediction models.

Index	Approximate Dependencies	# of Rows to Delete
1	$h_{gross1}\ h_{net1}\ h_{gross2}\ h_{net2}\ d' \rightarrow RI$	25
2	$H_{gross1}\ h_{net1}\ h_{gross2}\ h_{net2}\ RI \rightarrow d'$	20
3	$H_{gross1}\ h_{net1}\ h_{gross2}\ d'\ RI \rightarrow h_{net2}$	24
4	$H_{gross1}\ h_{gross2}\ h_{net1}\ d'\ RI \rightarrow h_{net2}$	23

Table 2: Approximate Dependencies Detected Using the TANE algorithm

Index	h_{gross1}	H_{net1}	h_{gross2}	h_{net2}	d'	RI
1	0.2	0	0.4	0	150	0
2	0.2	0	0.4	0	150	2
3	***0.2***	***0***	***0.6***	***0.5***	***150***	***0***
4	***0.2***	***0***	***0.6***	***0.5***	***150***	***3***
5	*0.2*	*0*	*0.4*	*0.2*	*150*	*0*
6	***0.2***	***0***	***0.4***	***0.2***	***150***	***5***
7	0.4	0.2	0.4	0	150	0
8	0.4	0.2	0.4	0	150	1
9	0.5	0	0.4	0	150	0
10	0.5	0	0.4	0	150	2
11	0.5	0.5	0.5	0.5	150	0
12	0.5	0.5	0.5	0.5	150	1
13	0.5	0	0.8	0	150	0
14	0.5	0	0.8	0	150	2
15	*0.5*	*0.4*	*1.0*	*0.4*	*150*	*1*
16	***0.5***	***0.4***	***1.0***	***0.4***	***150***	***6***
17	*0.6*	*0.2*	*0.5*	*0.2*	*200*	*1*
18	***0.6***	***0.2***	***0.5***	***0.2***	***200***	***6***
19	***1.3***	***1.1***	***1.2***	***0.4***	***150***	***0***
20	***1.3***	***1.1***	***1.2***	***0.4***	***150***	***3***

Table 3: Conflicting tuples identified by analyzing the first approximate dependency in Table 2.

From the results, it is obvious that the data set contained conflict relationships and associations among parameters. Some of them contained serious problems. For example, for specific pattern of h_{gross1}, h_{net1}, h_{gross2}, h_{net2} *and* d', the relative injection per active layer bear large difference, as <0.2, 0, 0.4, 0.2, 150, 0> in fifth tuple and <0.2, 0, 0.4, 0.2, 150, 5> in the sixth tuple, and <0.5, 0.4, 1.0, 0.4, 150, 1> in the fifteenth and <0.5, 0.4, 1.0, 0.4, 150, 6> in the sixteenth. With same parameters, differences of relative injection were up to 5%. With these conflict data in the training data, it is difficult to model correct pattern association among these parameters.

4.3 Experimental Results

This method was applied to predict the injection profiles in the South II and V Districts in the Daqing Oilfield. Averagely, the prediction accuracy was up to 82%. Generally, prediction accuracy is high for thick and high- injectivity strata, and thin and low-injectivity strata; prediction accuracy is low for thick but low-injectivity and thin but high-injectivity strata. This is because that the assumption on the relationship of thickness of strata and their permeability is invalid in those cases.

The results were applied in analyzing the residual oil distribution and designing the secondary re-perforation in the South II District in the Daqing Oilfield. Promising results were observed, with increased recoverable reserve of 5,370,000 tons and increased recovery of 4.5%.

In this section, detailed results are reported to demonstrate the effectiveness of the new approach, compared with the FFBP Neural Networks, and the benefit of data scrubbing in problem modeling using soft computing methods.

Results using the Raw Data: The injection profile prediction was mainly implemented by the new approach and FFBP neural networks. FFBP neural networks are well known for their capability in modeling non-linear and complicated problems. The problem with neural network is that it is difficult to set up a proper neural network, including architecture and parameters, for a given problem. Fig. 4 shows results from different neural networks, either with different architecture or with different parameters. It is obvious that, with same training and testing data sets, different FFBP neural networks generate different validating results. The optimization is difficult. Table 4 shows the validating results of these neural networks.

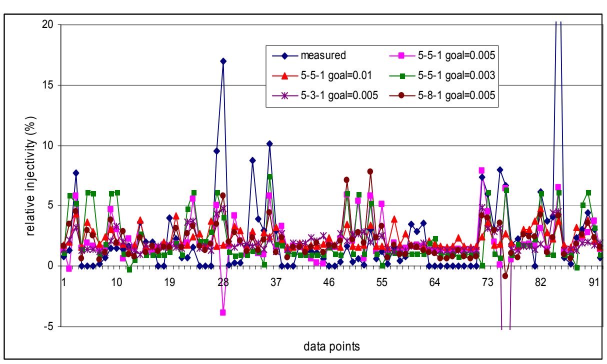

Fig. 4. Validating results from different FFBP neural networks for sampled testing data.

Modeling Methods	Threshold	
	1(%)	2(%)
5-5-1 goal=0.005	34.78	72.82
5-5-1 goal=0.01	35.87	72.82
5-5-1 goal=0.003	43.48	72.82
5-3-1 goal=0.005	42.39	72.82
5-8-1 goal=0.005	38.04	79.34
New approach	43.48	76.34

Table 4: Validating accuracies obtained from the new approach and different FFBP neural networks using the raw data

Results in Table 4 reflect the complexity in optimizing neural network setups. However, it is fairly easier to obtain an optimized model using the new approach. For our method, although it may not obtain highest accuracy in all thresholds, it achieved higher accuracy in most cases.

Table 5 shows the prediction accuracy using the FFBP and the new approach for the N2-D2-B447 well. The N2-D2-B447 is an injection well in the South II District. From its injection profile data, it has thin strata having large injectivity, such as S_{24a} and S_{25}, and thick strata having small injectivity, such as S_{216} and P_{21a}. These strata have poor prediction accuracy. Results show that, on same level of accuracy in validating process, new approach achieved higher accuracies under different precision requirements. Fig. 5 shows the predicted injection profiles of the well N2-D2-B447 using new approach and FFBP under configuration in the Table 4.

θ	5-3-1 goal=0.005	New Approach
1	27.8	41.7
2	41.7	75.8

Table 5. Injection profile prediction accuracy for the well N2-D2-B447 using the new approach and the FFBP neural network using the raw data

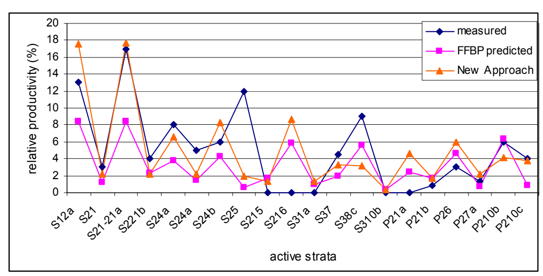

Fig.5. Predicted injection profiles for the N2-D2-B447 using the raw data.

Results with Cleaned Data: Results with cleaned data were obtained by re-running above experiments after removing bolded highlighted conflicting data patterns in Table 3. Table 6 shows the validating accuracy from the new approach and different FFBP neural networks using cleaned data. Table 7 shows the prediction accuracies from the new approach and the FFBP neural network configured as “5-3-1 goal=0.005.” These results show great improvements on accuracies under thresholds θ=1 and 2 for both the new approach and FFBP neural networks, and demonstrate the importance of consistent data used for problem modeling.

Modeling Methods	Threshold	
	1(%)	2(%)
5-5-1 goal=0.01	54.12	74.12
5-5-1 goal=0.005	54.12	75.29
5-5-1 goal=0.003	54.12	78.82
5-3-1 goal=0.005	57.64	77.65
5-8-1 goal=0.005	60	74.12
New approach	50.24	83.33

Table 6: Validating accuracies obtained from the new approach and different FFBP neural networks using the cleaned data

θ	5-3-1 goal=0.005	New Approach
1	30.56	54.44
2	72.22	83.33

Table 7: Prediction accuracy of the well N2-D2-B447 using the new approach and the FFBP neural network using the cleaned data

5. CONCLUSIONS AND DISCUSSIONS

Modeling complicated real-world problems is always full of challenge. In this paper, a new problem modeling approach is presented. The approach integrates two soft computing methods, the fuzzy subtractive clustering and the ANFIS, which enables it to construct a FIS automatically from training data set. A parameter optimization step is adapted to aid in generating optimized clustered data and hence the optimized FIS.

In problem modeling using soft computing methods, quality of training data is the key for stable results. Raw data obtained from real practice or process is always messed with different problems. Conflicting data is dangerous, especially when sampled data sets are small in size. It is shown by the prediction accuracy improvement in the practical problem.

The problem modeling strategy is justified by being applied in a critical problem in oilfield development – the injection profile prediction. Based on targeting problem, the detailed modeling procedure and methods could be different.

Compared with neural networks, this approach provides more promising results for intractable and complicated real-world problems. The new approach can also be applied to resolve internet related problem modeling, which are the hot topic of this decade.

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