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Integrating Neural, Fuzzy Logic, and Nero-fuzzy Approaches Implementing Ant Colony Optimization Routing Algorithm to Determine Reservoir Facies

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Abstract

Determining the reservoir facies and areas with high-quality reservoirs play a pivotal role in reservoir modeling as well as future drilling in developing oilfields. As an index which varies in line with changes in the reservoir characteristics, Flow Zone Indicator (FZI) could be an influential factor in dividing the facies. The present study attempts to propose an advanced, optimized model through integrating the intelligent systems to estimate the FZI in the whole oilfield. This Committee Machine (CM) integrates the predicted results obtained from the intelligent neural, fuzzy logic, and Nero-Fuzzy systems with defined weights. Optimized weights for each method are determined using the Ant Colony Optimization Routing (ACOR) Algorithm. In this study, to apply the methods, well log and seismic data were used from one of the oilfields in South Iran. At the first stage, seismic attributes which were far more associated with the target data (FZI) were selected by stepwise regression. Subsequently, a 3D cube flow indicator in the whole field was estimated with intelligent systems. Finally, various reservoir facies were classified by the means of Fuzzy C-Mean Algorithm. The results illustrate that the committee machine which utilizes ACOR outperforms other individual systems acting alone.

Keywords: Reservoir Facies, Committee Machine (CM), Fuzzy Logic, Nero-Fuzzy Systems, Ant Colony Optimization Routing (ACOR).

Introduction

What significantly contributes to the development of oil and gas fields is the analysis of facies taking into consideration the relationship between the reservoir parameters and seismic attributes. A glance over the literature suggests that investigating such an issue has enjoyed the close attention of researchers in the realm for long; to name but a few, Carr and Oliver (1996) depicted different parts of reservoir analyzing seismic attributes in Caddo Conglomerate in the Boonsville (Bend Conglomerate) gas field [1]. Michelena, et al. (1988) benefited from self-organizing maps with seismic attributes inputs to delineate the reservoir facies [2]. Moreover, to produce seismic facies classes, Barnes (2000) combined a set of seismic attributes, including amplitude variance, spacing, parallelism, continuity, divergence and hummockiness based on the descriptions of the seismic stratigraphic reflection patterns [3]. Additionally, West et al. (2002) classified seismic facies of stack and AVO data using the textural attributes and neural network. From amongst those researchers studying this field, Rastegarnia and Kadkhodaie (2013) can be named. They followed the fuzzy rules and integrated the seismic attributes to estimate the reservoir parameters. What is more, Diago, Ramos, and Andre (2013) benefited from fuzzy rules to recognize reservoir facies from well diagram [8]. Following them, Also, Yarmohammadi at el. (2014) delineated high porosity and permeability zones using the seismic-derived FZI data at Shah Deniz sandstone packages. The present study seeks to apply neural, fuzzy, neoro-fuzzy systems, and combine the obtained results using ACOR to analyze the reservoir facies. To do so, the afore-mentioned algorithms will be applied on the real data (i.e., one of the Iranian Southern offshore gas fields) and the results will be validated against the well log data. Moreover, the results obtained from the CMIS will be compared with those of single approaches so as to shed light on its superior efficiency and robustness over others. At the final stage, having extracted the FZI in the whole field by the CMIS, reservoir facies will be delineated by FCM clustering algorithm and the results will be compared with thin sections analyses.

Methodology

The proposed methodology for this study comprises of three stages. At the first stage, the optimum seismic attributes that correspond more strongly with the target data (FZI) are selected by stepwise regression algorithm. Second, intelligent approaches such as neural, fuzzy, and nero-fuzzy systems are applied to the seismic attributes, and the achieved FZI cube are calculated for the whole field. Next, to combine the results obtained from the previous approaches, a CMIS will be employed using ACOR. At the final stage, an FCM is applied to the CMIS outputs, and various facies are delineated.

Committee Machine with Intelligent Systems (CMIS)

Generally speaking, a CMIS consists of a group of intelligent systems which combine the outputs of each system and therefore reaps the benefits of all work with little additional computation. Thus, the model could outperform the best single network. A schematic diagram of CMIS is presented in the Figure 5.

There are different ways to integrate the intelligent systems output in the combiner. The simple ensemble averaging method is the most popular one (Naftaly et al., 1997; Chen & Lin, 2006) [14, 15].

Proper combination of the intelligent systems contribution (weight) in a CMIS could be achieved by a Genetic Algorithm (Lim, 2005 [16]; Chen & Lin, 2006 [15]; Kadkhodaie et al., 2009 [17]). One of the innovations this study benefits from is the use of ACOR to combine neural, fuzzy, and neoro-fuzzy models in the form of a CMIS. Such an algorithm is explained as follows:

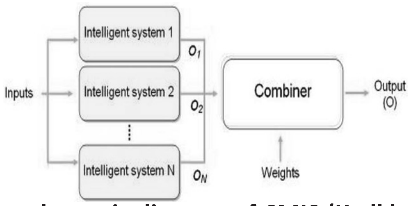

Figure 1: schematic diagram of CMIS (Kadkhodaie et al., 2009)

Discussion and Results

Graphical comparison and correlation coefficient (CC) between predicted and measured FZI values from neural, fuzzy, and neuro-fuzzy approaches and CMIS on sample data are demonstrated in figures 2a-d and 3a-d, respectively. In Figure 2, predicted values and real values are in red and black respectively.

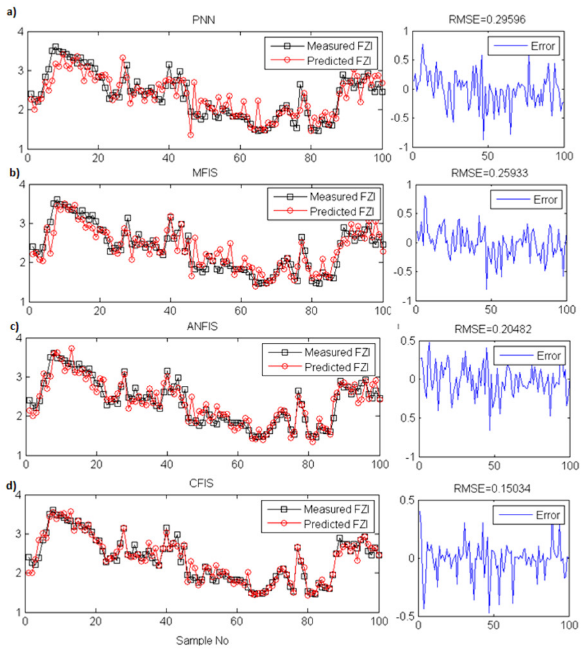

Figure 2: Predicted FZI and measurement error from neural, fuzzy, and neuro-fuzzy approaches and CMIS on sample data.

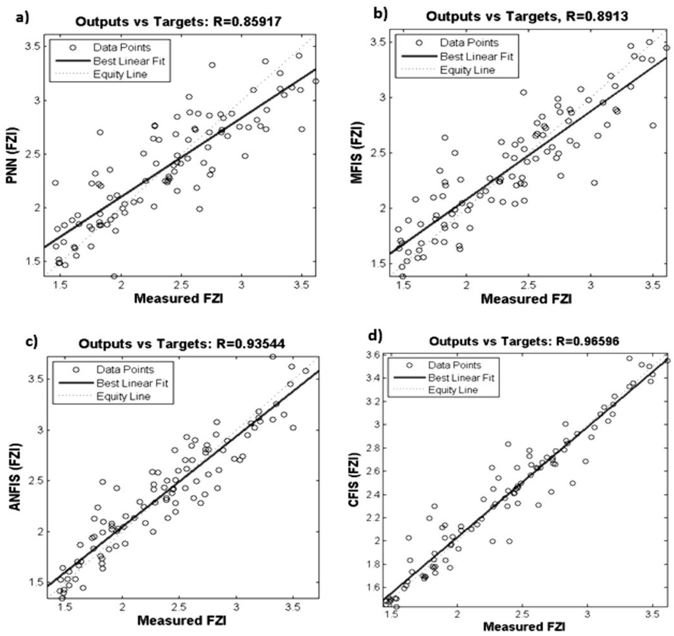

Figure 3: Correlation coefficient between predicted and measured FZI values from sample data using a) PNN b) MFIS c) ANFIS d) CFIS

Conclusion

The present study applied intelligent systems including neural, fuzzy, and neuro-fuzzy approaches to estimate FZI from 3D seismic attributes in one of the carbonate offshore gas fields, Southern Iran. The study demonstrated that integrating the outputs achieved from intelligent systems using a CMIS, which benefits from ACOR, can lead to a significant improvement in the accuracy of estimation of reservoir parameters. Based on the results obtained, CMIS provides more accurate estimation of FZI in comparison with that of individual systems. What is more, it is concluded that FCM clustering is a reliable and efficient approach in the prediction and identification of the reservoir facies from 3D FZI cube. Utilizing this approach, 6 facies in the studied gas field, whose data correspond strongly with thin sections analyses, were determined. Put it in the nutshell, it is concluded that the proposed methodology in this study, which benefits from the integration of results achieved from CMIS and FCM clustering algorithm, can be utilized as a reliable and efficient approach to delineate the reservoir facies.

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