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INTELLIGENT CONTROL OF CO_2-EOR PROCESS**

1. INTRODUCTION

Due to the limited geological resources of hydrocarbons, it is necessary to use them efficiently. Recovery factors obtained from the oil reservoirs produced with the use of the primary methods utilizing the natural reservoir energy are estimated to 20% [13, 17]. Secondary recovery methods which supply additional energy into the reservoir by water or gas injection are applied firstly in order to increase production. These methods allow to increase the recovery factor to about 50% [13, 17]. When secondary methods become economically ineffective, tertiary recovery methods are used to additionally increase the recovery factor of the reservoir. They are also known as Enhanced Oil Recovery (EOR) methods and affect the oil properties such as viscosity and density as well as supply energy supporting the production process [13].

One of the enhanced oil recovery methods is the CO_2-EOR method, which is based on carbon dioxide injection into partially depleted reservoirs in order to produce oil that cannot be recovered using primary or secondary methods. This method has been used to increase oil production for over 45 years and makes it possible to recover an additional 15–20% of oil resources [2]. The following factors affect the process effectiveness: reduction of the oil density and viscosity, reduction of the interfacial tension between oil and reservoir rock and evaporation of some oil components [13].

Several options of CO_2-EOR process can be separated depending on the carbon dioxide injection method. One of them is the WAG (Water Alternating Gas) method

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which consists of alternating injection of carbon dioxide and water [13]. The second option is the GSGI (Gravity Stable Gas Injection) method that utilizes the gravity drainage. Carbon dioxide injected into the upper part of the formation causes the oil displacement toward the production well, which is located at the bottom of the reservoir [13]. Another possibility is the cyclic carbon dioxide injection during the CO_2 huff & puff process, which consists of three stages: CO_2 injection, soaking and production [8]. Unlike the previous methods, carbon dioxide is injected directly into the production well. This well is then shut-in for a certain period of time to allow the carbon dioxide and reservoir fluids interaction. In the final process stage, oil is produced from the same well until a certain minimum production is achieved.

Oil production efficiency is related to the way it is run. The production scheme is most often based only on the engineering experience so it is not subjected to the optimization process, which affects the low recovery factors obtained from the oil reservoirs. Therefore, it is reasonable to conduct research on solutions that can improve the efficiency of hydrocarbon production by identification of its optimal control. It consists in determining the optimal values of relevant parameters defining the production schedule [4], which can be obtained by the use of artificial intelligence methods in combination with the optimal control theory and computer simulation of hydrocarbon reservoirs.

2. APPLICATION OF ARTIFICIAL INTELLIGENCE METHODS IN THE OIL AND GAS INDUSTRY

Artificial intelligence methods have great potential in solving complex engineering problems. For three decades, they have found numerous applications in the oil and gas industry [4]. Artificial intelligence methods are used, among others to interpret the results of well logging, determine the reservoir characteristics and reservoir fluids properties, optimize the drilling process and subsequent production as well as to select production process control [1]. The use of artificial intelligence methods for intelligent reservoir control allows to achieve higher recovery factors and additional economic benefits without significant financial investment as only the operation control scheme changes. The most popular methods of artificial intelligence in the oil and gas industry include artificial neural networks, genetic algorithms, expert systems and fuzzy logic.

Problems related to the exploration and production of hydrocarbon reservoirs are most commonly solved by the use of artificial neural networks. The artificial neural network is built of interrelated artificial neurons constituting elements that convert input signals into a single output value [16]. These networks have been successfully used to identify reservoir zones and the distribution of reservoir properties based on the results of gamma logging and density measurements [18]. Artificial neural networks also allowed to determine the well productivity after hydraulic fracturing and choose the well with the highest potential [9].

Genetic algorithms are based on the natural evolution theory [12]. They are used in many areas of the oil and gas industry. In genetic algorithms, possible solution constitutes a population of individuals living in an environment determined on the basis of a given problem. These methods found application in an optimization of the injection wells location and selection of the carbon dioxide injection rate in order to minimize the risk of CO_2 leakage during long term CCS process [15]. Genetic algorithms have also made it possible to characterize the reservoir on the basis of production data such as reservoir fluid rate and bottom hole pressure [11]. The combination of genetic algorithms and artificial neural networks has been used to optimize reservoir production. Hybrid algorithms constructed in this way enabled the selection of the number, type and location of injection and production wells as well as production and injection rates [14].

Expert systems are computer programs that mimic the decision-making process of an expert (human) in a given field [16]. They found application in supporting the selection of the right tertiary recovery method for the reservoirs based on its parameters [5]. Expert systems also made it possible to identify problems related to general complications caused by water and to recommend an effective solution [19].

In the case of fuzzy logic which enables a formal record of imprecise natural language concepts there are a number of intermediate values determining the membership degree between the lack of membership (absolute false) and full membership (absolute true) [12]. Fuzzy logic has made it possible to realistically assess the location of new wells on the reservoir thanks to the extended approach to the description of reservoir rock parameters [10]. However, fuzzy logic is most often used in combination with other artificial intelligence methods. For example, an expert system developed by Garrouch et al. [3] uses the theory of fuzzy sets to plan the shape and equipment of multilateral wells.

In addition, machine learning is also an important part of artificial intelligence in the case of optimization of industrial processes. Machine learning explores the study of algorithms that improve their performance along with the experience gained. Having a mathematical model representing the analyzed decision problem, it is possible to apply the machine learning algorithm in order to determine the parameters of the model that allows to solve a given problem.

3. CO_2-EOR PROCESS OPTIMIZATION

The problem of optimal CO_2-EOR process control is to determine such a control that maximizes the NPV value of the project. Process control can be considered as a strategy that depends on the control at each time step due to the limitations resulting from the practical process realization. A decision tree can be a model of such a problem. Attributes such as the average reservoir pressure or oil flow rate constitute the tree nodes while the limit values corresponding to the individual attributes are assigned to branches. Then leaves constituting nodes from which no edges leave determine the reservoir control by specifying actions that should be taken at a given time step. The problem of this approach is that limit values for selected attributes of a decision tree are most often selected arbitrarily on the basis of engineering experience, which does not guarantee an optimal decision. The original solution used in this work is to build a parameterized decision tree that enables to replace the arbitrarily chosen values by the parameters determined in the optimization process.

Considerations on the CO_2-EOR process optimization was based on a numerical model of a real gas-condensate reservoir characterized by a dual porosity system. This reservoir is in the final production phase despite the fact that it still contains almost 30% of the initial oil in place, what confirms the validity of the CO_2-EOR method application. It was assumed that the optimization of carbon dioxide injection will be carried out using the huff & puff method with the soaking stage skipped because in the analyzed case it had the opposite effect to the intended one [7]. For the CO_2-EOR method configured in this way a decision tree, shown in Figure 1, was developed. Its design was based on the conducted simulation tests and engineering knowledge. The proposed decision tree describes the decision process, which should be performed in each simulation time step to determine the control prevailing in the next step. The developed decision tree is used to classify whether carbon dioxide should be injected or production should be conducted under given reservoir and production conditions. This tree also enables automatic determination of the moment when the process should be completed due to reaching of the profitability limit.

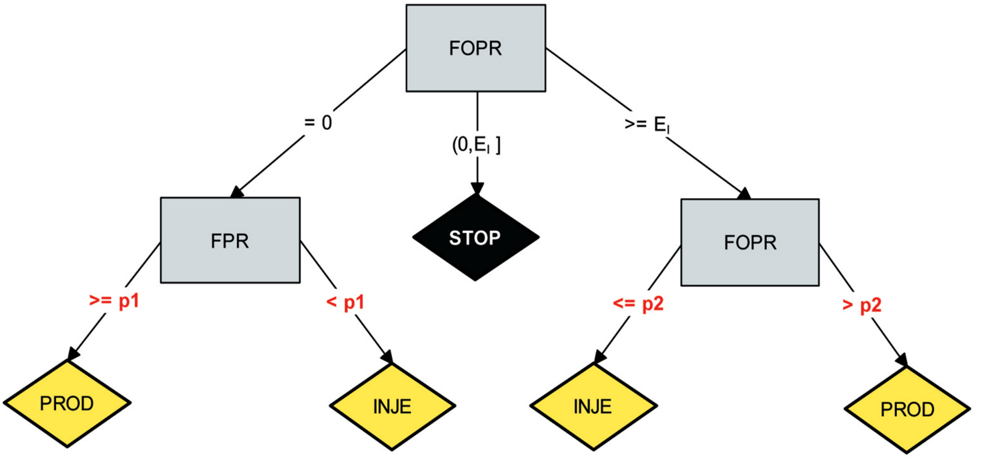

Fig. 1. Parameterized decision tree developed for the CO_2-EOR process

According to the decision tree proposed for the CO_2-EOR process carried out with the use of the huff & puff technique, the value of oil flow rate is firstly checked. When it equals zero then CO_2 injection is currently in progress, which is continued until the reservoir pressure limit value is reached. After it is exceeded, the production period is automatically started. However, oil flow rate greater than zero means that the production period lasts. If the obtained flow rate exceeds the economic limit, the production continues until a certain minimum oil flow rate is reached. For oil flow rate lower than the assumed level, the transition to the injection period takes place to rebuild the reservoir pressure. The above scheme is repeated up to the moment when the oil flow rate does not exceed the production profitability threshold despite the fact that the production period is in progress. Then, the CO_2-EOR process is automatically terminated due to the inability to continue production of the reservoir fluids. Thus, the developed decision-making scheme allows to determine not only the process control, but also the investment duration. In order to optimize the CO_2-EOR process, the limits of the average reservoir pressure to which the injection should be continued and the oil flow rate to which production should be carried out in each cycle of the huff & puff process were parameterized.

In order to determine the parameters of the proposed decision tree, the SMAC (Sequential Model-based Algorithm Configuration) optimization tool was used. This tool learns from previous results which parameters values bring more favorable outcomes [6]. Firstly, the tool collects data from the initial realizations and then it iteratively performs the following three steps included in the learning process [6]: on the basis of the data collected so far, it builds the search space model, uses this model to select subsequent parameters values, calculates the quality indicator value using the target algorithm to create a new data set. As a result of the SMAC tool operation, such parameters that minimize/maximize a given quality criterion are determined for the given algorithm [6].

A numerical procedure that facilitates the combination of the parameterized decision tree with the ECLIPSE reservoir simulator and the SMAC optimization tool was developed in order to determine an intelligent control of CO_2-EOR process. Such a solution enables full automation of the optimal CO_2-EOR process control selection. In each iteration, the SMAC tool returns parameters values for which a reservoir simulation is automatically runs. During the simulation, the reservoir control applicable in the next time step is determined on the basis of the decision tree. The value of the quality indicator which is the NPV of the project is calculated as a result of the simulation. This value constitutes the basis for the SMAC tool to determine subsequent parameters values. As a result of the proposed algorithm, the process control which maximizes the investment income is obtained after executing a specified number of iterations.

In order to evaluate the effectiveness of the proposed solution, a simulation with the limit values for the decision tree parameters arbitrarily selected on the basis of the previously performed tests and analysis was also carried out. This option reflects a more traditional way of selecting of the process realization method. The limit values determined on this basis are equal to 300 bar and 4 m^3/day.

4. RESULTS

As a result of the intelligent control of CO_2-EOR process determined with the use of the developed solution the parameters of the decision tree are set at 210 bar and 9 m^3/day. The results obtained for the optimized process and the option assuming the arbitrary selection of the decision tree parameters are compared to illustrate the validity of the developed solution. The dependence of cumulative oil production obtained during the process (Fig. 2) and the variation of investment income during its duration (Fig. 3) are presented for the comparative purposes.

Application of the created optimization algorithm causes an increase in the number of the huff & puff process cycles and a reduction of the investment duration. As a result, an increase in the oil production by 3.5% (Fig. 2) with a simultaneous decrease in the amount of carbon dioxide injected at that time by 11% was achieved during the CO_2-EOR process. The developed solution enables not only to increase the recovery factor of the reservoir, but also to reduce the process costs associated with the acquisition and injection of carbon dioxide due to its required volume reduction. After calculating the results on NPV value, the proposed algorithm implementation enables an increase in revenue by 31% compared to the non-optimized option. In addition, this profit is achieved without additional investment, because only the method of reservoir control is changed.

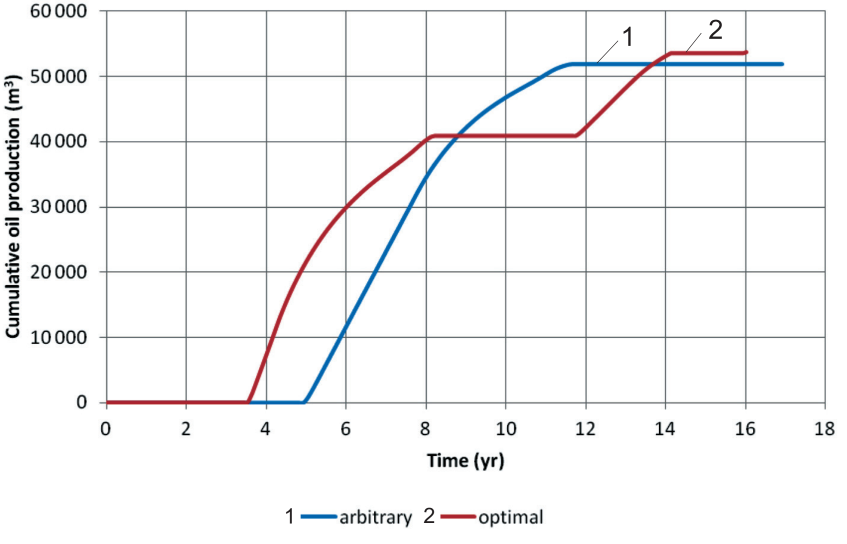

Fig. 2. The impact of the proposed solution on the cumulative oil production

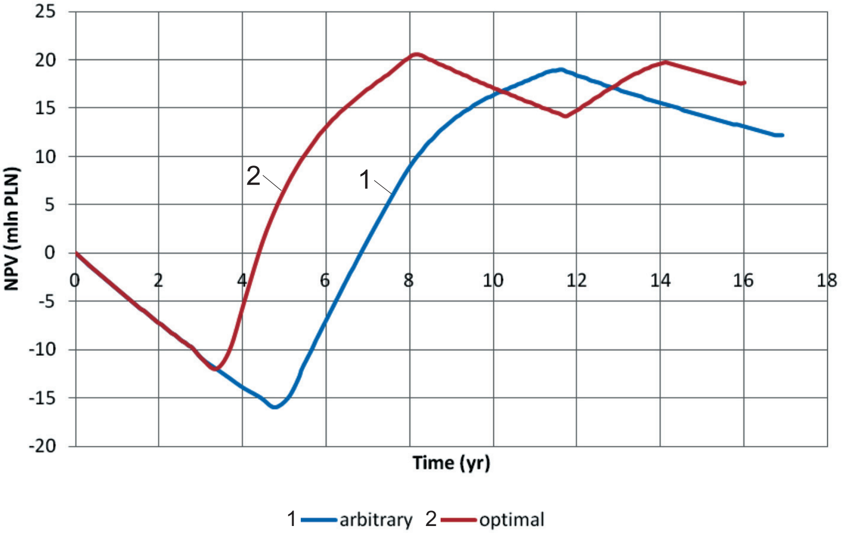

Fig. 3. The impact of the proposed solution on NPV

5. SUMMARY

An algorithm that allows automatic determination of the intelligent CO_2-EOR process control and is focused on maximizing the economic effect is proposed in this paper. A parameterized decision tree for the CO_2-EOR process carried out using the huff & puff technique was developed. It enables to replace the arbitrarily chosen values by the parameters determined in the optimization process. The proposed decision tree is used to classify whether carbon dioxide should be injected or production should be conducted under given reservoir and production conditions. This tree also enables automatic determination of the moment when the process should be completed. The parameters of the proposed decision tree were determined using the SMAC optimization tool. The obtained results show that the implementation of the proposed algorithm allows to increase the project income without additional investment, because only the control of CO_2-EOR process is changed. Moreover, the intelligent process control determined for the analyzed example also allowed to increase the recovery factor of the reservoir and to enhance the efficiency of the CO_2-EOR process.

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