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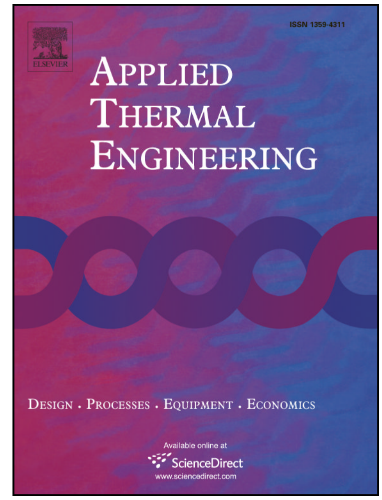

Research Paper

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Abstract

Thermal enhanced oil recovery (EOR) methods are commonly used to extract heavy oil from oilfields. Hot water injection into reservoirs reduces oil viscosity and increases its mobility to move toward production wells. Water flood EOR projects are traditionally implemented with rate and bottom-hole pressure (BHP) control of injection and production wells to recover more oil from reservoirs. Whereas, water injection temperature can also play an important role in overall oil recovery, especially in sandstone rocks in which the relative permeability is a function of both the temperature and saturation. The present study aims to optimize hot water injection process in heavy oilfields using particle swarm optimization (PSO) approach. Effects of water injection temperature, and the water injection rate and BHP of producers are investigated on cumulative oil production of heavy oil reservoirs. First, through optimization of the hot water flooding process in a 2D heterogeneous reservoir with 13 wells, it has been shown that optimal values exist for the water injection temperature of different wells. Secondly, the idea has been tested in a 3D field reservoir successfully. Results show that PSO can properly be implemented for optimization of hot water injection projects. Furthermore, optimal control of water injection temperature can improve oil recovery.

Keywords: Particle swarm optimization (PSO), temperature control, hot water injection, thermal enhanced oil recovery, relative permeability.

List of Acronyms

2D	Two dimensional	COP	Cumulative oil production
3D	Three dimensional	EOR	Enhanced oil recovery
ABC	Artificial bee colony	NPV	Net present value
ANN	Artificial neural network	PSO	Particle swarm optimization
BHP	Bottom hole pressure	RSM	Response surface methodology
CCS	Cyclic steam stimulation	SAGD	Steam-assisted gravity drainage
CMG	Computer modelling group	SQP	Sequential quadratic programming

1. Introduction

According to the recent energy outlook which was published by British Petroleum, because of the expected growth in the world economy and the rising earth's population, it is predicted that the global energy consumption to increase by 34% between 2014 and 2035 [1]. Fossil fuels are the main source of the world's energy that are commonly exploited from hydrocarbon reservoirs. Generally, a large portion of oil is trapped inside reservoir rocks after the primary depletion stage, in which oil is exploited by natural driving mechanisms. To access the most amount of petroleum resources, enhanced oil recovery (EOR) techniques such as water flooding, thermal methods, chemical methods and CO_2 injection [2] are employed. All of these techniques are attempting to move more oil toward production wells with different mechanisms such as increasing the reservoir pressure and improving the oil mobility. According to available statistics, heavy oil forms more than 65 percent of the world's proven resources [3]. Thermal EOR methods have been extensively employed to enhance heavy oil recovery, and are often effectively used in these reservoirs. These methods aim to increase the internal energy of crude oil by heat injection (e.g. hot steam injection) or heat generation (e.g. combustion of oil) inside the reservoir to reduce the heavy oil viscosity and increase its mobility. Steam flooding [4], hot water flooding [5], cyclic steam stimulation (CSS) [6], steam-assisted gravity drainage (SAGD) with horizontal wells [7] and fire flooding [8] are some practical thermal EOR methods that are commonly implemented to increase the amount of heavy oil that can be extracted from an oil fields. For instance, in a hot water flooding project, hot water is injected into the reservoir through some injection wells to move the trapped oil quantities toward production wells. The performance of this process strongly depends on the swept volume of the reservoir by the injected fluid. The heterogeneity of the reservoir, the density of oil and injected water in line with the injection and production scenarios can substantially affect the sweep efficiency of the EOR project. The sweep efficiency of the project will be reduced if the injected water reach the production wells in a short time and a large amount of water would be produced, instead of oil, from production wells. Accordingly, optimal control of decision parameters of EOR projects is crucial to access the most amount of energy resources available underground. Optimization of EOR projects, from a glance, can be divided into two general types [9]: 1- optimization of well locations in which the best place for well drilling is estimated in a manner to maximize the oil production [10, 11]; 2- optimization of well controls, in which by variation of well rates or their bottom-hole pressure (BHP), is tried to maximize the amount of oil or gas production [12, 13]. Some works have also focused on optimization of both the well locations and controls [14, 15].

Different research works have been done to optimize oil production by well controls. Heirung et al. [16] conducted a well control project for a small 2D reservoir during water flooding process by direct transcription method. Tapia et al. [17] performed a discrete time optimization for CO_2 allocation and scheduling to enhance oil recovery in line with carbon storage underground. Brouwer [18] used a heterogeneous reservoir model with two intelligent horizontal wells to optimize water injection process. Zhao et al. [19] used the simulated annealing method to optimize steam injection with solvent in thin heavy oil reservoirs. Choobineh et al. [20] employed the SQP and ABC algorithms to optimize water injection process in a heterogeneous reservoir using streamlines. They also showed that a hybrid optimization algorithm, which is initialized by ABC and advanced with SQP, can converge faster than ABC and SQP to the global optimum condition.

Numerous optimization algorithms have been developed yet, which based on their principal idea and procedure, can be classified into two main categories: 1- gradient-based methods; and 2- population-based schemes. Gradient-based approaches have the advantage of fast convergence to an optimal point using gradient vectors. However, they suffer from the fact that might get stuck in local extremums and converge to sub-optimum answers in complex problems. In addition, computation of gradient vectors is a very time consuming procedure when a large number of decision variables exists. Therefore, usually for the problems such as EOR projects – in which the fluid flow physics is very complex and are dealing with a relatively high number of decision variables – instead of using gradient-based approaches population-based methods are more appropriate to be employed. These methods search the decision space thoroughly and their results do not depend on the selected starting points. Furthermore, they don't have limitations of gradient methods, since they are needless to computation of gradient vectors [21].

Recently, population-based methods such as evolutionary algorithms [22, 23], particle swarm optimization (PSO) [24, 25], artificial bee colony (ABC) [26] and genetic algorithm (GA) [27, 28] are used very frequently for optimization of various engineering problems. Guyaguler and Horner [7] hybridized the GA with the polytope algorithm to make use of the trends in the search space in order to optimize well placement. Sayyafzadeh and Keshavarz [29] used GA to find optimal values for gas injection composition and its injection rate in a coal-bed methane reservoir. Salmachi et al. [30] also used GA to find the optimum location of drilling a new well in coal-bed methane reservoirs. Dossary and Nasrabadi [31] found optimal well locations with imperialist competitive algorithm and compared its performance with GA and PSO in their problem. Naderi and Khamechi [10] employed the metaheuristic bat algorithm to find optimal well locations and compared it with GA and PSO. Espinet and Shoemaker [32] compared different optimization algorithms in CO_2 sequestration projects. Asadollahi et al. [33] implemented 5 different gradient-based and gradient-free optimization techniques for production optimization. They observed that optimization with gradient-based SQP method has the high risk of getting trapped in a local optimum. In another work, Zhang et al. [34] used the gradient-based method of steepest descent to optimize well pattern and compared their results with those of PSO. This comparison indicates that though the gradient-based algorithm converges faster than PSO; the gradient algorithm is likely to fall into local optimal results if initial step sizes are not chosen appropriately. According to the literature, PSO shows a good performance for optimization of different engineering problems. A variety of research studies exist that implemented PSO successfully in electronics and electromagnetics [35], biomechanics [36], controllers [37], engine design [38], entertainment [39], financial risk analysis [40], graphics and visualization [41], image analysis [42], metallurgy [43], robotics [44], turbine blade design [45], signal processing [46] and more. An analysis of different application fields of PSO is written by Poli [47] and a comprehensive review of recent studies on PSO algorithm with introduction of some potential areas for future studies is presented by Bonyadi and Michalewicz [48]. Interested readers are referred to these references to further know about PSO development and applications.

PSO has also found a great deal of attention in EOR projects. A general work does not exist to compare PSO with other alternative methods. However, researchers used PSO in different EOR projects and some comparison data exist between the performance of PSO and other metaheuristic techniques that can be used as the reference about results obtainable with PSO. Janiga et al. [49] employed PSO and four other nature-inspired optimization algorithms to find the optimal polymer injection strategy to enhance oil recovery. They indicate that results of all the five implemented nature-inspired algorithms are comparable and among them PSO could find the highest figure of net present value (NPV). Eshraghi et al. [50] conducted an EOR project with miscible CO_2 injection into the reservoir using PSO, GA and ABC algorithms and compared their performance with each other. They mentioned that all the three algorithms result in favorable outcomes, while in their problem, ABC and PSO exhibit the better performance with respect to GA. Hou et al. [51] suggested a hybrid PSO method using the uniform design algorithm to initialize candidate solutions of PSO and tested the method in a CSS project. They concluded that the hybrid PSO technique is able to obtain the best CSS development strategy for heavy oil reservoirs on both technical and economic sides. Lang and Zhao [52] performed an oil well production scheduling problem optimization with an improved PSO algorithm and compared its results with those of a commercial software. They stated the improved PSO, compared with the commercial software, could obtain the optimal schedule faster. Siavashi et al. [9] used PSO to find the optimal location of wells with a novel streamline-based objective function. They first tested PSO in a 2D homogeneous reservoir and found the 5-spot arrangement as the optimal solution. Next, implemented PSO in a complex 3D reservoir successfully and proved its capability to solve these problems. Shafiei et al. [4] have developed a new screening tool based on artificial neural networks (ANNs) optimized with PSO to appraise the performance of steam flooding in viscous oil naturally fractured reservoirs. Their results indicate that the hybrid PSO-ANN model is greatly capable to screen steam flooding in viscous oil reservoirs. The same method has also been used by Ahmadi et al. [53] to precisely forecast the productivity of horizontal wells in pseudo-steady conditions.

Ghadami et al. [54] optimized a chemical flooding project, made use of PSO and response surface methodology (RSM) techniques to find the optimum oil recovery. They concluded that PSO is a proper choice for optimization of chemical flooding EOR projects.

Many research works have been done to optimize thermal EOR processes. However, most of them rely on optimization of well rate and pressure, and their locations in conjunction with different thermal EOR schemes. Cuadros et al. [55] optimized horizontal well placement for heavy oil production of a field. Hou et al. [51] performed an optimization of operational parameters of CSS by horizontal wells in heavy oil reservoirs. Al-Gosayir et al. [56] presented the optimization of steam-over-solvent injection method in order to enhance heavy oil recovery from fractured carbonate reservoirs. Queipo et al. [57] optimized steam injection rate in a SAGD process by a solution methodology which includes the construction of a fast surrogate. Galvao et al. [58] conducted an optimization of operational parameters of steam injection with solvent in heavy oil reservoirs. They found the optimal distance between wells and the steam injection rate for different percent values of injected solvents. All of these research studies and many others are confined to constant temperature conditions. Furthermore, the effect of temperature on relative permeability is ignored in these works, whereas some empirical investigations [59, 60] show significant dependency between relative permeability and temperature for sandstone rocks. The same phenomena are reported for chalk [61], dolomite and limestone [62] reservoirs.

Only a few research works have been done concerning the effect of temperature on performance of thermal EOR projects. Pillai and Muralidhar [63] presented a numerical study of cold and hot water injection in a simple porous formation model. They reported that an increase in temperature of the injected water improves oil recovery in general. Hamouda et al. [61] have investigated the impact of dependency of relative permeability to temperature on

EOR process and showed a significant difference between results of temperature-dependent and –independent relative permeability.

Optimization of the water injection temperature is important, because: 1- replacing the maximum temperature with the optimized temperature can significantly reduce the energy consumption of thermal enhanced oil recovery process; and 2- can provide access to more natural energy resources by increasing the water breakthrough time (the time required for the injected water to reach a production well) and improving the sweep efficiency of water injection process. To the authors' knowledge, no general work exists to focus on effects of the injected hot water temperature on heavy oil recovery considering other well controls such as the well rate and pressure, and accounting the dependency of relative permeability to temperature. In the present paper, enhanced oil recovery optimizations have been conducted for 2D and 3D reservoir models, and the effects of water injection temperature, water injection rate and BHP of producers on oil recovery are investigated, and results are compared with each other. In order to compare the effect of each parameter on total oil production, first an optimization is performed with fixed well rates and BHPs, while the water injection temperature is optimized. Next, the optimization is done with constant temperature and variable well rates and pressures. Finally, BHP of producers, and water injection rate and temperature of injectors are optimized simultaneously.

Dependency of the relative permeability to the temperature from one side and the close coupling of saturation, temperature and pressure make this problem very nonlinear. Since, gradient-based optimization methods might be stuck in local optimal conditions, and PSO algorithm can search the domain globally and exhibits a good performance in other EOR projects conducted by other researchers. Hence, this method can be an appropriate choice to optimize the problem.

2. Methodology

2.1 Governing equations

Assuming two-phase (phase pressures are always higher than their bubble pressure, and therefore no gas phase exists in the reservoir), immiscible flow of water and oil, and ignoring capillary pressure effects, the mass conservation equations for water and oil phases can be written as follows [64, 65]:

$$\frac{\partial\left(\phi\rho_w S_w\right)}{\partial t}+\nabla\cdot\left(\rho_w \mathbf{u}_w\right)=\dot{m}_w \tag{1}$$

$$\frac{\partial\left(\phi\rho_o S_o\right)}{\partial t}+\nabla\cdot\left(\rho_o \mathbf{u}_o\right)=\dot{m}_o \tag{2}$$

where ϕ represents the porosity and ρ_j , S_j and $\dot{m}_j$ represent respectively the density, the saturation and the mass flow rate per unit volume of the jth phase. $\mathbf{u}_j$ is also the Darcy velocity of the jth phase which is defined based on Darcy's law as follows:

$$\mathbf{u}_j=-\mathbf{k}\frac{k_{rj}}{\mu_j}.\,(\nabla p_j+\rho_j g\nabla D) \tag{3}$$

In Eq. (3), D is the depth, and p_j and μ_j are the jth phase pressure and viscosity, respectively. $\mathbf{k}$ is the absolute permeability tensor and k_{rj} is the relative permeability of the jth phase and is a function of the phase saturation and temperature in this study.

In addition, it is assumed that porous media are saturated with fluid phases, hence:

$$S_w+S_o=1 \tag{4}$$

All fluid phases are considered to be in thermal equilibrium with the solid rock phase. Therefore, to calculate the temperature the energy conservation equation can be written as follows [64, 66]:

$$\frac{\partial}{\partial t}\left(\phi\sum_{j=w,o}\rho_j S_j U_J+(1-\phi)\rho_r C_r T\right)+\nabla.\left(\sum_{j=w,o}\rho_j \mathbf{u}_j H_J\right)-\nabla.\left(K_T\nabla T\right)=q_H \tag{5}$$

U_j and H_j are respectively specific energy and special enthalpy of j[th] phase. C_r and ρ_r are respectively specific heat capacity and density of the rock. In addition, K_T is the total thermal conductivity of a block containing the rock and fluid phases. T is the absolute temperature and q_H represents the heat source.

Eqs. (1) to (5) are solved simultaneously using CMG-STARS [67] – a commercial software for simulation of thermal reservoir studies – and variations of the saturation and temperature, and oil production rates from producers are resolved during the hot water injection process.

2.2 Particle swarm optimization (PSO)

The idea of PSO was first proposed by Eberhart and Kennedy [68] for the optimization of continuous non-linear functions. Like other metaheuristic methods which are inspired from the nature, PSO is a stochastic optimization technique and is inspired by the ability of birds to flock and search for foods. In this method a group (swarm) of particles (the candidates for solution) is distributed as points in the N-dimensional space. In which N shows the number of variables that we want to optimize them. Each particle has two N-dimensional vectors including the position and velocity vectors. These vectors show quantity and the rate of variation of decisions variables, respectively. The position and velocity vectors of i[th] particle are defined respectively as follows [9]:

$$\mathbf{X}_\mathbf{i}^t=[x_{i1}x_{i2}\dots x_{iN}]^t \tag{6}$$

$$\mathbf{V}_\mathbf{i}^t=[v_{i1}v_{i2}\dots v_{iN}]^t \tag{7}$$

In each timestep, when a particle moves, its direction is adjusted in accordance to the best position of the particle ($\mathbf{X}_\mathbf{i}^l$) and also the best position of all the other ones that had been met in the past timesteps ($\mathbf{X}^g$). In this paper, each particle contains information about water injection temperature and rate, and the BHP of producers. For each particle, the objective function (fitness) – cumulative oil production volume in this study – is calculated using its current local position vector and when a particle finds a position that is better than all of its previous positions, the new best position will be saved in the local best position vector ($\mathbf{X}_\mathbf{i}^l$). Next, the best position among all particles (swarm) in that specific step will be saved in the global best position vector ($\mathbf{X}^g$).

The position and velocity vectors are updated in each step according to the following relations [9, 69]:

$$\mathbf{V}_\mathbf{i}^{t+1} = \eta \mathbf{V}_\mathbf{i}^{t} + \alpha_1 \gamma_1 (\mathbf{X}_\mathbf{i}^{l} - \mathbf{X}_\mathbf{i}^{t}) + \alpha_2 \gamma_2 (\mathbf{X}^{g} - \mathbf{X}_\mathbf{i}^{t}) \tag{8}$$

$$\mathbf{X}_\mathbf{i}^{t+1} = \mathbf{X}_\mathbf{i}^{t} + \mathbf{V}_\mathbf{i}^{t+1} \tag{9}$$

where η is the inertia weight and controls the effect of the previous particle velocity on its current velocity. γ_1 and γ_2 are uniformly distributed variables in the range of [0,1], and α_1 and α_2 are positive parameters known as the cognitive and the social factors, respectively. They determine the effectiveness of each individual and collective term in the particle's motion. The control parameters of PSO are adjusted by the suggested values by Clerc and Kennedy [70] as $\eta = 0.7298,\ \alpha_1 = \alpha_2 = 1.4962$.

The above-mentioned steps will be repeated for several times until the solution meets the convergence condition or after a certain number of iterations [71]. The convergence criterion in this study is defined as the condition that all the velocity vectors of particles are lower than a critical value. In this study, the number of particles is 50.

3. Problem description

In order to test the effect of variation of operational controls on oil recovery and to optimize them, it is required to define a problem and prepare a numerical experimental setup. This setup includes reservoir models containing heavy oil in which the relative permeability of fluid phases and their viscosity depend on temperature. Afterward, different optimization projects will be conducted to optimize cumulative oil production with temperature, rate and BHP control. In this section, the problem is described and fluid properties and the reservoir models are represented.

3.1 Fluid properties

According to the Beal's empirical research [72] which has been done for 96 different oil samples, heavy oil viscosity can be defined as a function of API gravity and temperature. For the heavy oil with API=20, the viscosity is 70 cP at 20°C and reduces to 1 cP when temperature increases up to 90 °C (as exhibited in Fig. 1). The water viscosity is considered to be constant and equal to 0.5 cP. This assumption is reasonable, since the water viscosity variations with temperature are limited in the temperature range used in this study.

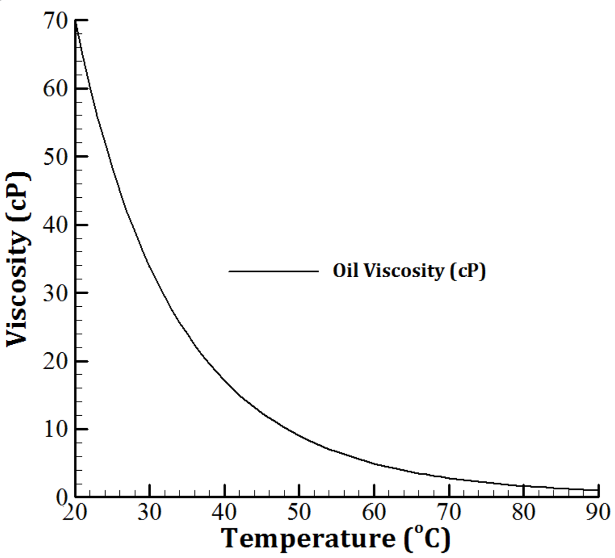

Fig. 1 Viscosity variations of oil with temperature

The density of fluid phases in terms of temperature and pressure are describes by the following relation [73]:

$$\rho_j(T,p)=\rho_j^{ref}\exp\left[c_j\left(p-p_{ref}\right)-\alpha_j\left(T-T_{ref}\right)\right] \tag{10}$$

In the above relation, c_j=10^{-7} kPa^{-1} and α_j=10^{-4} K^{-1} are the compressibility and the thermal expansion coefficient of the jth phase, respectively. $p_{ref}=100\,\text{kPa}$ and $\text{T}_{ref}=273\,\text{K}$ are respectively the reference pressure and temperature. ρ_j^{ref} is density of jth phase at the reference temperature and pressure, which is set to 998 and 938 kg.m^{-3} for water and oil phases, respectively [74]. Other thermal property values of fluid phases and rock which are used in this article are presented in Table 1 [75].

Table 1 Thermal property values of rock and fluids [75] .

Property	Value
Rock thermal capacity $(\rho_r C_r)$	2300 $\text{kJ}(\text{m}^3\,\text{K})^{-1}$
Water specific thermal capacity $(\overline{C}_{P,L})_W$	4.19 $\text{kJ}(\text{Kg}\,\text{K})^{-1}$
Oil specific thermal capacity $(\overline{C}_{P,L})_O$	2.02 $\text{kJ}(\text{Kg}\,\text{K})^{-1}$
Rock thermal conductivity	3.5 $\text{W}(\text{m}\,\text{K})^{-1}$
Water and oil thermal conductivity	0.6 $\text{W}(\text{m}\,\text{K})^{-1}$

Assuming the reservoir consists of sandstone rocks. For such reservoirs, the relative permeability of fluid phases are defined as functions of both the saturation and the temperature. According to the empirical research done by Maini and Okazawa [76], the relative permeability of sandstone reservoirs could be expressed as follows:

$$\begin{aligned} k_{rw} &= \frac{(S^*)^{n_w}+1.01\,S^*}{1.01} \\ k_{ro} &= \frac{(1-S^*)^{n_o}+1.01\,(1-S^*)}{1.01} \\ S^* &= \frac{S_w-S_{wc}}{1-S_{wc}-S_{or}} \end{aligned} \tag{11}$$

In which n_w and n_o are empirical temperature dependent powers and are calculated from Table 2, with linear interpolation. In addition, S_{wc} and S_{or} are assumed to be constant and equal to 0.22 and 0, respectively.

It's worthy to mention that the relative permeability is a rock and fluid property and various functions are suggested with other researchers to estimate it. In this study, the Maini and Okazawa's relation is used as an instance to define relative permeability of fluid phases to define our numerical experimental setup for a sandstone rock.

Table 2 Empirical values for n_w and n_o as a function of temperature [76].

T (°C)	n_w	n_o
21	1.56	1.99
60	0.625	1.97
100	1.19	3
150	2.3	2.68
200	2.09	1.34

3.2 Reservoir models

In the present study, two types of reservoir models (including a 2D and a 3D) are utilized in order to simulate hot water flooding in heavy oil reservoirs. The heterogeneity of the both reservoirs are derived from the SPE-10 reservoir model. SPE-10 is a 3D realistic heterogeneous reservoir model organized by the Society of Petroleum Engineers as a comparative solution project to compare the performance of different numerical reservoir simulators [77]. The complete model contains more than 1 million grid blocks in 85 layers, and optimization in the full model is very time consuming. Hence, in this study for the 2D reservoir only one layer of the main model are used. The 3D model is also an upscaled version of the main model on a coarse grid. The porosity distribution in the reservoirs is assumed to be homogeneous and φ=0.2 is considered for its value. Other details of the two implemented reservoirs are described in the subsequent sub-sections:

3.2.1 2D Reservoir model

In order to test the effect of optimization of indicated parameters during hot water flooding process in a reservoir model, a 2D heterogeneous problem with 13 wells is considered as the experimental setup. The model is a 360×660×9 m^3 horizontal reservoir with one layer and 60×220×1 cells, and the permeability of the field is depicted in Fig. 2. It is assumed that no flow can pass through the reservoir boundaries and the average initial pressure of the reservoir is 20 MPa. The uniform initial value of 0.78 has also considered for oil saturation. The well-known Peaceman [78] model is used to define well treatment with well-bore diameter of 0.1524 m and skin factor of s=0.

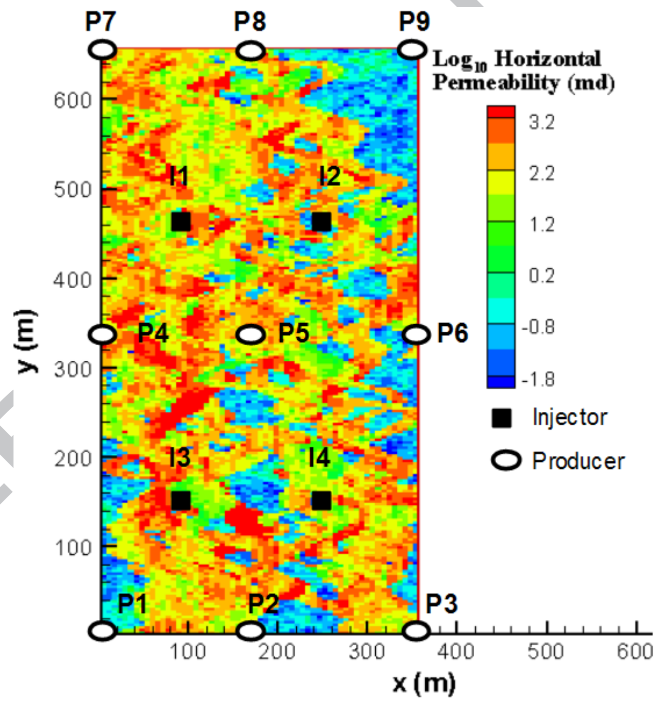

Fig. 2 Permeability distribution and the well placement in the 2D reservoir model.

3.2.2 3D Reservoir model

The 3D model is a 365.8×670.5×51.8 m^3 domain with no flow boundaries including a vertical injector well at the center of the reservoir that injects the constant rate of 2000 m^3/day of hot water with variant temperatures (between 25°C and 90°C) into the reservoir. Four vertical producers are drilled at the 4 corners of the reservoir and are controlled by a constant BHP during the water injection time. It is assumed that well perforation is done in all well layers. As previously mentioned, the model is an upscaled version of the main model (using arithmetic averaging) including 30×55×17 cells. The horizontal permeability of the field is shown in Fig. 3, and the vertical permeability of each cell is 0.3 times the horizontal permeability of that cell. Similar to the 2D reservoir model, the same initial pressure and oil saturation values are used for the 3D model, and the wells are modeled by Peaceman's relation with the same skin factor and well-bore diameter.

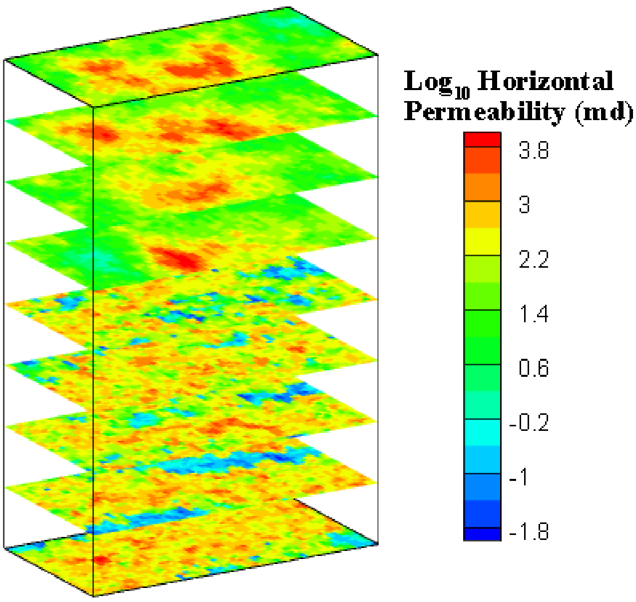

Fig. 3 Horizontal permeability of the upscaled SPE-10 model in its different layers [77]

4. Results and discussion

In this section, results are presented in two sub-sections for the 2D and 3D reservoirs. The 2D model is used to perform a detailed sensitivity analysis, since different phenomena can be clearly exhibited in a 2D model. In common thermal EOR projects, BHP and rates are optimized to maximize the objective function with constant injection temperature. Hence, in this study, first, the sole effect of temperature on COP is investigated to show that an optimal temperature exists to maximize COP. Next, to find out how temperature can affect COP when that is optimized in line with BHP and rates, it is required to optimize the problem in a common manner with only BHP and rate control to provide a reference for comparison. In the next step, that is our contribution, temperature, BHPs and rates are controlled simultaneously and its results are compared with those of the reference case (that is optimized only with BHP and rate control). Finally, to show that the proposed method is capable to work in a more complex 3D field, the same procedure has been repeated in the 3D reservoir and results are compared with each other.

4.1 2D experimental setup

For the 2D model described in section 3.2.1, the optimization is performed. To appraise the effect of variation of each parameter on COP, a base state hot water flooding scenario is required. After each optimization problem, the optimal results will be compared with those of the base state condition. Details of the base state situation are described in Table 3, and all simulations for the current reservoir model are performed for 4000 days. The four injectors are controlled with a specified water injection rate and all the nine producers are under constant BHP during the simulation time. It's expected by increasing the water injection temperature, oil viscosity reduces and leads to the higher oil mobility and increases the COP. Hence, for the base state the water injection temperature is set to the highest value of 90 °C. It will be shown in the subsequent sections that this fact is not generally true and an optimal temperature might exist to optimize COP.

Table 3 The variable details of the base situation

Variable	Value
Water injection temperature (°C)	90
Water injection rate (m^3/day)	40
BHP of producers (kPa)	5000

For optimal design of hot water injection, decision parameters are limited to the constraints presented in Table 4.

Table 4 Constraints for optimal selection of decision variables

Variable	Lower bound	Upper bound	Constraint
Water injection temperature (°C)	25	90	------------
Water injection rate (m^3/day)	0	160	Total water injection rate is 160 m^3/day
BHP of producers (kPa)	1000	10000	-----------

4.1.1 Water injection temperature optimization

As previously mentioned, first, the water injection temperature in the four injectors are selected as decision variables to be optimized. The convergence history of PSO algorithm is presented in Fig. 4 and the optimized values are summarized in Table 5.

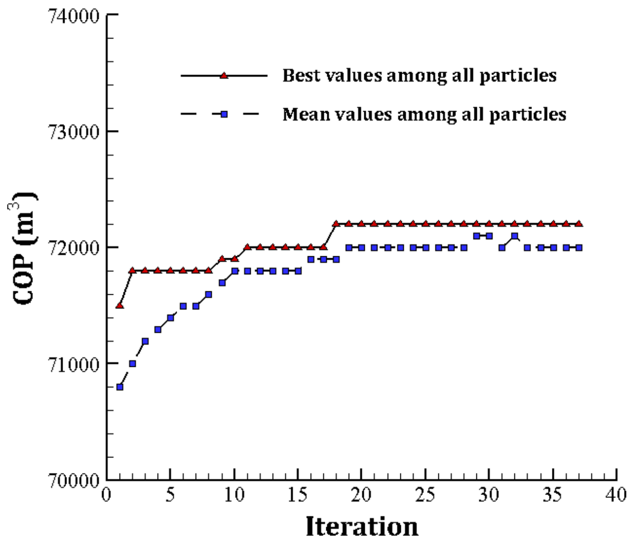

Fig. 4 The convergence history of PSO for water injection temperature optimization

As can be seen, PSO converges to the optimal point after 37 iterations and the optimal temperature in each injector is different from the others. Also, it is observed that the optimal water injection temperature is not the upper bound temperature limit (i.e. 90 °C), and by optimal control of the temperature more oil could be recovered with less energy consumption for heating the injected water.

Table 5 Optimized water injection temperature values for each injector

Injector name	I1	I2	I3	I4
Water injection temperature (°C)	39.0	60.1	25.7	62.4

Fig. 8 compares COP of the temperature optimized state and the base state during the hot water flooding process. Results indicate that COP, after a 4000 days period, improves more than 7% only by controlling the water injection temperature.

For more investigation of the impact of temperature optimization on hot water flooding performance and sweeping the oil, distribution of oil saturation after 4000 days of water flooding for the base and optimized cases are shown in Fig. 5 and Fig. 6, respectively.

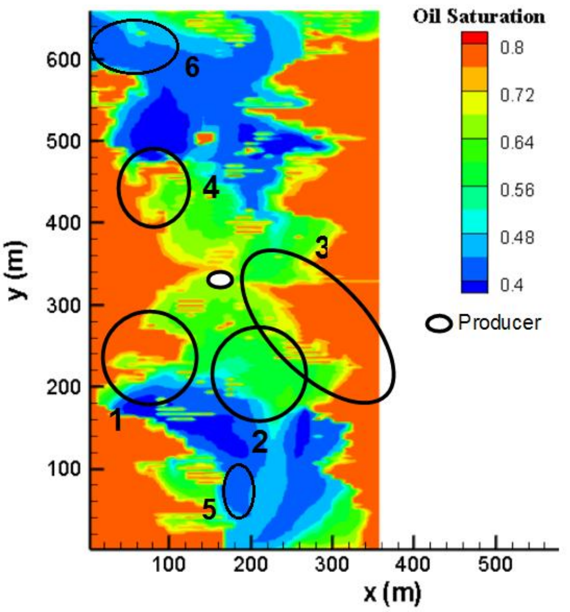

Fig. 5 Distribution of oil saturation after 4000 days for the base situation (not optimized state)

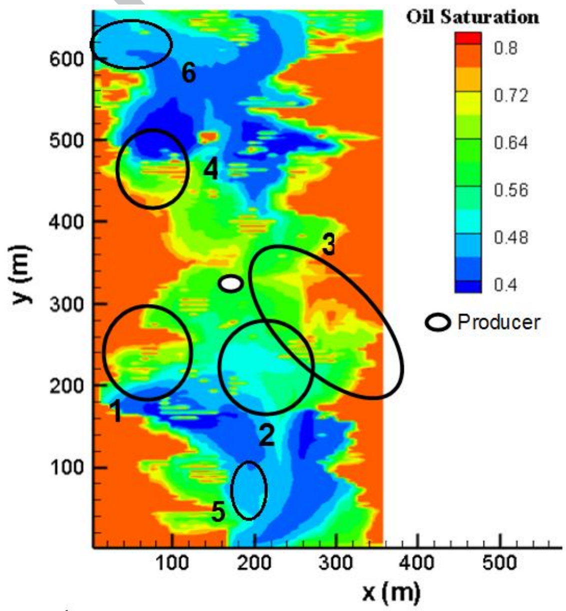

Fig. 6 Distribution of oil saturation after 4000 days for the case with optimized water injection temperature

Comparison of Fig. 5 with Fig. 6 reveals that for the optimized case, especially in the regions outlined by circles, the injected water could advance better into the reservoir to displace the oil phase. Hence, it has been shown that the water injection temperature control could improve sweeping efficiency and enhanced cumulative oil recovery. At first glance, it might be implicated that the highest water injection temperature should lead to the higher COP. This fact might be true for some specific cases, but that is not generally true. Increasing water injection temperature from one side can reduce oil viscosity with subsequent mobility increment, but from the other side can also reduce the relative permeability after a given temperature (with wettability alteration) which leads to mobility decrement. Furthermore, increasing the oil mobility could not always lead to a higher COP. Depending on the heterogeneity of the reservoir and its conditions, injected hot water can pass through oil and reach to production wells without proper heat transfer to oil phase and sweeping the trapped oil inside the reservoir. Increasing the water injection temperature can expedite the water breakthrough time and increases the portion of water production from producer wells (known as water cut), which causes the lower amount of oil recovery from the reservoir. In Fig. 5 and Fig. 6, two water channels between injection and production wells are indicated with 5 and 6 numbers. As can be seen in these regions, for the optimized state, water is pushing oil toward production well, while for the base state water passed through oil and reached to a production well. The same phenomenon has also been reported by Hamouda and Karoussi [79] in their experiment on chalk rock samples, in which by increasing the water injection temperature up to 80 °C oil production improves, while by more temperature increment oil production decreased.

4.1.2 Rate and BHP optimization

Enhanced oil recovery projects are commonly implemented with rate and BHP control of wells. In this part, PSO is performed to find the optimal water injection rates of the 4 injectors and the BHP of the 9 producers to reach the maximum COP, when the water injection temperature is 90°C. Results of this section are used as a reference to compare results of our proposed method (presented in section 4.1.3) with those of common projects. The optimal values for the mentioned parameters are listed in Table 6.

Table 6 Optimized BHP values of producers and water injection rates

Producer name	P1	P2	P3	P4	P5	P6	P7	P8	P9
BHP (kPa)	2347	1756	8442	9204	8796	4660	1115	1888	1970

Injector name	I1	I2	I3	I4
Water injection rate (m^3/day)	29.1	82.1	19.7	29.1

Comparison of the optimized COP (BHP and rate optimized state) with the base state is also depicted in Fig. 8. Results show that an amount of more than 30% increase in COP after 4000 days of hot water flooding, with the rate and BHP control of the 13 wells.

4.1.3 Temperature, rate and BHP optimization

In this section, the water injection temperature and rate in four injectors in line with BHP of the nine producers (17 parameters overall) are optimized simultaneously, and results are compared with those obtained in the previous section. Therefore, the real impact of optimizing the water injection temperature on COP can be observed precisely. Fig. 7 exhibits the convergence history of PSO and shows that PSO could converge after 44 iterations.

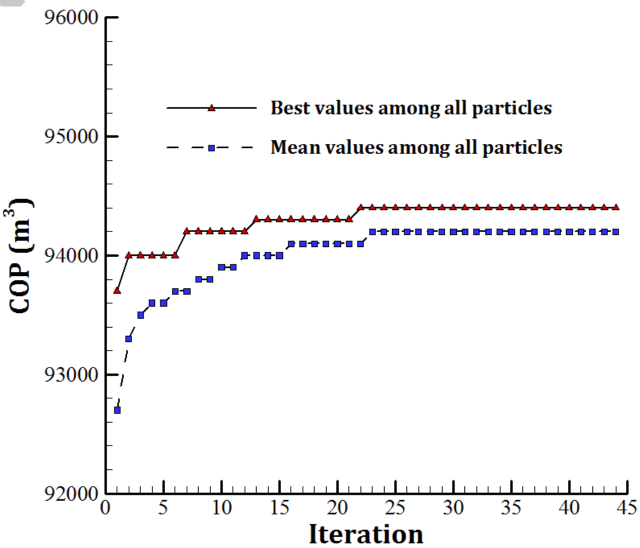

Fig. 7 The convergence history of PSO for temperature, rate and BHP optimization

The optimal estimated injection temperatures in injectors are summarized in Table 7. In this case, the optimal water injection temperatures are almost similar and confined in a limited range around the maximum injection temperature (90 °C). As illustrated in Fig. 8, comparison of COP of this case with the previous case (in which the water injection temperature was 90 °C) reveals that simultaneous optimization of temperature with other well constraints can considerably improve COP (about 7.2%).

Table 7 Optimized BHP values of producers and water injection temperatures and rates

Producer name	P1	P2	P3	P4	P5	P6	P7	P8	P9
BHP (kPa)	3420	2810	9340	9750	7770	7250	1100	7580	1460

Injector name	I1	I2	I3	I4
Water injection rate (m^3/day)	31.1	13.7	84.1	31.1
Water injection temperature (°C)	88.3	84.2	89.7	80.4

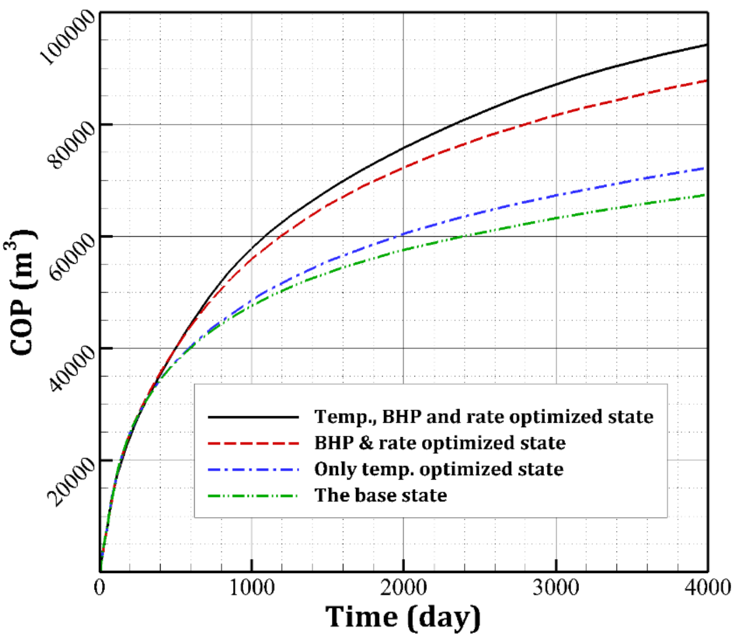

Fig. 8 Comparison of the different optimized states and the base state COP values during 4000 days of hot water flooding

Also comparing results of Table 5 and Table 7, indicates that the optimal water injection temperatures in injectors depend on the well rate and BHP values, and by variation of these parameters, the optimal temperatures could change remarkably.

To further investigate the impact of optimal control of temperature in injection wells on COP, the distribution of oil saturation for the case with optimal rate and BHP (Fig. 9) is compared with that of the case with optimal temperature, rate and BHP (Fig. 10). Obviously after optimal control of the water injection temperature, the lower amount of oil remains in the reservoir especially in the region inside the black ellipse in Fig. 10.

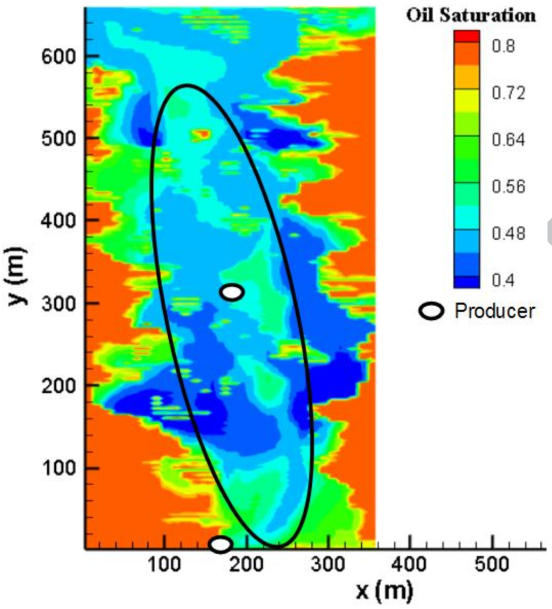

Fig. 9 Distribution of oil saturation after 4000 days for the case with optimized rates and BHPs

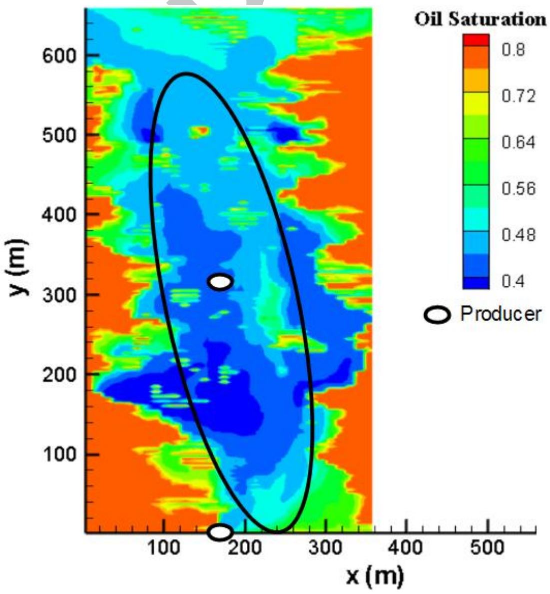

Fig. 10 Distribution of oil saturation after 4000 days for the case with optimized water injection temperatures, rates and BHPs

The reason of the mentioned fact was explained in section 4.1.1, but to further scrutinize it the water cut curves of production wells for the two previous states are depicted in Fig. 11. As can be seen, optimization of temperature with rate and BHP, delayed the water breakthrough time (the time that water cut starts to grow). Hence, the injected water could maintain for a longer time inside the reservoir to exchange its heat with oil and push it toward production wells.

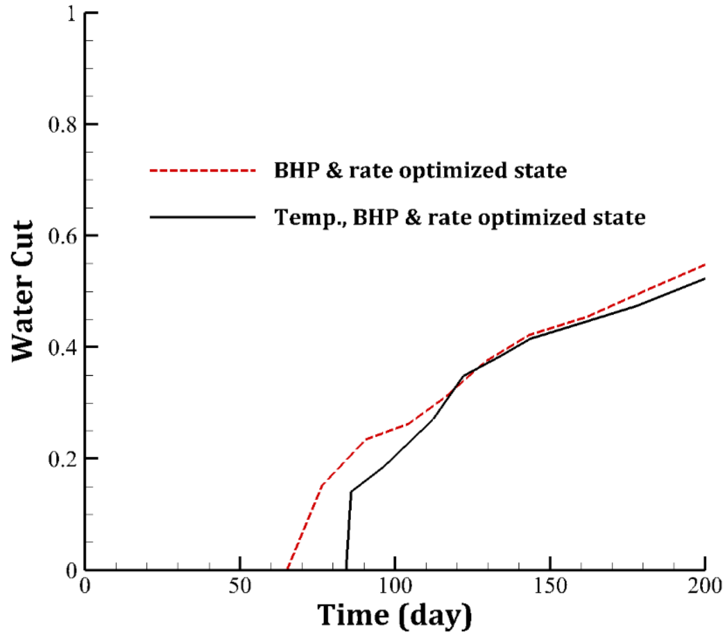

Fig. 11 Comparison between water cut of two optimized cases.

4.2 3D field test

In this section, enhanced oil recovery with optimal control of water injection temperature is tested in the 3D field reservoir model introduced in section 3.2.2. Since the 3D reservoir includes a single injector and in our study (similar to the 2D experimental setup) the total water injection rate is assumed to be constant, BHP of producers will be optimized and the effect of water injection temperature on COP will be investigated. Details of operation variables for the base case are the same as the 2D model (Table 3), except for the water injection rate which is set to 2000 m^3/day. Because the 3D reservoir is larger than the 2D model, a longer time is required to be depleted; hence water is injected with a higher rate and simulation is performed for a longer time (8000 days).

Optimization is also performed with the same constraints which are exposed on the water injection temperature and BHP of producers in the 2D experimental setup (Table 4).

After implementation of PSO, the optimal value of 59.9 °C has been found as the optimal value of water injection temperature. In this situation, the BHP of producers are supposed to be constant and the same as the base state. Results of COP (Fig. 14) show that the sole optimization of water injection temperature had led to 4.1% improvement in COP after 8000 days of hot water injection.

For more investigation of the effect of temperature optimization on hot water flooding performance and sweeping the oil in different layers of the 3D reservoir, distribution of oil saturation after 8000 days of water flooding for the base and optimized cases are shown in Fig. 12 and Fig. 13, respectively. As can be seen in these figures, in some regions (especially the regions which are specified with circles) the oil saturation of the optimized case is lesser than the base state case.

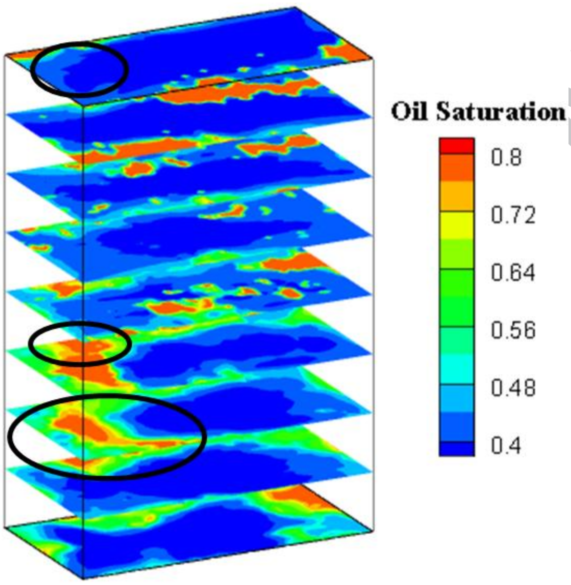

Fig. 12 Distribution of oil saturation after 8000 days for the base situation (not optimized state)

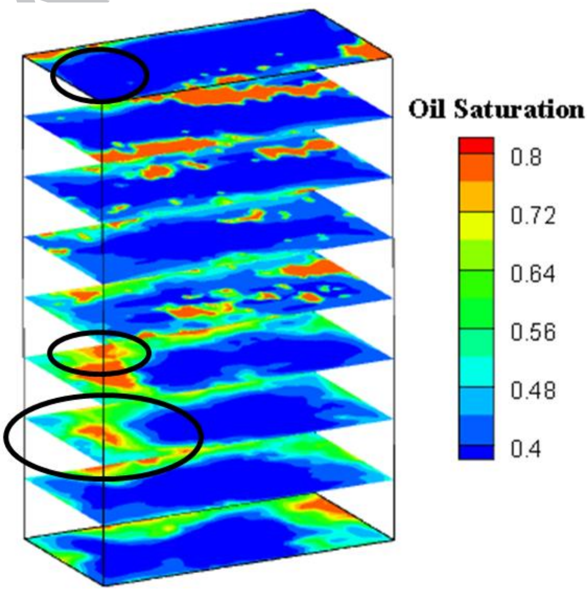

Fig. 13 Distribution of oil saturation after 8000 days for the case with optimized water injection temperature

Since traditionally for this problem only BHP in producers are controlled to enhance oil recovery, another optimization is performed with BHP control in production wells. For this case, results indicate that COP will improve up to 2.2% in comparison with the base case, which show that the water injection temperature control has a higher impact on COP compared with BHP control.

Now, optimization is implemented with controlling BHP and water injection temperature simultaneously using PSO with 50 particles. The convergence history of PSO is depicted in Fig. 15 and shows that PSO converges to the optimal state after 39 iterations. The optimal BHP and water injection temperature are also described in Table 8. As shown in Fig. 14, COP has been improved more than the two previous cases and its overall improvement reached to the value of 5.4% in comparison with the base state.

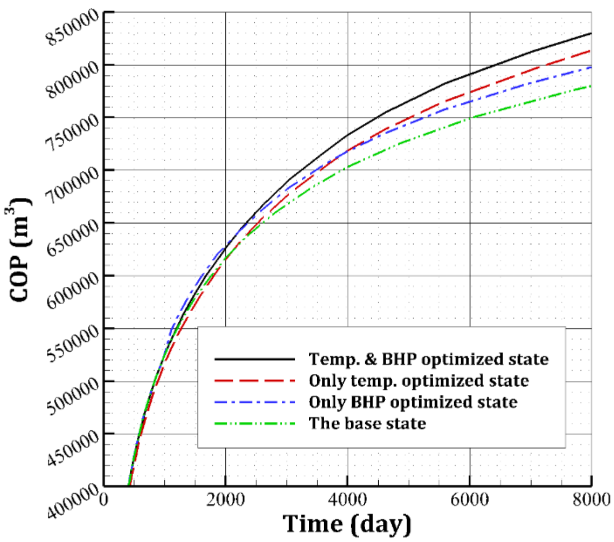

Fig. 14 Comparison of the three optimized states and the base state COP values during 8000 days of hot water flooding

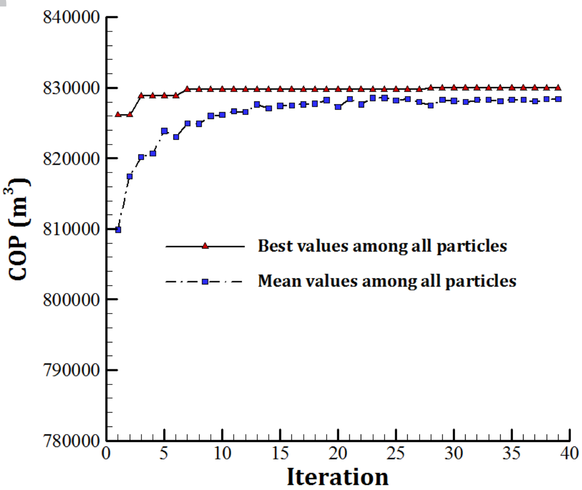

Fig. 15 The history of convergence during optimization

Table 8 Optimized water injection temperature & BHP values of producers

Producer Name	P1	P2	P3	P4
BHP (kPa)	5394	5964	7632	5829
Water injection temperature (°C)		61.9		

Oil saturation distribution in different layers of the reservoir after 8000 days of hot water flooding, for the BHP optimized and the BHP & temperature optimized cases are illustrated in Fig. 16 and Fig. 17, respectively. As can be observed, when in addition to BHP the water injection temperature is also optimized, in the outlined regions of the reservoir oil could be swept better than the case with only optimal BHPs.

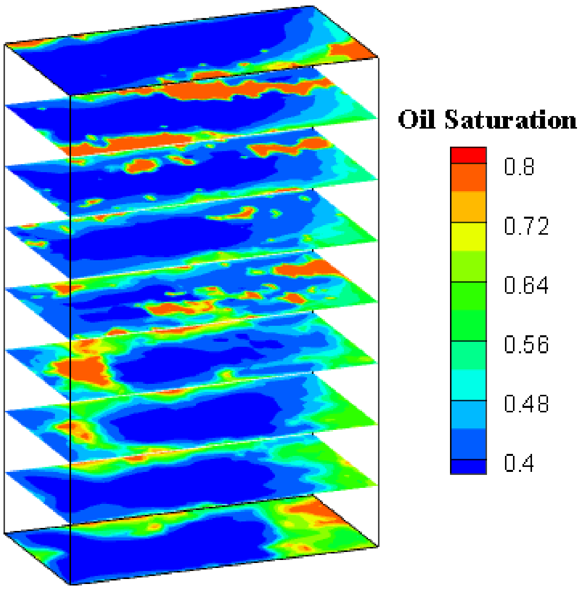

Fig. 16 Distribution of oil saturation after 8000 days for the BHP optimized situation

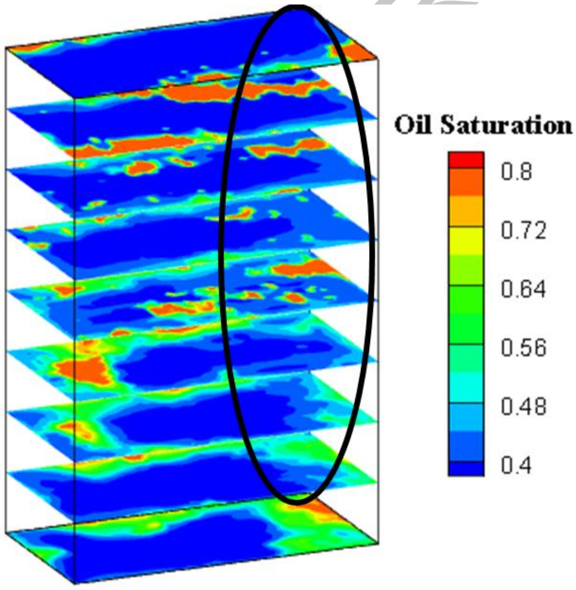

Fig. 17 Distribution of oil saturation after 8000 days for the case with optimized BHP and water injection temperature

5. Conclusions

Thermal enhanced oil recovery with hot water injection has been investigated, and in addition to optimal control of water injection rates and bottom-hole pressure (BHP) of producers – which are traditionally done in these projects – the effect of optimal control of water injection temperature on oil recovery was discussed. The metaheuristic method of particle swarm optimization (PSO) has been implemented successfully to find optimal values of decision variables. Two sample problems – 2D and 3D heterogeneous oilfield models, derived from the tenth SPE model with temperature dependent relative permeability functions – were designed to test the method, and hot water injection with different conditions were performed in these reservoirs. The 2D model includes 4 injectors and 9 producers (13 wells), in which the total water injection rate is constant and should be optimally allocated between the 4 injectors. Three optimizations were conducted with 1- optimal control of water injection temperature only; 2- optimal control of well rates and BHPs; and 3- optimal control of water injection temperature, rate and BHP of producers. Results presented in terms of cumulative oil production volume and oil saturation distribution in the reservoir. The three mentioned cases showed respectively, 7%, 30% and 37.2% improvement in cumulative oil production of the reservoir during 4000 days of hot water injection. Results prove that temperature plays an important role in hot water flooding projects. In addition, its optimal value is not necessarily the same as the maximum working temperature (90°C here), and by temperature control the energy consumption for heating the water can be reduced too. Afterward, another optimization project was done in a 3D field reservoir. Outcomes of the 2D problem have been confirmed through results of the 3D problem. Results show that in some layers by optimal control of water injection temperature oil had been swept better and oil production improved. It has been shown that the water injection temperature is an important parameter in thermal enhanced oil recovery projects and the oil production can substantially improve by optimal control of water injection temperature.

6. References

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Highlights

- Hot water injection thermal enhanced oil recovery process is optimized in oilfields
- Injection temperature & well controls are optimized by PSO to maximize oil recovery
- Relative permeability and viscosity of oil is defined as a function of temperature
- The problem is tested in 2D & 3D models with various injection and production wells
- Optimal control of water injection temperature can improve oil recovery