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Smart wells and model-based field production optimization

Inteligentne odwierty i optymalizacja produkcji oparta na modelu złoża

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ABSTRACT: This paper is devoted to model-based optimization of smart well controls. Reservoir models are usually far from perfect because of the limited volume and quality of the available raw data, and the methods used to construct them, therefore model-based production optimization is extremely difficult and requires constant improvement of existing as well as the development of new approaches to its solution. The paper considers examples of some important, in our opinion, development tasks and shows possible ways of solving them, as well as a brief analysis of the results obtained with the help of approaches and methods that reflect different points of view on the uncertainty of the initial information and the accuracy of the forecast. Among the tasks considered: 1) separate and combined deployment of a smart injector and an EOR method (hot water injection); 2) use of smart wells to optimize the development of a small offshore oil field. As shown in the paper, the first task proved that quite significant synergy can arise due to the combined deployment of two IOR techniques (hot water injection and a smart injector). It also highlighted that synergy is quite insensitive to the uncertainty impact. The second task showed that the use of smart wells in combination with a proactive development strategy can significantly reduce the impact of uncertainty in the reservoir characterization on the reservoir performance. The economic efficiency of the proactive strategy in the considered example was proven to be 2–4 times higher when compared with the reactive control strategy.

Key words: enhanced oil recovery (EOR), improved oil recovery (IOR), combined deployment, synergy, uncertainty impact, reactive and proactive strategy, "smart" well, high-tech well, optimization tasks.

STRESZCZENIE: Artykuł jest poświęcony optymalizacji zarządzania inteligentnym odwiertem opartej na modelu złoża. Modele złóż są zwykle dalekie od doskonałości z powodu ograniczonej ilości i jakości dostępnych danych oraz metod używanych do ich tworzenia, dlatego optymalizacja produkcji oparta na modelu jest niezwykle trudna i wymaga ciągłego doskonalenia zarówno istniejących jak i rozwoju nowych rozwiązań. W artykule rozważono przykłady kilku ważnych, w naszej opinii, zadań rozwojowych i wskazano możliwe sposoby ich rozwiązania, przedstawiono również krótką analizę wyników uzyskanych za pomocą sposobów i metod, które odzwierciedlają różne punkty widzenia na temat niepewności danych początkowych i dokładności prognoz. Omawiane zadania obejmują: 1) oddzielne i połączone wdrożenie inteligentnego odwiertu zatłaczającego i metody EOR (zatłaczanie gorącej wody); 2) wykorzystanie inteligentnych odwiertów do optymalizacji zagospodarowania małego podmorskiego złoża ropy naftowej. Jak przedstawiono w artykule, prace wykonane w ramach pierwszego zadania udowodniły, że może wyniknąć dość znacząca synergia, dzięki połączonemu wdrożeniu dwóch technik IOR (zatłaczania gorącej wody i inteligentnego odwiertu zatłaczającego). Należy podkreślić, że synergia ta jest dość niewrażliwa na wpływ niepewności. Badania przeprowadzone w celu realizacji drugiego zadania wykazały, że wykorzystanie inteligentnych odwiertów w kombinacji z proaktywną strategią zagospodarowania może znacząco zmniejszyć wpływ niepewności charakterystyki złoża na jego wydajność. Efektywność ekonomiczna strategii proaktywnej w rozważanym przykładzie okazała się 2–4 razy wyższa w porównaniu do reaktywnej strategii zarządzania.

Słowa kluczowe: wspomaganie wydobycia ropy naftowej (EOR), ulepszone wydobycie ropy naftowej (IOR), połączone wdrożenie, synergia, wpływ niepewności, strategia reaktywna i proaktywna, odwiert inteligentny, odwierty zaawansowane technologicznie, zadania optymalizacji.

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Simulation study of the combined effect of smart completion and EOR deployment

This section represents a reduced version of our previous study (Khrulenko and Zolotukhin, 2014). The aim of it is to emphasize some important observations that might assist in further attempts to optimize reservoir performance.

In our study we chose two improved oil recovery (IOR) methods for a heavy oil reservoir: hot water injection and smart completion.

Hot water injection is quite common thermal IOR technique for heavy oil reservoirs that enables to decrease oil viscosity and facilitate its flow through the reservoir.

Smart (or intelligent) well is a well equipped with downhole sensors and valves to control inflow/injection to separated perforation intervals, in real-time mode, without well interventions, to optimize production/injection. In this work we used an injection well with smart completions.

Uncertainty impact on the synergy was another issue we were aiming to cover in this paper. Quite a number of modern techniques for assisted history matching and model-based production optimization (for a thoughtful review on this subject refer paper by Peters et al., 2010) employ the concept of multiple property realizations (ensemble) in order to account for the geological uncertainty. We adopted this approach and used an ensemble-based optimization technique.

Problem statement

Reservoir model. In this work we considered the following case study: a heavy oil (50 cP at reservoir conditions, $T_0 = 50°C$) reservoir made up of four stacked layers (Fig. 1) is developed by using waterflooding. The inverted 9-spot pattern system

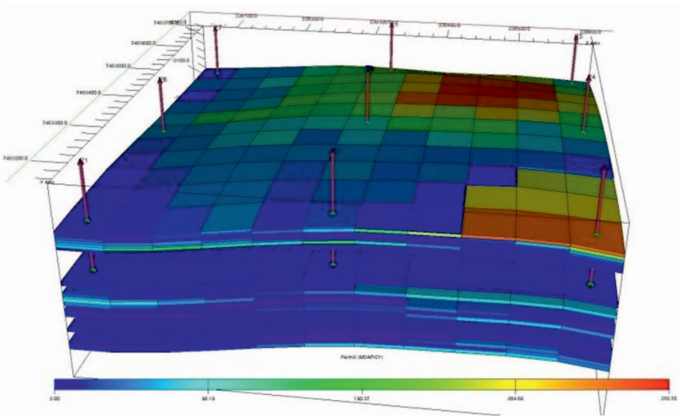

Fig. 1. General layout of simulation model with permeability distribution. Drainage strategy – inverted 9-spot pattern

Rys. 1. Ogólny układ modelu symulacyjnego z rozkładem przepuszczalności. Strategia sczerpania – odwrócony schemat 9-punktowy

in a commingled manner was used as a production strategy for all layers. Reservoir heterogeneity is quite high and layer permeabilities drastically differ from each other. Production starts with cold water injection ($T_{inj} = 20°C$).

After continuous injection of cold water for six years, smart completions and hot water injection have been considered as IOR techniques to boost production and increase ultimate recovery.

The following scenarios were considered in this case-study:

A. Continuation of cold water injection (the base scenario);
B. Hot water injection;
C. Smart completion deployment so that the stream injected may be re-allocated between the layers;
D. Smart completion of the injector combined with hot water injection.

Model and methods used

The wells' operational control sets were defined as follows:

- Producers operated under liquid rate group control of 200 Sm^3/day with secondary BHP limit for each well.
- Water injector operated on 100% voidage replacement mode.

Optimization of hot water injection. Hot water injection during the whole reservoir lifetime might be economically inefficient; therefore, it is quite common when hot water slug injection is used instead. i.e. after a period of hot water injection, the hot water slug is driven further by cold water.

The following objective function was formulated to account for economic and technological efficiency of the process:

$$G = \sum_{i=1}^{N} \frac{Q_{oi} \cdot P_{oi} - Q_{wi} \cdot r_{wi} - H_i}{(1 + \varepsilon)^i} \tag{1}$$

here:

N – reservoir lifetime, years,
Q_{oi} – oil production over year i,
Q_{wi} – water production over year i,
P_{oi} – oil price, 50 \$/bbl,
r_{wi} –produced water disposal expenses, 1 \$/bbl,
ε – discount rate, 10%,
H_i – cost of water heating within year i, calculated as follows:
$H_t = (Q_{winj})_i \cdot h \cdot (T - T_0)$
where:
$(Q_{winj})_i$ – water injection over year i,
h – unit cost of water heating: 0,1 \$/(Sm^3 · °C),
T – temperature of injected water,
T_0 – surface temperature, 20°C.

We used Pattern Search method from Matlab Optimization Toolbox (The MathWorks, 2013) to optimize injection temperature and duration of the hot water injection.

Smart well model. The conventional well model (ECLIPSE, 2013) was used to simulate the first 6 years of commingled injection. Then, we defined four virtual wells (one for each layer) in order to model inflow control valves of the smart injector. We used the group control for these virtual injectors and guide rates to control the injection allocation. A guide rate w_k is a weight for sublayer i that defines the share s_k of the total injection that will be allocated for it, i.e.:

$$s_k = w_k / \sum_{i=1}^{4} w_i \tag{2}$$

The guide rates w_k were used as the optimization variables for cases with the smart injector.

Optimized control of injector smart completions. The same objective function was used to optimize allocation of injected water among the layers. In this case $H_t = 0$ and then (1) reduces to (Khrulenko and Zolotukhin, 2014):

$$G = \sum_{i=1}^{N} \frac{Q_{oi} \cdot P_{oi} - Q_{wi} \cdot r_{wi}}{(1 + \varepsilon)^i} \tag{3}$$

Take a note that this objection function doesn't account for expenses related to smart completion installation as this cost, varying greatly for different solutions and vendors, is a constant, and therefore, does not affect the optimization.

In our study we used EnOpt method (Chen et al., 2009) to optimize smart completion settings. 14 years of production were split into 28 half-year optimization intervals. As one control variable was assigned for each Inflow Control Valve (ICV) at a given optimization interval, the total number of optimization variables were 4 × 28 = 112. I.e. every ICV at a given optimization interval was controlled by one variable. We left out other details regarding EnOpt parameters used in the study, since it would require a most lengthy description of the method itself.

Uncertainty of reservoir properties was represented by means of an ensemble of model realizations. However, it is not described in this section since it is not considered as the most important result in this study as compared with the synergy effect. For those interested in the impact of the reservoir uncertainty and the robust optimization study on overall reservoir performance we recommend our original paper (Khrulenko and Zolotukhin, 2014).

Overview of the numerical experiments. The numerical experiments were organized as follows:

I. Reference (or known geology) realization study – one realization was selected from the ensemble and used for the optimization to evaluate the case of known geology. The following cases were evaluated:
   A. Base case – do-nothing-strategy, uncontrolled hot water injection over the reservoir lifetime;
   B. Hot water injection – optimized hot water injection;
   C. Smart completion;
   D. Simultaneous deployment of hot water injection and smart completion.

The optimized parameters of hot water injection were taken from case *B*, while smart completion settings were optimized anew.

This study was limited to optimization of injected volumes distributed between the layers and didn't consider optimization of the hot water injection. It was intentionally done in order to simplify the analysis and to make it more transparent.

Table 1. Results for the reference realization study

Tabela 1. Rezultaty wykonanych badań odniesienia

Scenario	Parameter	Reference model	Ensemble			
			min	max	mean	STD
Case *A*. Base case	ORF [%]	26.48	23.86	33.00	29.10	2.76
	NPV [mln USD]	43.74	38.05	54.21	46.92	4.38
Case *B*. Hot water injection	ORF [%]	28.24	25.46	35.52	31.24	2.99
	NPV [mln USD]	44.35	38.54	55.43	47.78	4.54
	ΔORF [%]	1.76	1.60	2.64	2.14	0.28
	ΔNPV [mln USD]	0.61	0.45	1.32	0.86	0.23
Case *C*. Smart injector	ORF [%]	27.75	24.96	34.83	30.50	2.96
	NPV [mln USD]	45.18	39.33	55.94	48.40	4.59
	ΔORF [%]	1.27	0.90	2.09	1.40	0.27
	ΔNPV [mln USD]	1.44	0.98	2.08	1.49	0.28
Case *D*. Combined deployment	ORF [%]	31.15	27.75	39.52	34.28	3.43
	NPV [mln USD]	47.55	41.28	59.48	50.96	5.02
	ΔORF [%]	4.67	3.89	6.80	5.19	0.75
	ΔNPV [mln USD]	3.80	2.95	5.75	4.04	0.73
Case *B* + *C* (straight sum)	ΔORF [%]	3.03	2.69	4.50	3.54	0.48
	ΔNPV [mln USD]	2.05	1.71	3.23	2.35	0.44
Synergy: $S = D - (B + C)$	ORF synergy [%]	1.64	1.10	2.68	1.64	0.34
	NPV synergy [mln USD]	1.75	1.08	2.71	1.70	0.36

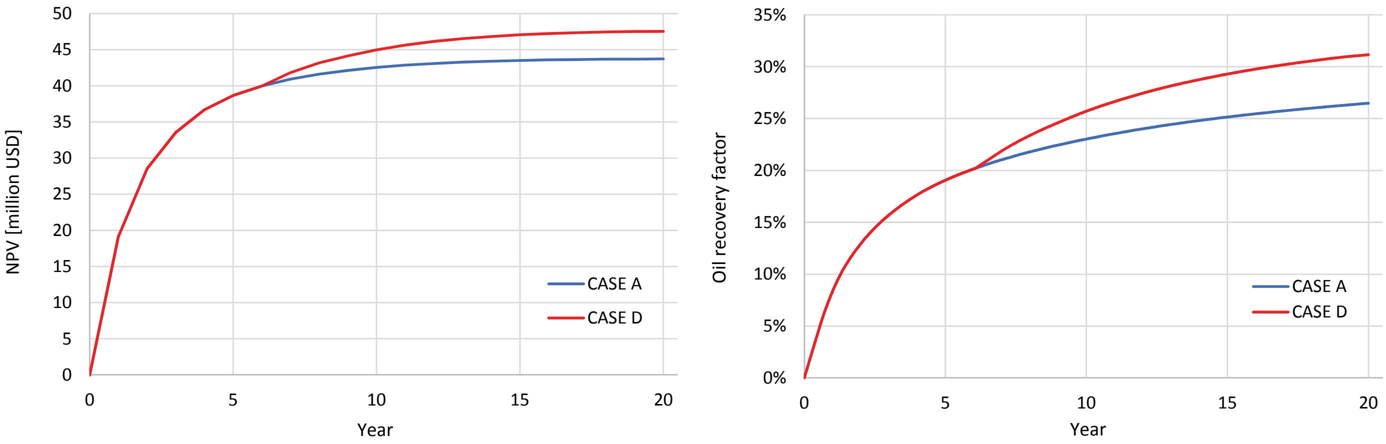

Fig. 2. NPV and ORF for the base reference model (Case *A*) and the optimized reference model (combination of smart wells and hot water injection, Case *D*)

Rys. 2. Wartość bieżąca netto i współczynnik sczerpania złoża ropy naftowej dla bazowego modelu odniesienia (Przypadek *A*) oraz zoptymalizowany model odniesienia (połączenie inteligentnych odwiertów i zatłaczania gorącej wody, Przypadek *D*)

Synergy for the reference model. As can be readily seen from Table 1, the combined deployment results in the incremental Net Present Value (NPV) and oil recovery larger than a straight sum of those for cases *B* and *C*. i.e. the simulation results proved existence of tangible synergy. According to the synergy definition given above, we calculated it as:

$$S = D - (B + C)$$

As follows from the table the synergy is quite significant both for NPV (+1.75 mln USD) and the oil recovery factor (ORF) (+1.64%). A combined effect of smart completion and EOR deployment (case *D*) as compared with the reference case *A* is shown in Fig. 2.

The following main conclusions drawn from this study are summarized below:

- the simulation results proved that quite significant synergy can arise due to combined deployment of two IOR techniques;
- since we didn't perform robust optimization of the hot water injection, we believe the potential synergy is even greater;
- it appeared that synergy is quite insensitive to the uncertainty impact.

Mitigation of the geological uncertainty impact on reservoir performance by smart well technology

This section summarized results of our earlier study [6]. The aim of it, is to emphasize some important observations that might assist in further attempts to optimize reservoir performance.

The second goal is to compare the efficiency of reactive and proactive strategies for optimizing reservoir performance.

The problem considers a small offshore oil field, planned to be developed by three wells as subsea tie-back with produced wellstream transported as a multiphase flow to a nearby producing platform on a larger field (Khrulenko and Zolotukhin, 2011). Smart completion has been considered as a means to maintain production and to avoid well interventions caused by increasing watercut. It was necessary to assess whether deployment of smart completions, is a cost-effective solution.

Although three exploration wells have been drilled there was still a strong degree of uncertainty in the reservoir properties description. A lot of simulation models can be built on the same set of initial data. Five realizations of porosity and permeability were chosen and considered to be sufficient to provide a representative vision of possible reservoir performance (Fig. 3).

The simulated field consists of two formations; each of them encloses the massive reservoir, fault-bounded in the east (Khrulenko and Zolotukhin, 2011). The upper formation is 40 m thick, the lower formation's thickness is 45 m. Oil-water contacts of the upper and lower target intervals occur at depths 3300 and 3525 m with the initial reservoir pressure 330 and 352.5 bar, respectively.

The model consists of 20 × 58 × 81 blocks with a typical size 100 m ×100 m ×1.25 m and with 54019 active cells.

A non-volatile black oil model was used with oil viscosity at the reservoir conditions equal to 0.55 cp and water viscosity of 0.3 cp.

Oil resources for various model realizations were kept approximately at the following levels:

- For the upper reservoir: 10.65 mln sm^3;
- For the lower reservoir: 26.1 mln sm^3.

There are planns to develop the field using three wells; each of them drains the upper reservoir through deviated interval,

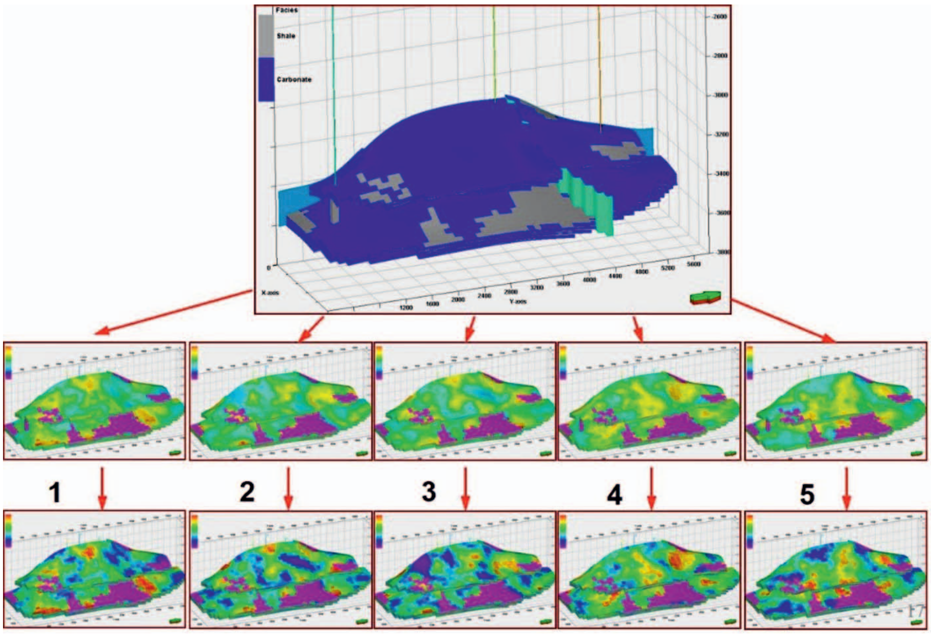

Fig. 3. Model realizations

Rys. 3. Realizacje modelu

and the lower reservoir – through the horizontal interval. Three perforation intervals were specified for each well: one in the upper formation and two (approximately equal in length) – in the lower formation. In case of smart completion these intervals are controlled independently by ICVs, each of them can be set in 10 possible positions ("shut", 8 intermediate, "fully open").

The following system of parameters, controlling the wells operation, was set (in the order of significance):

- Liquid rate of 1650 m^3/d for all wells;
- Minimum tubing head pressure (THP): 40 bar;
- Minimum bottomhole pressure was limited by the oil bubble-point pressure (245 bars).

Framework for modeling and optimization

Previously these types of model-based optimization strategies (proactive strategies) were presented in several publications (refer, for instance, (Yeten et al., 2004; Obendrauf et al., 2006; Emerick and Portella, 2007; Chen et al., 2009; van Essen et al., 2010; Su and Oliver, 2010) and showed good results. We do believe that it is difficult and inefficient to implement the aforementioned approaches in full field reservoir models directly, because they would result in large, multidimensional and time-consuming optimization problems. The essence of the proposed approach is to divide the initial model into a few small ones. Thus, these small models, having smaller dimensions than the initial one, can be easily optimized separately by means of the above-described approach.

In this work the proactive optimization strategy was implemented in the following manner:

- time of prediction was divided into a number of optimization steps;
- the commercial reservoir simulator (Eclipse) was coupled with Matlab-based program add-in enabling to control the ICV settings. Over every optimization step the controller performs multiple runs of a model to determine a combination of ICV settings that delivers the maximum of a target function by means of Direct Search (Emerick and Portella, 2007) method. Cumulative oil production was used as the objective function;
- three sector models were defined near each well (Fig. 4). The eliminated part of the reservoir was taken into account by means of the Flux Option (Meum et al., 2008). This option enables the simulator to produce the flux-file containing boundary conditions for sector models. Then the flux-file can be used for reduced runs;
- when sector models are optimized, it's necessary to check if the solution obtained for them, has a good match with the full field solution. In this work the discrepancies of well oil rates and oil production were used as the fitting criteria. In case of a poor match (discrepancy of more than 1% for either parameter) the outer cycle of optimization is repeated.

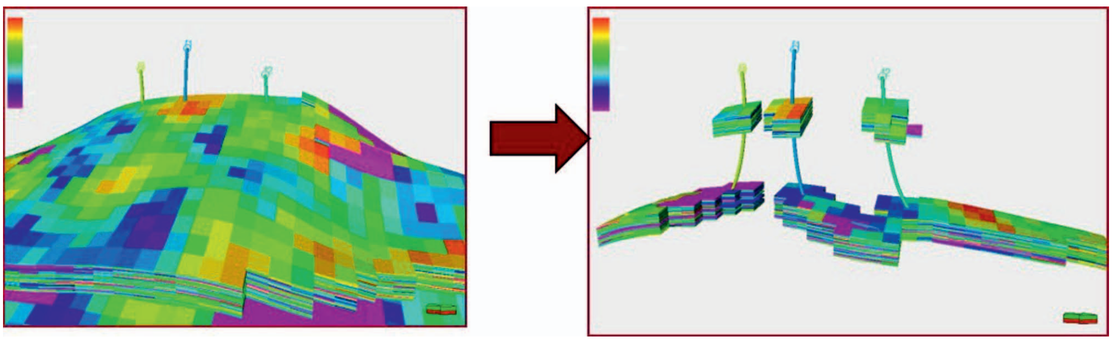

Fig. 4. The initial reservoir model and sectors defined around wells

Rys. 4. Wstępny model złoża i sektory zdefiniowane wokół odwiertów

Assessment of the "smart" well deployment effect in terms of NPV

When production profiles both for conventional and "smart" case are obtained, it's possible to make an economic analysis of ICV deployment. Since the objective was to compare "smart" vs. conventional well completions, the economic effect was expressed as the difference between NPVs of the smart completion and the base case:

$$NPV^* - NPV = \sum_{i=1}^{N} \frac{(Q_{oi}^* - Q_{oi}) \cdot P_{oi}}{(1 + \varepsilon)^i} - (E_o^* - E_o) \qquad (4)$$

where:

Q_i^*, Q_i – produced during the i-th time step oil volumes with smart and ordinary completion, respectively,

E_o^*, E_o – cost of smart and ordinary completion.

In this evaluation the oil price P_{oi} is 50 \$/bbl, discount rate ε is 12%, additional cost of smart completion (E_o^*, E_o) is 2 mln \$/well. Taxes were not taken into account in this study.

instant production performance (increasing the well oil rates, reducing the water and gas production, etc.) by means of a certain optimization routine (or a rule) that utilizes data of well zone tests, carried out earlier, to determine the best combination of ICV settings. On the other hand, proactive strategies use reservoir models, enabling to predict reservoir performances over a certain time horizon (or optimization step). Thus, the reservoir model serves as a «crystal ball» that helps to determine the ICV settings delivering the maximum of the target function (it can be, say, oil production) in the future.

Reactive strategies (refer, for instance (Naus et al., 2006; Grebenkin and Davis, 2010) can easier be implemented in a real oil field than proactive ones. However, proactive strategies can be much more rewarding.

An example of comparative study of both strategies was performed in Zolotukhin et al. (2011). Fig. 5 illustrates results of that study for reactive and proactive control strategies. As follows from the considered example the proactive strategy is almost twice more effective than the reactive one, although the cost of former is 2.5 mln USD higher.

Results

Five reservoir models corresponding to the different porosity-permeability realizations were built using stochastic approach and run with smart and ordinary completion strategies. Results of the simulation runs are summarized in Table 2 below.

Table 2. Production performance simulation results for ordinary and smart completion

Tabela 2. Wyniki symulacji wydobycia dla zwykłego i inteligentnego uzbrojenia odwiertów

Reservoir model #	Ordinary completion		"Smart" completion		$Q_o^* - Q_o$	Incremental ORF
	Q_o	ORF	Q_o^*	ORF*		
	[mln sm^3]	[%]	[mln sm^3]	[%]	[mln sm^3]	[%]
1	17.21	48.20	17.59	49.27	0.38	1.075
2	17.79	49.11	18.30	50.54	0.52	1.431
3	17.03	47.12	17.93	49.63	0.91	2.515
4	16.34	45.09	18.13	50.05	1.80	4.958
5	17.67	49.00	18.12	50.22	0.45	1.256
At average	17.20	47.70	18.02	49.94	0.81	2.247

As follows from the Table, the spread in the ORF values caused by poor reservoir description exceeds 4% for ordinary completion while for the "smart" completion stays within 1.27% (columns 3 and 5). In addition, the mean ORF value is 2.24% higher for the "smart" completion case as compared with conventional completion strategy. This means, that "smart" completion both improves the overall reservoir performance and effectively reduces the uncertainty impact caused by poor reservoir characterization.

The proposed approach showed good computational performance. Usually 1–2 outer iterations were well enough for a model to converge within the required accuracy.

Finally, there is one interesting question: what kind of the model-based reservoir performance optimization is more efficient: reactive or proactive one?

Reactive optimization strategy is aimed at improving

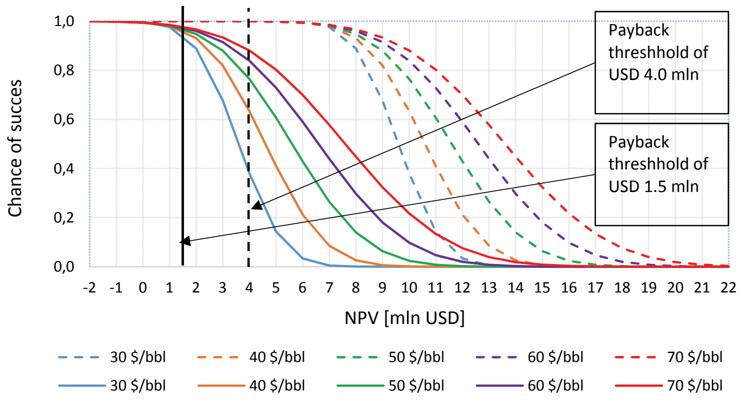

Fig. 5. Comparison of efficiency of reactive and proactive control strategies versus oil prices

Rys. 5. Porównanie skuteczności strategii reaktywnej i proaktywnej względem cen ropy

Conclusions

1. The proposed approach allows to estimate the amount of incremental oil that could be produced by using the smart well technology. Although in real reservoir engineering a practice model's ability to correctly predict reservoir behavior is often a matter of dispute (or belief), it's feasible to build a model enabling to predict reservoir performance over a certain time horizon (or optimization step) combining smart well technology and proactive strategy.
2. The proposed approach showed good computational performances. 1–2 external iterations were required for most of the optimization steps to converge.
3. Although Direct Search method turned out to be an effective and robust way in solving optimization problems, it doesn't guarantee that the global optimum is found.
4. Smart wells are capable of mitigating the impact of geological uncertainty on reservoir performances. The overall effect (both NPV and incremental oil) was always positive, but not for all wells. In every case there were at least one or more smart wells that produced less oil than conventional 'dumb' ones.
5. Proactive strategies in many cases can be much more rewarding. In the considered example the economic efficiency of the proactive strategy proven to be 2–4 times higher when compared with the reactive control strategy.

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