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ORIGINAL RESEARCH

Application of the closed loop industrial internet of things (IIoT)-based control system in enhancing the oil recovery factor and the oil production

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Abstract

A non-linear large scale stochastic optimisation model for enhancing the oil production and the recovery factor of the offshore oil reservoirs is proposed. The model aims at minimising the miss-match between mathematical model and the actual dynamic behaviour of the reservoir and the exploitation time, while maximising the oil production and the recovery factor. The model involves the three dimension (3D) oil reservoirs equipped with a few vertical injection and production wells. The limited number of wells is one of the major features of the common oil reservoirs in the middle-east region. The proposed model consists of the primarily mathematical model of the 3D reservoir, a model update algorithm and a large scale constrained non-linear optimisation algorithm. The input to this model is the daily production rate of the oil, natural gas and water produced from the oil reservoir and the output is the optimal injection rate to be injected to the injection wells in order to maximise the oil production and the recovery factor. In order to evaluate the performance of this model, the authors apply this model on part of one of the Iran's offshore oil reservoirs and study the performance improvement due to the proposed model and compare its performance with the performance of the available Improved Oil Recovery (IOR) technique. It is illustrated that the proposed model can increase the oil production from the reservoir up to 47.96% and reduce the exploitation period up to 66.66% compared with those of the available technique.

KEYWORDS

Kalman filters, predictive control

1 | INTRODUCTION

1.1 | Motivation and backgrounds

One of the growing application of the Operation Research (OR)-based decision systems is in the oil and gas industry. The motivation for introducing this model for oil and gas industry is the global demand for fossilised energy and an urgent need for improvement in the efficiency and productivity from oil reservoirs, which are often very old in order to properly respond to the increasing global demand for oil and gas. In particular, the available oil and gas reservoirs are very limited and exploration and utilisation of new resources are very time consuming and expensive and cannot full fill the immediate global demand for energy. In Iran, for example, more than half of the Iran's oil reservoirs (around 80%) are in the second half of their life. The Improved Oil Recovery (IOR) technique is mainly used in this country to exploit oil from these old reservoirs. This technique is known as a proactive method because it implements the primary mathematical model of the reservoir for predicting the reservoir behaviour for the entire life time of the reservoir, which is unrealistic resulting in a poor

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efficiency and productivity. As a result of that the oil recovery factor, which is the percentage of the recoverable oil initially in the reservoirs using this technique, is only 29% in Iran. This means that using the available exploitation techniques in Iran only 29% of the available oil can be extracted and the rest will remain unusable in reservoirs for ever. This calls for developing and utilising more advanced techniques that significantly improve the efficiency and productivity from the available reservoirs.

The invention of Industrial Internet of Things (IIoT) communication modules has enabled us to interconnect distributed sensors, instruments, actuators and other networked devices of the oil/gas reservoirs to computers resulting in a closed loop OR-based decision system. This paper aims to illustrate the potential of such a relatively very cost effective and easily implementable decision system for significant improvement of the efficiency and productivity from the available oil and gas reservoirs. In the proposed system, gateways connect the distributed sensors and actuators to the Internet allowing the exchange of data between this network and a remote computer server. This computer server is equipped with optimisation, estimation, machine learning or artificial intelligent algorithms. The input to these algorithms is the real time data collected by sensors and the output is the generated proper commands for distributed actuators computed so that the efficiency and productivity are enhanced [1–10]. Due to the uncertainty in exchange of information between distributed sensors and actuators and gateways, as well as complexity in the environment equipped with the network of these sensors and actuators, we need to develop a large scale stochastic non-linear operation research model that is obviously much difficult to develop with respect to the commonly used small scale deterministic models. Some of the available results for the compensation of the uncertainty in communication can be found in Refs. [11–17].

The proposed stochastic model allows for real time data collection and exchange. Using the collected real time data from reservoir, the model should regularly update the reservoir mathematical model based on the available data, for example, daily production and the injection rates. This calls for the development and implementation of an advance filter that is able to estimate the states of a very large scale non-linear system in reasonable time with high precision. The model needs to regularly update the reservoir mathematical model because reservoir behaviour is dynamic and it changes frequently. The lack of explicit mathematical expression for describing the reservoir dynamics is one of the major difficulties for designing such a filter. Very often the model for describing the dynamics of reservoir is provided by an Eclipse file. Another difficulty in the realisation of such a filter is the dimension of reservoirs, which results in a very long computation time for advance filters, while the updated mathematical model generated by the filter should be ready by the end of the day based on the measurement provided at the beginning of the day in order to have a real time planning. To overcome these drawbacks, we use the ensemble Kalman filter in this paper. The successful applications of the ensemble Kalman filter for the reservoir monitoring and model update have been reported in several papers, for example, [18–21]. Generating new ensembles to be used in the ensemble Kalman filter from the primary mathematical model embedded in a software package, for example, Eclipse or Mrst etc. is possible. To reduce the computation time for updating the mathematical model, we can use M parallel computers each responsible for generating a new ensemble. Also, the ensemble Kalman filter is very suitable for updating the model of very complex non-linear dynamics. Hence, it is suitable filter for updating the model of oil and gas reservoirs. The proposed OR-based decision system then uses the updated mathematical model in a non-linear Model Predictive Control (MPC) algorithm, which implements a large scale constrained non-linear optimisation algorithm, to compute the optimal injection rate not only for the pressure stabilisation but also for the maximising oil production. This involves a very complex optimisation problem subject to non-linear large scale reservoir dynamics and operational constraints; and therefore, advance numerical optimisation methods should be implemented to solve it.

The proposed closed loop OR-based decision system regularly updates the optimal injection rate based on new measurements from the reservoir. Hence, unlike the commonly used techniques, it compensates the uncertainty and complexity of the reservoir management and, therefore, produces an optimal multi-valued injection rate based on the current behaviour of the reservoir (instead of a single-valued injection rate based on the primary mathematical model). Thus, it is expected that this system enhances the productivity and efficiency compared with those of the available techniques. The main objective of this paper is to investigate this question and to illustrate the impacts of the proposed model in upstream oil and gas industry.

Under the unrealistic assumption that the reservoir primary mathematical model is the true representation of the reservoir dynamics for the entire life of the reservoir, Refs. [3–8] show that the optimal multi-valued injection rate technique enhances the oil production by 30% and the oil recovery factor by 3%. It can also reduce the water injection rate for the pressure stabilisation by 25% compared with the currently used IOR technique. Refs. [9, 10] show that the combination of the ensemble Kalman filter with multi-valued injection rate technique results in a better exploitation efficiency. Aforementioned references are concerned with the 2D (two-dimensional) reservoirs, which have narrow thickness. There are also concerns with the 2D reservoirs equipped with the horizontal production and injection wells with many injection and production outlets and many observation points. Moreover, they do not assume any faults in the reservoir.

1.2 | Paper contributions

Refs. [9, 10, 18–21] suggest that the real time data collection from the oil reservoir and the exchange of real time data between reservoir and a remote computer server that runs the ensemble Kalman filter, and a large scale non-linear

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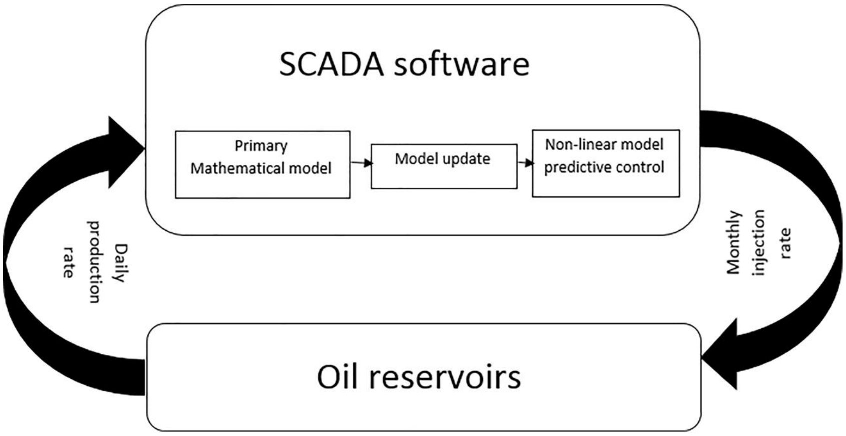

FIGURE 1 The components of the proposed model.

optimisation algorithm for the computation of the optimal multi-valued injection rate facilitate improvement in the oil productivity and exploitation efficiency for the 2D oil reservoirs. Nevertheless, the dynamics of the oil reservoirs in the middle-east region including Iran are very different from the dynamics considered for the reservoirs in Refs. [9, 10, 18–21]. Iran's offshore oil reservoirs, for example, similar to the other oil reservoirs in the middle-east region are 3D (three-dimensional) and are very thick. They include faults and are equipped with a few production vertical wells and few vertical injection wells and, therefore, the number of observation and actuation points are very limited in these reservoirs. Also, the assumption that the primary mathematical model of the reservoir is a legitimate model for the reservoir entire life time is not realistic for these reservoirs. Because most of the reservoirs in this region are of the type of the carbonate reservoirs and, therefore, injection results in new cracks in the reservoir rocks and thus the dynamic model of the reservoir is getting away from its primary mathematical model after injection. Hence, it is worth studying the impacts of the proposed closed loop OR-based decision system for the improvement of the productivity and the exploitation efficiency of this type of reservoirs.

To the best of our knowledge, this paper is the first paper addressing the impacts of multi-valued injection rate on 3D reservoirs equipped with a few vertical and horizontal wells. To achieve this goal, this paper introduces the following closed loop OR-based decision system. In this large scale stochastic non-linear model, distributed sensors are the available separators on the surface of the oil reservoir. At the end of the day, the daily production of oil, gas and water can be determined from separators. We can supply the computation layer of the OR-based decision system with the daily production of separators manually; or we can equip each separator unit with an IIoT module and using this module we can provide the remote computer server with the daily production rates of the oil, natural gas and water from each production well. In other words, the input to the proposed model is the knowledge from reservoir that can be gathered by the available infrastructure on the field. As it is shown in Figure 1, the remote computer server is equipped with three software packages: The primary mathematical model of the oil reservoir, a model update algorithm which is the ensemble Kalman filter and the non-linear MPC algorithm [22] that involves a single objective cost functional known as the injection Net Present Value (NPV) subject to operational constraints and the large scale non-linear stochastic mathematical model of reservoir. The model update algorithm uses the collected data from separators and using the primary mathematical model updates the reservoir model. Then, the updated model is used in the non-linear MPC algorithm to compute the optimal multi-valued injection rate for each injection well. The primary mathematical model is the reservoir model obtained using seismic tests, core sampling etc., during the comprehensive study of the oil reservoir, which is repeated every 3–5 years. This model is available as an Eclipse or Mrst file. The non-linear MPC of this paper is based on the optimisation algorithms of the Mrst tool box, which is a MATLAB toolbox developed for reservoir simulation. This computation is updated every month based on the updated model for the reservoir and the computed optimal injection rate is communicated to the injection controlled valves to be injected to the oil reservoir. In this paper this system is implemented on small part of one of the Iran's offshore oil reservoirs. Using extensive computer simulations, we study the impacts of the currently used IOR technique as well as the proposed model (with and without the model update sub-package) on the exploitation efficiency of this reservoir. The outcomes of this study is interesting because it is a bit different from the results reported in the literature for the 2D reservoirs. In particular, this paper illustrates that for Iran's offshore oil reservoirs, there is no gain in implementing the ensemble Kalman filter in terms of the exploitation efficiency improvement compared to the efficiency improvement for the 2D reservoirs. Also, unlike the results reported for the 2D reservoirs, it is illustrated that the proposed model for the 3D reservoirs can increase the injection rate by 21.79%. However, it can increase the oil production by 47.96% and decrease the exploitation time by 66%. Hence, the proposed model is a very facilitating technology for the improvement in the clean oil production and

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TABLE 1 The major benefits of stakeholders from the proposed model.

Stakeholder	Benefits
The reservoir owner (Iran)	The recovery factor enhancement
The reservoir owner (Iran)	Higher rate of oil and gas production
The reservoir owner (Iran)	Faster depleting shared reservoirs
Corporate oil producer (TotalEnergies)	Higher rate of oil and gas production
Environment	Faster depleting reservoirs and therefore lower damage to environment

the exploitation efficiency of the middle-east oil reservoirs. It can satisfy all the stakeholders' needs as shown in Table 1.

1.3 | Paper organisation

The paper is organised as follows: the Introduction was presented in Section 1. The second section is devoted to the problem formulation. In this section the oil reservoir considered in this paper is also described. Section 3 is devoted to the experimental results. In Subsection 3.1 the impact of the currently used IOR technique on the exploitation efficiency of the Iran's offshore oil reservoirs is studied. In Subsection 3.2 the impact of the proposed model without the model update sub-package on the exploitation improvement of the oil reservoir of Section 2 is studied. Subsection 3.3 is devoted to the impact of the proposed model equipped with the model update sub-package on the exploitation improvement. In Subsection 3.4, we compare the performances of the proposed model (with and without the model update sub-package) with the performance of the available IOR technique. Finally, we conclude the paper in Section 4 by summarising the main contributions of the paper and presenting the future research directions.

2 | PROBLEM FORMULATION

The basic block diagram of the proposed model is shown in Figure 1. In this figure, the SCADA software is the computer programme of the remote computer server. This computer programme comprises of the following three sub-packages: The primary mathematical model of the reservoir, a model update algorithm and a non-linear MPC algorithm. Because the field devices (separators and controlled surface valves) are already available in the surface of the oil reservoir and the communication layer of the proposed model can be easily constructed by adding IIoT modules to each separator and controlled valve, in this section we only focus on the computation layer of the proposed model; that is, the SCADA software shown in the block diagram of Figure 1.

2.1 | Primary mathematical model

Petroleum resources are found within porous rocks that have sufficient interconnected void space to store and transmit fluids. Two petrophysical properties are fundamental in reservoir modelling. The first one is the rock porosity, ϕ, is a dimensionless quantity that denotes the void volume fraction of the medium available to be filled by fluids [23]. The second property is the permeability, K, is a measure of the reservoir rock's ability to transmit a single fluid at certain conditions [23]. Its unit is Darcy [23]. A single phase flow dynamic in a porous medium is described by the combination of the fundamental properties of conservation of mass with the Darcy's law, as follows [23]:

Conservation of mass [23]:

$$\frac{\partial(\phi\rho)}{\partial t}+\nabla.(\rho\vec{v})=q. \tag{1}$$

Here, ρ is the density and $\nabla.$ is the inner product operator. q is the fluid source/sink term used to model wells. It is described by

$$q=WI(p_{wb}-p_b), \tag{2}$$

where WI is the well index, p_{wb} is the well bore pressure and p_b is the perforated blocks pressure. $\vec{v}$ is the velocity of fluid in the porous medium, which is described by Darcy's law as follows [23]:

$$\vec{v}=-\frac{K}{\mu}(\nabla p-\rho\vec{g}), \tag{3}$$

where μ is the viscosity of the fluid and $\vec{g}$ is the earth gravity vector. In a reservoir we normally have a three - phase fluid: $\alpha = \{o, w, g\}$, where o denotes oil, w water and g denotes natural gas. For such a reservoir we have eq. (1) and eq. (3) for each phase linked through the saturation factors S_w, S_o and S_g ($S_w + S_o + S_g = 1$) as follows:

$$\begin{aligned}&\frac{\partial(\phi\rho_\alpha)}{\partial t}+\nabla.(\rho_\alpha\vec{v}_\alpha)=q_\alpha,\\&\vec{v}_\alpha=-\frac{Kk_{r\alpha}}{\mu_\alpha}(\nabla p_\alpha-\rho_\alpha\vec{g}),\quad \alpha=\{o,g,w\}.\end{aligned} \tag{4}$$

Here, $k_{r\alpha}$ is a dimensionless scaling factor known as relative permeability, which is a function of saturation factors. The pressures p_o, p_w and p_g are related by the so called capillary pressure, p_c, as follows: $p_{cow} = p_o - p_w$ and $p_{cgw} = p_g - p_w$, where p_{cow} and p_{cgw} are also the functions of the saturation factors.

The above equation is a non-linear partial differential equation and, therefore, in order to be solved by digital computers we need to discretise it using, for example, the finite element method [24] to approximate it by a network of the so called grids described by a network of ordinary differential

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equations. Then, we need to discretise this network of ordinary differential equations in time in order to be able to solve it by digital computers. For this model, if we choose the gas and water saturation factors and also the oil pressure as the state variables, we reach to the following state space representation for the reservoir.

$$\begin{aligned} X_{k+1} &= X_k + F(\theta, X_k, U_k), \\ Y_k &= G(\theta, X_k, U_k). \end{aligned} \tag{5}$$

Here, X_k is the state vector, which includes the state variables of all discretised grids (i.e., the oil pressure and the gas and water saturation factors of all grids), and θ is a vector that includes the porosity and permeability coefficients of all grids. Note that if we use the Cartesian coordinate for discretisation, then the permeability coefficient of each grid is represented by a 3×3 tensor, as follows: $K = \begin{pmatrix} k_x & k_{xy} & k_{xz} \\ k_{yx} & k_y & k_{yz} \\ k_{zx} & k_{zy} & k_z \end{pmatrix}$. In the above equation, U_k is the vector of injection rates to be injected by the injection wells and Y_k is the vector of oil, gas and water production rates from the production wells. k is the time index measured in day.

2.2 | Non-linear model predictive control

For both techniques (IOR and the proposed OR-based techniques), we use the following cost functional, known as the injection NPV to determine the optimal injection rates for the injection wells.

$$J = \sum_{i=1}^{L} \frac{G_o[i]q_o[i] + G_g[i]q_g[i] - G_w[i]q_w[i] - G_{wi}[i]q_{wi}[i]}{(1+d)^{\frac{i}{\tau}}} \Delta t. \tag{6}$$

Here i is the time index measured in days, L is the exploitation life time, d is the discount factor, $\tau = 365$, Δt is the time interval between 2 injection rate updates, $G_o[i]$ is the oil price measured in $\$/stb$, $G_g[i]$ is the gas price, $G_w[i]$ is the cost of separating water from oil and gas in separators and $G_{wi}[i]$ is the cost of injecting water to the reservoir. In the above cost functional $q_o[i]$ is the total oil produced in day i, $q_g[i]$ is the total natural gas produced, $q_w[i]$ is the total water produced and $q_{wi}[i]$ is the total water injected to the reservoir in day i.

When we use the IOR technique, prior exploitation from oil reservoir, this cost functional is maximised subject to the reservoir dynamics (5) and the operational constraints in order to obtain the optimal fixed valued injection rate $q_{wi}(= q_{wi}[1] = \ldots = q_{wi}[L])$. Then, during the exploitation phase from the reservoir, water is injected by injection wells with fixed rates so that the summation of the injection rates is equivalent to the optimal fixed rate q_{wi}, which has been computed off line. To observe the pressure stabilisation requirement, this optimisation is also subject to the following operational constraint: $q_o[i] + q_g[i] + q_w[i] = q_{wi}[i]$. Note also that another operational constraint is $U_{\min} \prec U_k \prec U_{\max}$, where $U_{\min}$ and $U_{\max}$ are known lower and upper bounds on the injection vector U_k, respectively. Note that in the above optimisation problem, L is very large, typically 30–40 years, and the reservoir dynamics (5) is non-linear and large scale (the dimension of X_k ranges from 150,000 to 1,500,000 and the dimension of θ ranges from 100,000 to 1,000,000) and the problem is a constrained non-convex optimisation problem. Hence, solving this non-convex non-linear constrained optimal control problem is subject to a heavy computational complexity and it may take several months to be completed by very powerful computers.

Nevertheless, when we use the proposed OR-based technique, the optimal injection rate is computed online using the available measurements from the reservoir, for example, the daily production rates of oil, water and natural gas from the reservoir and the water injection rate. In order to perform this online computation, in this technique the receding horizon idea or the so called MPC [22] is implemented to reduce the associated computational load, as follows: First of all in the proposed OR-based decision technique, we consider the following modification in the cost functional (6):

$$J = \sum_{i=1}^{L} \frac{G_o[i]q_o[i] + G_g[i]q_g[i] - G_w[i]q_w[i] - G_{wi}[i].\sum_{j=1}^{n} q_{wi,j}[i]}{(1+d)^{\frac{i}{\tau}}} \Delta t. \tag{7}$$

Here, $j \in \{1, 2, \ldots, n\}$ denotes the index of the jth injection well and $q_{wi,j}[i]$ is the injection rate of the jth well at day i. Using this modified cost functional, the optimal injection rate for each injection well can be computed separately. Now, suppose we are in day k and we need to update the injection rates. This is done using the cost functional (8), which is extracted from the cost functional (7), taking into account the available information up to this day. Subsequently, the computed optimal rates $q^*_{wi,j}[k]$ are implemented to the reservoir for the next Δt days by the injections wells $j \in \{1, 2, \ldots, n\}$. Then, at the day $k + \Delta t$ we update the injection rates again and we implement them to the reservoir for the next Δt days and so on and so forth. To perform this operation, we consider the following cost functional, which is extracted from the cost functional (7)

$$J_k = \sum_{i=k}^{k+N.\Delta t} \frac{G_o[i]q_o[i] + G_g[i]q_g[i] - G_w[i]q_w[i] - G_{wi}[i].\sum_{j=1}^{n} q_{wi,j}[i]}{(1+d)^{\frac{i}{\tau}}} \Delta t, \quad N \in \{1, 2, 3, \ldots\}. \tag{8}$$

Here, $N.\Delta t$ is the prediction horizon (N is fixed); and because it is much smaller than L the computational complexity associated with this optimisation problem is much smaller than that of the IOR technique. Therefore, the optimal injection rates, which are obtained from this technique, can be implemented online. Note that the above MPC problem is also subject to the following additional constraint:

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$$
\begin{aligned}
&q_{wi,j}[k] = q_{wi,j}[k+1] = \ldots = q_{wi,j}[k+\Delta t-1]\\
&.\\
&.\\
&.\\
&q_{wi,j}[k+(N-1)\Delta t] = q_{wi,j}[k+(N-1)\Delta t+1] = \ldots = q_{wi,j}[k+N\Delta t-1].
\end{aligned}
\tag{9}
$$

This type of constraint can be easily handled using the so called the re-sampling method. That is, in the dynamic model (5) under the assumption that the input vector, $U_k = \left(q_{wi,1}[k] \ldots q_{wi,n}[k]\right)'$, is subject to the above constraint, we compute the output vector, Y_k, for the time instants $k + \Delta t$, $k + 2.\Delta t, \ldots, k + N.\Delta t$ and we use them in the above MPC problem.

To implement this closed loop feedback strategy in the proposed OR-based decision system, a model update algorithm, such as the ensemble Kalman filter [18–21] is implemented to estimate the state variables, X_k, and θ online using the available measurements, Y_k, where the estimations $\hat{X}_k$ and $\hat{\theta}$ are used in the dynamic model (5) instead of X_k and θ to generate Y_k, $\hat{Y}_{k+\Delta_t}$, …, $\hat{Y}_{k+N.\Delta_t}$ that includes information about $q_o[i]$, $q_g[i]$ and $q_w[i]$ of the cost functional (8) for the time instants $i = \{k, k+\Delta_t, \ldots, k+N.\Delta_t\}$. Note that most of the relevant papers in the literature, for example, Refs. [3–8] do not implement this model update strategy and assume the primary model of the reservoir (5) is the legitimate model for the entire reservoir life time, which is an unrealistic assumption. The ensemble Kalman filter is described next.

2.3 | Model update

For the model update we use the ensemble Kalman filter to estimate the state variables and porosity and permeability vector, θ, each time the injection rate is updated using the available measurements, Y_k, and U_k [18–21]. In order to use this filter we need to have a linear relation between the measurement vector and the state variables. Therefore, we define the augmented variable $S_k = \begin{pmatrix} X_k \\ \theta \\ Y_k \end{pmatrix}$ to reach the following dynamic model for the reservoir.

$$
\begin{aligned}
S_{k+1} &= \mathcal{F}(S_k, U_k) + W_k,\\
O_k &= C.S_k + V_k.
\end{aligned}
\tag{10}
$$

Here, C is a matrix that maps S_k to Y_k. As the measurement is always subject to noise, in the above dynamic, we include the noise term V_k which is an i.i.d. Gaussian process with mean zero and variance R. Using the seismic test combined with the core sampling, we can also have an estimation of S_0. Obviously, this is an estimate and, therefore, it is subject to error. Hence, for S_0 we also assume a Gaussian distribution with known mean and variance Q. For the use of the ensemble Kalman filter, we also include the process noise W_k to the above dynamic. W_k is an i.i.d. Gaussian process with mean zero and known variance Q. For the above non-linear dynamic model, the ensemble Kalman filter has the following description:

$$
\begin{aligned}
\hat{S}_k &= \hat{S}_{k|k-1} + K_k\left(O_k - C\hat{S}_{k|k-1}\right),\\
K_k &= P_{k|k-1}C'\left(CP_{k|k-1}C' + R\right)^{-1}.
\end{aligned}
\tag{11}
$$

In this filter, $\hat{S}_{0|-1}$ and $P_{0|-1}$ are computed as follows: denote M realisations of $S_0 \sim N\left(\overline{S}_0, Q\right)$ by $\left(S_0^{(1)}, \ldots, S_0^{(M)}\right)$, then

$$
\hat{S}_{0|-1} = \frac{1}{M}\sum_{i=1}^{M} S_0^{(i)}.
\tag{12}
$$

Now, define $L_{0|-1}$ with M columns as follows:

$$
L_{0|-1} = \frac{1}{\sqrt{M}}\left(S_0^{(1)} - \hat{S}_{0|-1} \quad S_0^{(2)} - \hat{S}_{0|-1} \quad . \quad . \quad . \quad S_0^{(M)} - \hat{S}_{0|-1}\right).
\tag{13}
$$

Then, $P_{0|-1} = L_{0|-1}L'_{0|-1}$. Now, as soon as observing O_0, we have the following estimation for $\hat{S}_0$.

$$
\begin{aligned}
\hat{S}_0 &= \hat{S}_{0|-1} + K_0\left(O_0 - C\hat{S}_{0|-1}\right),\\
K_0 &= P_{0|-1}C'\left(CP_{0|-1}C' + R\right)^{-1}.
\end{aligned}
\tag{14}
$$

Now, in order to estimate S_1 at the time instant $k = 1$, we need to compute $\hat{S}_{1|0}$ and $P_{0|1}$. In order to perform this computation, using the dynamic model (10) and M realisations of $W_0 \sim N(0, Q)$ denoted by $\left(W_0^{(1)}, \ldots, W_0^{(M)}\right)$, we compute M realisations of $S_1^{(i)}$ as follows by the knowledge of U_0:

$$
S_1^{(i)} = \mathcal{F}(\overline{S}_0^{(i)}, U_0) + W_0^{(i)}, \;\; i = \{1, 2, \ldots, M\}.
\tag{15}
$$

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Note that $\overline{S}_0^{(i)} = \begin{pmatrix} X_0^{(i)} \\ \hat{\theta} \\ Y_0 \end{pmatrix}$, where $\hat{\theta}$ is the estimation of θ obtained from the previous step and $X_0^{(i)}$ is obtained from $S_0^{(i)}$ as follows: $S_0^{(i)} = \begin{pmatrix} X_0^{(i)} \\ \theta \\ Y_0 \end{pmatrix}$. Then,

$$\hat{S}_{1|0} = \frac{1}{M}\sum_{i=1}^{M} S_1^{(i)}. \tag{16}$$

Now, define $L_{1|0}$ with M columns as follows:

$$L_{1|01} = \frac{1}{\sqrt{M}}\left(S_1^{(1)} - \hat{S}_{1|0} \quad S_1^{(2)} - \hat{S}_{1|0} \quad . \quad . \quad . \quad S_1^{(M)} - \hat{S}_{1|0} \right). \tag{17}$$

Then, $P_{1|0} = L_{1|0}L'_{1|0}$. Now, as soon as observing O_1, we have the following estimation for $\hat{S}_1$.

$$\begin{aligned} \hat{S}_1 &= \hat{S}_{1|0} + K_1\left(O_1 - C\hat{S}_{1|0}\right), \\ K_1 &= P_{1|0}C'\left(CP_{1|0}C' + R\right)^{-1}. \end{aligned} \tag{18}$$

By following a similar procedure, $\hat{S}_k$ is obtained for the rest of time instants. It is shown in Refs. [10–18] that for two - dimensional reservoirs equipped with many production and injection wells and, therefore, many observation points, the ensemble Kalman filter as described above, provide a good estimation of the state variables and parameters of the reservoir.

This model update is very time consuming. In order to significantly speed up the computation associated to this model update, we can use M computers, where each computer is responsible to compute one ensemble (e.g. $S_1^{(i)}$ in eq. (15)) in parallel with other computers.

2.4 | The case study

In this paper, we are concerned with the part of Iran's offshore oil reservoir with the thickness of 3057 m. It consists of two main layers: Oil only layer with the thickness of 305.7 m on the top and below this layer we have a two-phase layer of oil and water with the water saturation factor of 26%. The permeability in the reservoir varies between 5 and 31 mD. The porosity varies between 5% and 37%. The initial pressure of this reservoir is 4000psi and its temperature is 227 Fahrenheit. We consider a part of this reservoir with the dimensions of 1000 × 1000 m square. This part includes one injection well and four production wells. We discretise this part by a 25 × 25 × 10 grids, as shown in Figure 2.

The model described by Figure 2 is a simplified primary mathematical model that will be used for the optimisation and model update. In fact, there are two big faults in this part of the reservoir; therefore, its true primary model perhaps has the actual representation described by Figure 3.

Throughout, we use the simplified primary mathematical model of Figure 2 for the model update and optimisation purposes; while, the measurements are obtained from the actual representation of Figure 3. Also, the outcome of the model update and optimisation, which is the optimal injection rate is applied to the actual representation of Figure 3. Note that for the mathematical model of Figure 2 we assume that the porosity and permeability of each grid is 21% and 18 mD, respectively; while the porosity and permeability of the actual model are not exactly known at each grid and vary between 5% and 37% and 5 mD to 31 mD, respectively (see Figure 4). Note that for the simplified mathematical model we consider a diagonal 3 × 3 tensor for the permeability coefficients. For computer simulation, we set the parameters according to Table 2. We also set L = 720, N = 3, Δt = 30, $U_{\min}$ = 0 and $U_{\max}$ = 5,608,152. This upper bound for the injection rate is

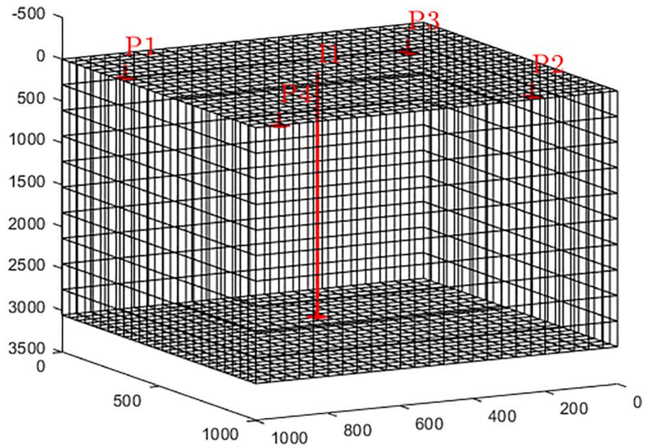

FIGURE 2 The simplified primary mathematical model considered for the reservoir of the case study.

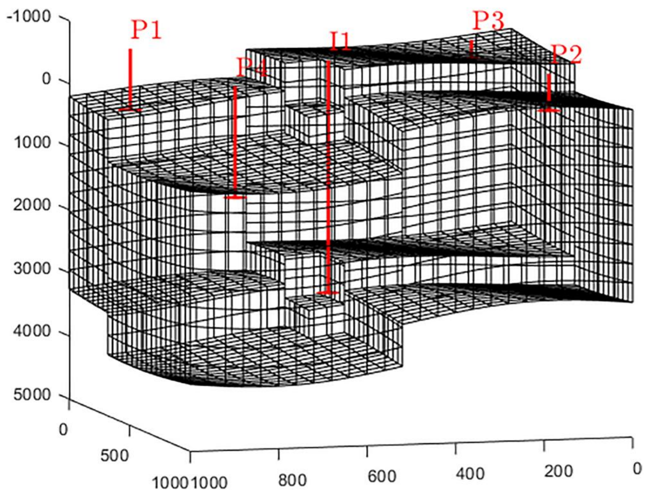

FIGURE 3 The actual primary representation for the reservoir of the case study.

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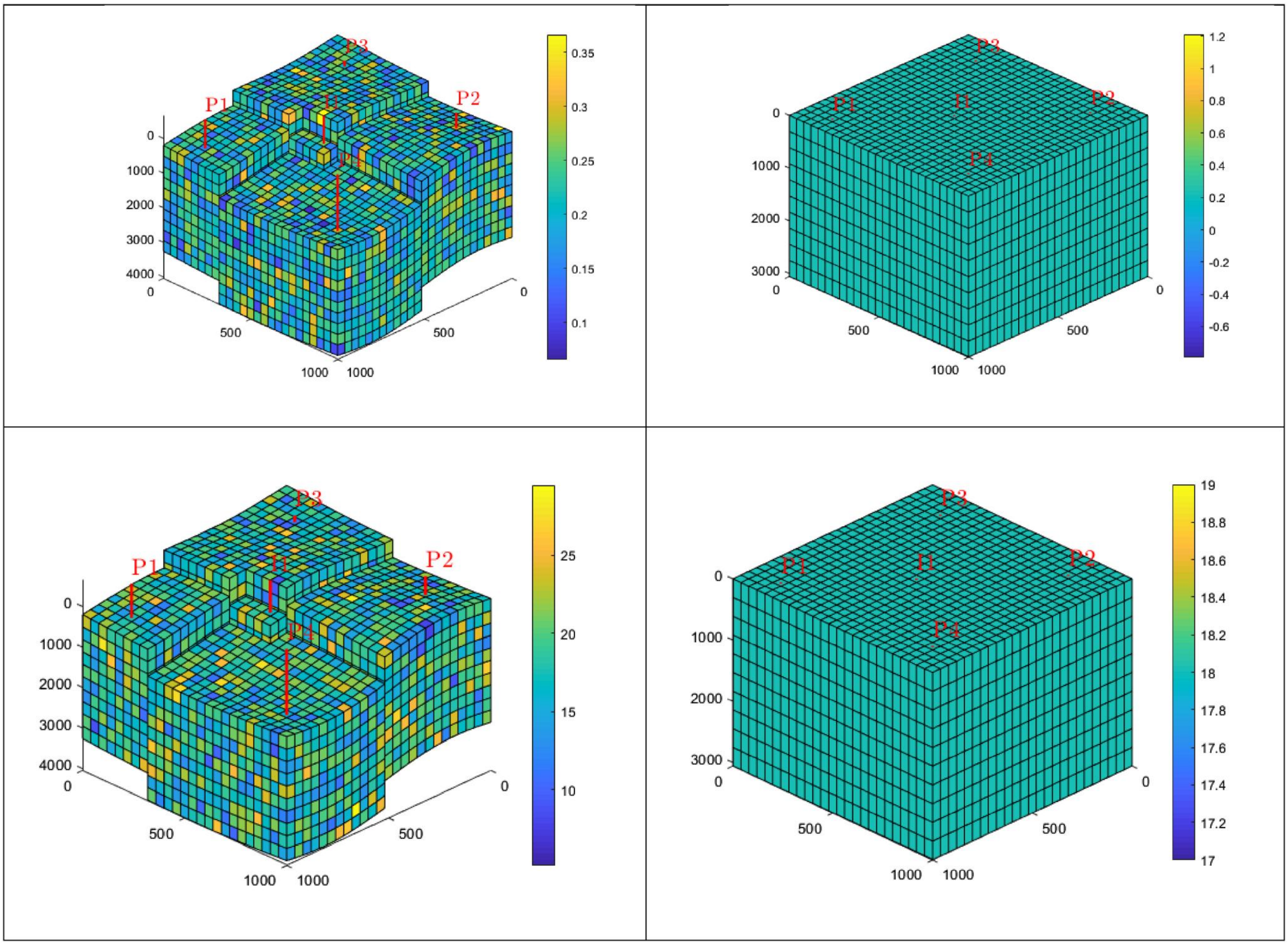

FIGURE 4 Left figures: The porosity and permissibility (in the x direction) of the actual representation of the reservoir of the case study. Right figures: The porosity and permissibility (in the x direction) of the simplified mathematical model.

TABLE 2 Reservoir properties.

Symbol	Description	Value	Unit
c_r	Rock compressibility	10^{-6}	Pa^{-1}
ρ_o	Oil density	770	$\frac{Kg}{m^3}$
ρ_w	Water density	1000	$\frac{Kg}{m^3}$
c_o	Oil compressibility	10^{-5}	Pa^{-1}
c_w	Water compressibility	10^{-5}	Pa^{-1}
μ_o	Oil viscosity	5	cp
μ_w	Water viscosity	0.3	cp
n_o	Corey power for oil	2	–
n_w	Corey power for water	2	–
G_o	Oil price	30	$\$/stb$
G_w	Cost for separating water from oil	7	$\$/stb$
G_{wi}	Cost for injecting water	7	$\$/stb$
d	Discount factor	0.1	–

unrealistic, which also results in unrealistic production rates that are beyond the capacity of the actual production wells. However, in order to speed up the computer simulations to have a fair comparison between the available IOR technique and the proposed closed loop IIoT-based control technique, we choose this upper bound.

3 | EXPERIMENTAL RESULTS

This section is devoted to the experimental results. In Subsection 3.1 the impact of the currently used IOR technique on the exploitation efficiency of the Iran's offshore oil reservoirs is studied. In Subsection 3.2 the impact of the proposed model without the model update sub-package on the exploitation improvement of the oil reservoir of Section 2 is studied. Subsection 3.1 is devoted to the impact of the proposed model equipped with the model update sub-package on the exploitation improvement. In Subsection 3.4, we compare the performances of the proposed model (with and without the model

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update sub-package) with the performance of the available IOR technique.

3.1 | The impact of the available Improved Oil Recovery technique

In the available IOR technique the injection NPV is solved once based on the primary mathematical model and the computed fixed valued injection rates are applied to reservoir until in the next comprehensive study of reservoir (it takes 3–5 years), the reservoir model is updated and based on the new model the fixed valued injection rates are updated. Figure 5 illustrates the injection NPV when the available IOR technique is applied to the reservoir of the case study. In this technique, model update is not used and the simplified mathematical model of Figure 2 (the primary mathematical model) is used to maximise the cost functional (6) subject to the mathematical model of Figure 2 and the operational constraints in order to obtain the optimal fixed valued injection rate. Note that this optimisation is performed off line and then the optimal fixed valued injection rate is applied to the actual representation of Figure 3 for the reservoir of the case study to obtain the red curve of Figure 5. In comparison, in the proposed OR-based decision system, the optimisation is repeated every month based on the updated model for the reservoir; therefore, the output within the time frame of two successive comprehensive studies is a multi-valued injection rate. Figure 5 for the IOR - based technique illustrates that the maximum value for the injection NPV is achieved at the day 360. After that day the injection NPV has a decreasing trend and, therefore, there is no gain in exploitation from the reservoir. Hence, at the day 360 the reservoir is abandoned. Table 3 summarises the main features of this technique and Table 4 illustrates the total amount of the oil and water produced from each production well before the reservoir is abandoned. Figure 6 illustrates the daily injection rate and the daily total production rates of oil and water from the reservoir when the available IOR technique is used for this reservoir.

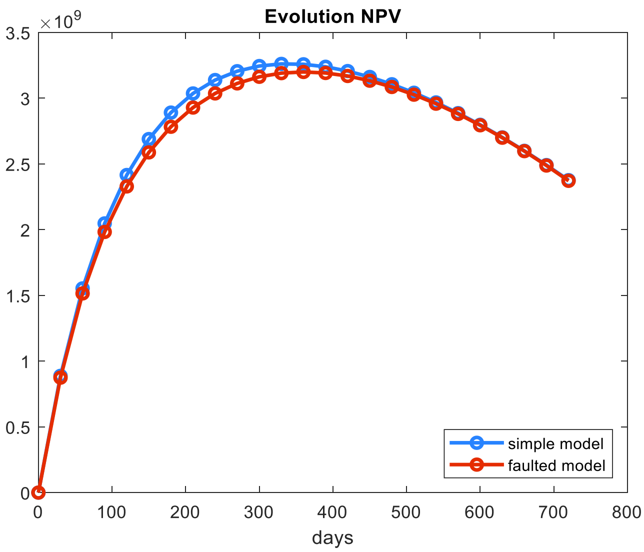

FIGURE 5 The comparison of the Net Present Values (NPVs) when the Improved Oil Recovery (IOR) technique is implemented. Red curve: the Net Present Value (NPV) when the optimal injection rate is applied to the actual representation of the reservoir. Blue curve: when it is applied to the simplified mathematical model of the reservoir.

Remark III. 1 Figure 5 also illustrates the impact of the simplified model of Figure 2 in the IOR technique, which is an open loop control strategy. In particular, the blue curve represents the NPV when the simplified model is an exact representation of the true dynamics of reservoir. As it is clear from Figure 5, even this unrealistic assumption, does not result in a significant improvement in the NPV compared with the other more realistic case (illustrated by the red curve).

3.2 | The impact of the closed loop OR-based decision system without the model update sub-package

Figure 7 illustrates the injection NPV when the OR-based decision technique without the model update sub-package is applied on the reservoir of the case study. Here, model update is not used and the simplified mathematical model of Figure 2 is used to maximise the cost functional (8) subject to the mathematical model of Figure 2 and the operational constraints to obtain the optimal multi-valued injection rate. Note that in order to perform this receding horizon optimal control strategy, the measurements from the actual representation of Figure 3 for the reservoir of the case study is used. Therefore, this optimisation is online. This figure illustrates that the maximum value for the injection NPV is achieved at the day 120. After that the injection NPV has a decreasing trend and, therefore, there is no gain in exploitation from the reservoir. Hence, at the day 120 the reservoir is abandoned. This figure includes two curves. The red curve is the injection NPV for the

TABLE 3 The main features of the Improved Oil Recovery (IOR) technique.

T_{max} (days)	NPV_{max}($b\$$)	Total water injected (Mstb)
360	3.19	552.55

TABLE 4 The total amount of the water and oil produced from each production well when the Improved Oil Recovery (IOR) technique is implemented.

Well	Water (Mstb)	Oil (Mstb)
P_1	70.22	67.91
P_2	62.80	75.33
P_3	56.48	81.65
P_4	65.13	72.99

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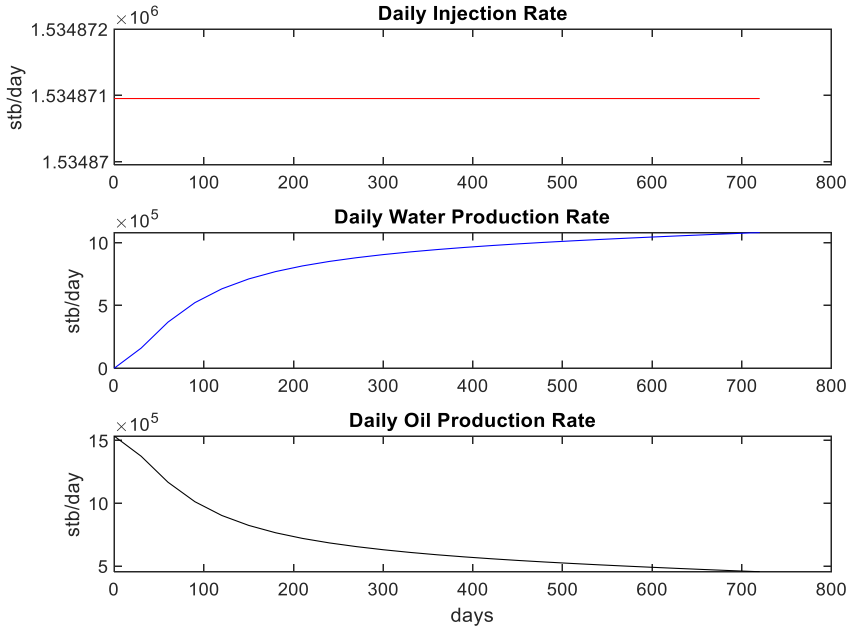

FIGURE 6 The daily injection rate and the daily total production rates of the oil and water produced from the reservoir when the Improved Oil Recovery (IOR) technique is implemented.

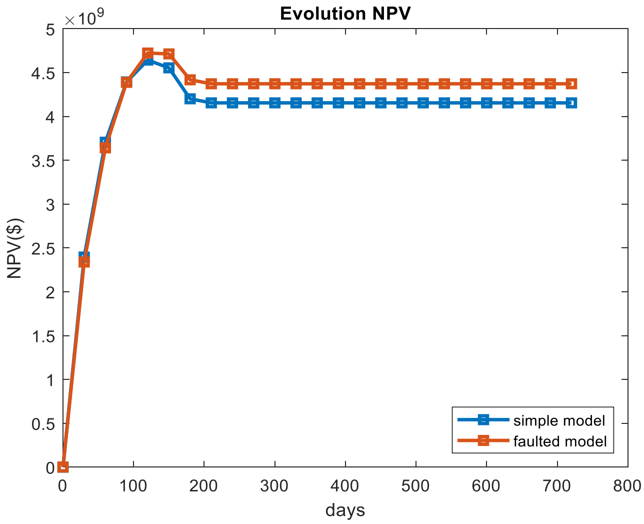

FIGURE 7 The comparison of the NPVs when the proposed IIoT-based control technique without the model update sub-package is implemented. Red curve: the Net Present Value (NPV) when the optimal injection rate is applied to the actual representation of the reservoir. Blue curve: when it is applied to the simplified mathematical model of the reservoir.

actual representation of the reservoir of the case study, and the blue curve is the injection NPV when the optimal injection rate is applied to the simplified mathematical model. That is, in this case it is assumed that the mathematical model used for the optimisation is the exact representation of the reservoir behaviour. As it is clear from Figure 7, these two curves are almost identical. This indicates that although in this case the optimal injection rate is obtained using the simplified mathematical model, due to the existence of the closed loop feedback, the impacts of the model miss-match between the reservoir actual behaviour and the mathematical model is almost compensated. This also indicates that for the reservoir of the case study, there is not any performance improvement if we use the model update algorithm as the closed loop feedback very well compensates the effects of the miss-match between the reservoir actual behaviour and the simplified mathematical model of the reservoir. This will be illustrated in more details in the next section. It is also interesting to note that the NPV of the actual representation outperforms the NPV of the ideal case (when the simplified mathematical model is the actual representation of the reservoir dynamics). This is due to the existence of non-zero off diagonal terms in the tensor matrix of the permeability coefficient of each grid of the actual representation. Table 5 summarises the main features of this technique and Table 6 illustrates the total amount of the oil and water produced from each production well before the reservoir is abandoned. Figure 8 illustrates the daily injection rate and the daily total production of the oil and water produced from the reservoir when the proposed OR-based decision technique is used for this reservoir.

3.3 | The impact of the closed loop OR-based decision system equipped with the model update sub-package

Figure 9 illustrates the injection NPV when the OR-based decision technique equipped with the model update sub-package is implemented on the reservoir of the case study. Here, the model update sub-package is used to estimate the state variables and the porosity and permeability vector using the mathematical model of Figure 2, which is used to generate M ensembles of the state vector and the porosity and permeability vector and the measurements are obtained online from the actual representation of the reservoir of the case study. This online estimation is used to maximise the cost functional

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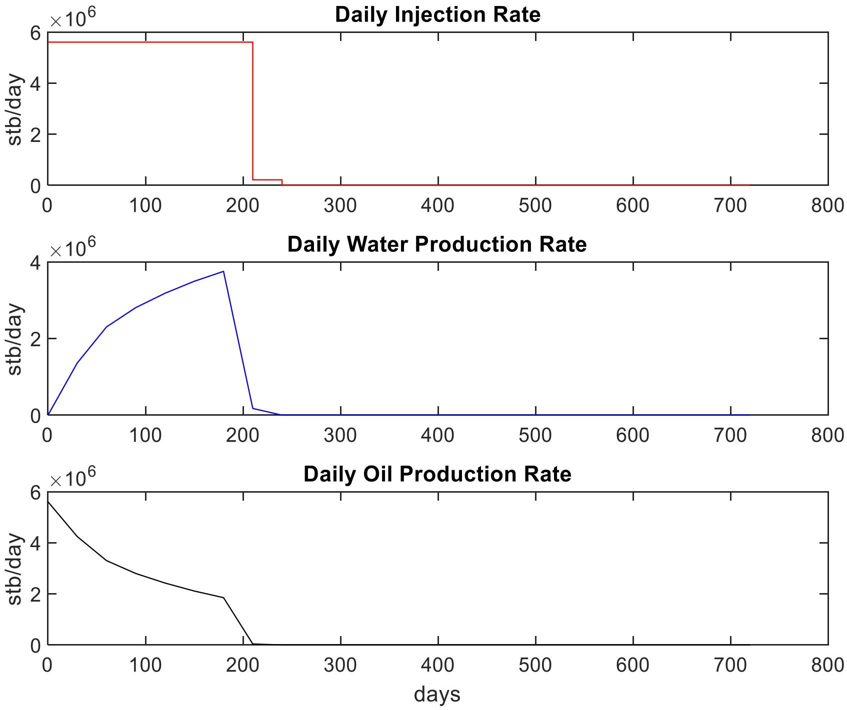

FIGURE 8 The daily injection rate and the daily total production rates of the oil and water produced from the reservoir when the OR-based decision technique is implemented.

TABLE 5 The main features of the IIoT-based control technique.

T_{max} (days)	NPV_{max}($b\$$)	Total water injected (Mstb)
120	4.72	672.97

TABLE 6 The total amount of the water and oil produced from each production well when the IIoT-based control technique is implemented.

Well	Water (Mstb)	Oil (Mstb)
P_1	75.2	85.26
P_2	74.79	100.72
P_3	58.96	107.95
P_4	80.61	89.34

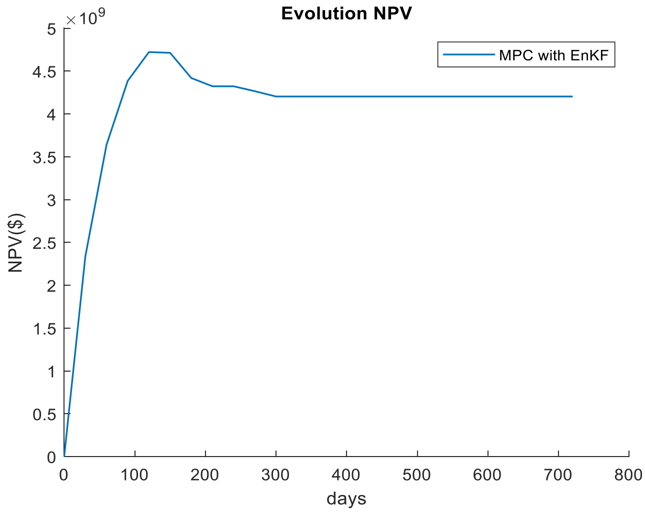

FIGURE 9 The Net Present Value (NPV) when the optimal injection rate obtained from the OR-based decision technique equipped with the model update sub-package is applied to the actual representation of the reservoir.

(8) subject to the operational constraints in order to obtain the optimal injection rate online. Note that in order to perform this estimation and subsequently optimisation, the measurements from the actual representation of Figure 3 for the reservoir of the case study is used. This figure illustrates that the maximum value for the injection NPV is also achieved at the day 120. After that the injection NPV has a decreasing trend and, therefore, there is no gain in exploitation from the reservoir. Hence, at the day 120 the reservoir is abandoned. Table 7 summarises the main features of this technique and Table 8 illustrates the total amount of the oil and water produced from each producing well before the reservoir is abandoned. Figure 10 illustrates the daily injection rate and the daily total production of the oil and water produced from the reservoir when the OR-based decision technique equipped with the model update sub-package is applied to this reservoir.

The above figures and tables show that there is no gain in using the OR-based decision system equipped with the model update sub-package in terms of the exploitation efficiency respect to the OR-based system without this sub-package for the exploitation of Iran's offshore oil reservoirs. This is quite different from the available results in the literature (e.g. Refs.[9, 10]). As it is shown in Figure 7 when we use the OR-based decision system without the model update sub-package although the optimal injection rate is obtained using the simplified mathematical model, due to the existence of the

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closed loop feedback, the impacts of the model miss-match between the reservoir actual dynamic and the mathematical model is almost completely compensated. This means that no performance improvement can be obtained using the model update algorithm as the closed loop feedback strategy very well compensates for the effects of the miss-match between the reservoir actual behaviour and the simplified mathematical model for the reservoir.

In order to evaluate the performance of the ensemble Kalman filter, Figure 11 illustrates the estimation of the daily production of the water from the production wells and Figure 12 illustrates the estimation of the daily production of the oil from these wells. Note that for the ensemble Kalman filter, we set $M = 100$, $R = 0.0027.I$, where I is the identity matrix with the appropriate dimension and Q is a diagonal matrix with different elements. Note also that we are able to measure the daily production of water and oil from the production wells; and therefore, we are able to compare the accuracy of the estimation provided by the ensemble Kalman filter. As it is clear from these figures, the ensemble Kalman filter provides accurate estimations for these parameters that are measured.

TABLE 7 The main features of the OR-based decision technique equipped with the model update sub-package.

T_{max} (days)	$NPV_{max}(b\$)$	Total water injected (Mstb)
120	4.72	672.97

TABLE 8 The total amount of the water and oil produced from each production well when the OR-based decision technique equipped with the model update sub-package is implemented.

Well	Water (Mstb)	Oil (Mstb)
P_1	74.12	84.22
P_2	76.15	101.92
P_3	58.57	107.57
P_4	80.85	89.54

Remark III. 2 The permeability and porosity coefficients mainly change by the reservoir pressure [23]. Therefore, as the available IOR technique and the proposed OR-based decision technique implement a pressure stabilisation method, these parameters do not significantly change during the exploitation period of the reservoir. Hence, if the simplified model of Figure 2 is an exact approximation of the reservoir dynamics, with or without the model update algorithm it predicts these coefficients with high accuracy during the life time of the reservoir.

3.4 | Comparison

Table 9 compares the performances of the proposed closed loop OR-based decision system equipped with and without the model update sub-package with the performance of the available IOR technique.

From this table it follows that the closed-loop OR-based decision system without the model update sub-package can increase the oil production by 47.96% and reduce the exploitation period by 66.67% compared with the available IOR technique. This is consistent with the available results in the literature (e.g. Ref. [3] - (Lorentzen et al., 2006)). The aforementioned references also show that the optimal multi-valued injection rate technique can increase the oil production by 30%

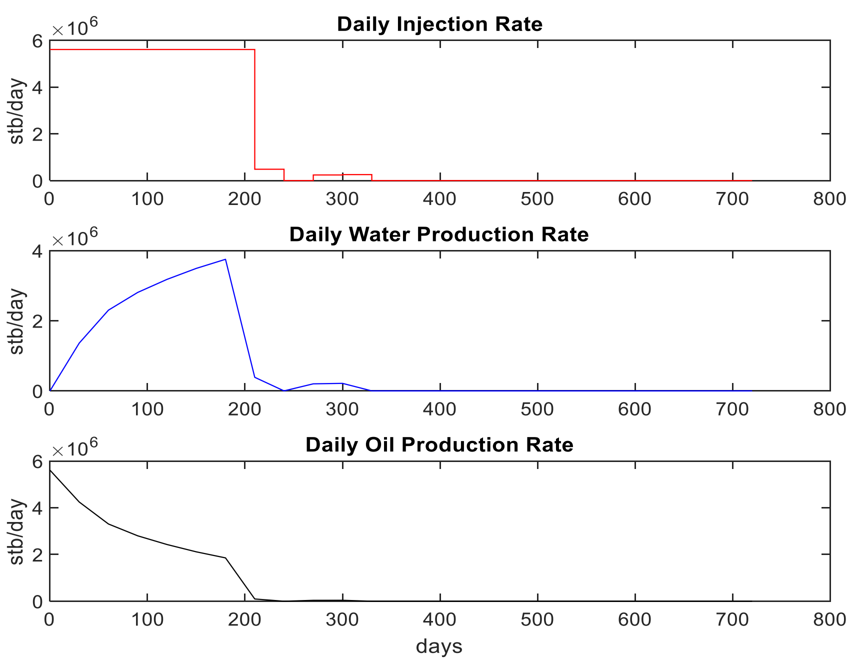

FIGURE 10 The daily injection rate and the daily total production of the oil and water produced from the reservoir when the OR-based technique equipped with the model update sub-package is implemented.

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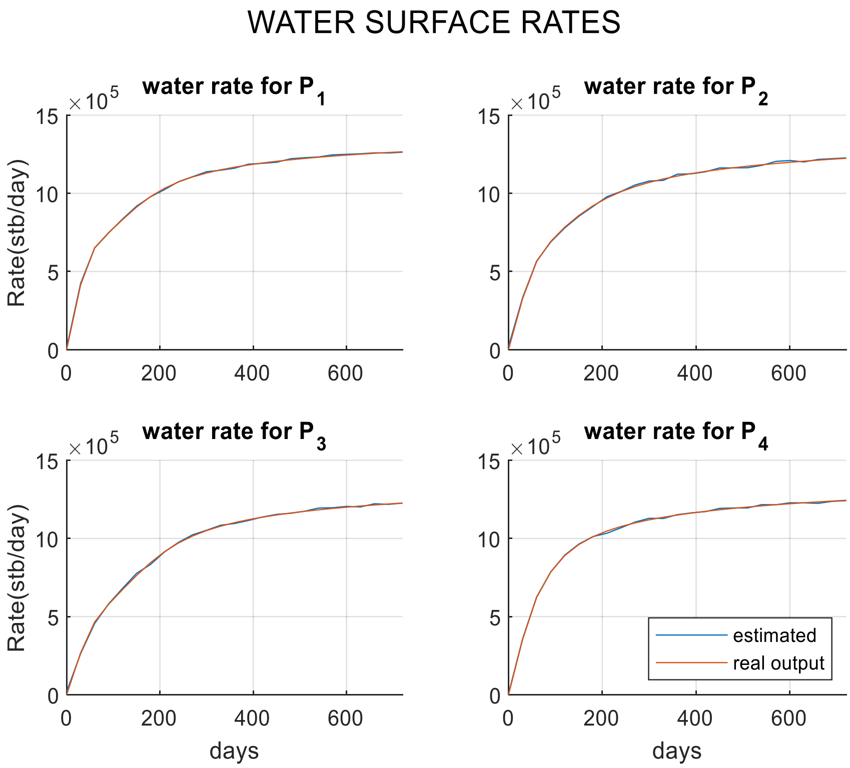

FIGURE 11 Blue: the estimated value. Red: the actual value.

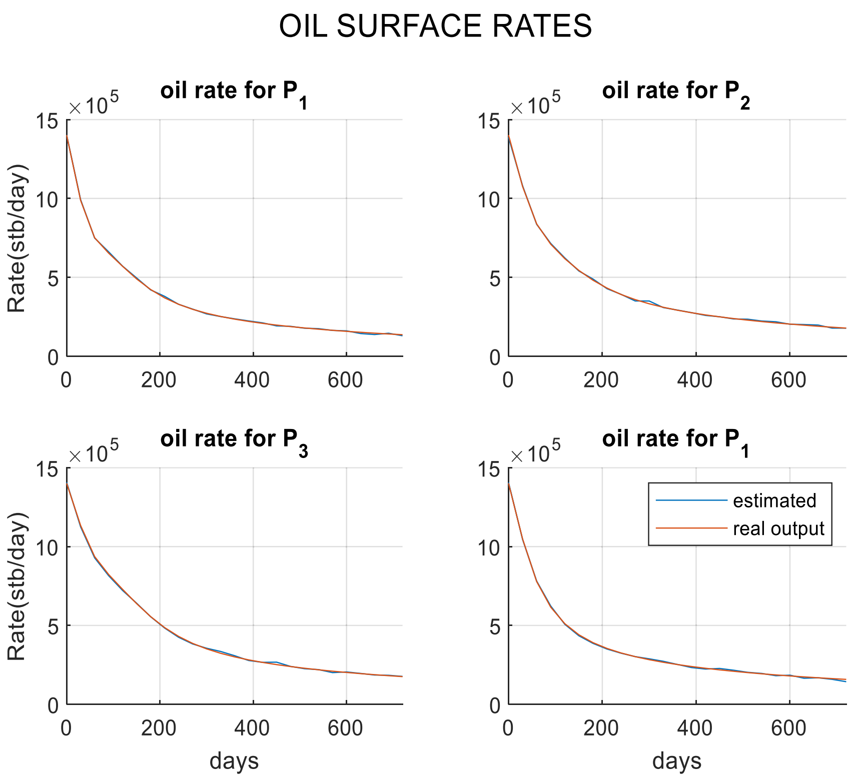

FIGURE 12 Blue: the estimated value. Red: the actual value.

from 2D reservoirs. However, unlike the available results in the literature (e.g. Ref. [3] - (Lorentzen et al., 2006)) for Iran's offshore reservoirs (3D reservoirs), the proposed closed loop OR-based decision system can increase the total water injected. Under the condition simulated, the total water injected using the proposed OR-based decision system has increased by 21.79% compared with the available IOR technique. This water is mainly obtained from the reservoir, which is a fossilised salty water. It can be only used for the injection to the reservoir. Nevertheless, this result is different from the results

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TABLE 9 The comparison between the performances of the available Improved Oil Recovery (IOR) technique and the proposed closed loop OR-based decision technique equipped with and without the model update sub-package.

Technique	NPV_{max} (b$)	EP(days)	TWI(M STB)	TWP(M STB)	TOP(M STB)
A	3.19	360	552.55	254.65	297.9
B	4.72	120	672.97	289.7	383.27
C	4.72	120	672.97	289.7	383.27

Abbreviations: EP: Exploitation Period, TWI: Total Water Injected, TWP: Total Water Produced, TOP: Total Oil Produced, A: The available IOR, B: The OR technique without the model update sub-package, C: The OR technique with the model update sub-package.

reported for 2D reservoirs. [3] - (Lorentzen et al., 2006) illustrate a reduction in the water injected up to 25%. From the above table it also follows that, unlike the available results in the literature for 2D reservoirs (e.g. Ref. [9], (Brouwer et al., 2004)), there is no gain in terms of the exploitation efficiency in using the OR-based decision system equipped with the model update sub-package compared with the case of without this sub-package when exploiting from Iran's offshore oil reservoirs, which have many faults and limited injection and observation points.

As shown above, the proposed technique while significantly enhances the exploitation efficiency of oil reservoirs with respect to the available IOR technique in terms of the oil production and the exploitation time and therefore the recovery factor, it is easily implementable due to its software based nature. To implement the proposed model, purchasing extra and expensive equipment is not required. We just need to supply the model with the daily production from reservoir and at the end of the month tune the injection rates of the injection wells based on the optimal injection rates computed by the model. Obviously, after tuning the injection rate, we can supply the model with the value of the tuned injection rates. In this way, the injection rates are also measured by the model. In other words, the optimal measurable injection rates are the outputs of the OR-based decision system. The optimal injection rates are computed based on the updated model for reservoir using a non-linear model predictive algorithm so that they sweep oil towards production wells, resulting in higher production and, therefore, higher efficiency and recovery factor very cost effectively. The non-linear model predictive controller is subject to the operational constraints including the minimum and maximum capacities of the production and injection wells. Considering these operational constraints, minimises the risk of the implementation of the proposed OR-based decision system. This is another positive aspects of the proposed model. The updated reservoir model provided by the model is also very helpful for top managers to come up with a better long terms reservoir planning and management.

4 | CONCLUSION AND DIRECTIONS FOR FUTURE RESEARCH

This paper introduced an application of the closed loop OR-based decision system for enhancing the oil production and hence the recovery factor of the offshore oil reservoirs in the middle-east region. It has been shown that using the proposed OR-based decision system, the amount of the recoverable oil can be increased up to 47.96%; therefore, this system can significantly improve the middle-east oil production and the oil recovery factor. Also, this paper has shown that the proposed OR-based decision system can decrease the exploitation time by 66% respect with the available techniques. This is very important when exploiting from the reservoirs shared with other countries. For example, the Iran's offshore oil reservoirs are mainly shared with neighbouring countries; therefore, it is important for this country to deplete the shared reservoirs before neighbouring countries deplete them. The advantages of the proposed model respect with the other available techniques for enhancing the oil recovery factor, such as the smart well technology [25] is the ease of implementation with a very low cost. Moreover, it was shown in this paper that for the middle-east offshore oil reservoirs, which are three-dimensional and include faults with a few vertical production wells and few injection wells, there is no gain in terms of the exploitation efficiency when the ensemble Kalman filter is implemented. This is quite different from the available results in the literature given for the two-dimensional reservoirs (i.e. when the reservoir is not thick) equipped with horizontal injection and production wells with many outlets and observation points.

In this paper, a very small part of Iran's offshore oil reservoirs were simulated. Nevertheless, the middle-east and in particular Iran's offshore oil reservoirs are very large scale reservoirs; therefore, a centralised computer server proposed in this paper will not be able to perform the computation required for proper tuning of the settings of the injection valves in real time. In order to overcome this drawback, one way is to implement the fog and edge computing concepts and to exploit the computers of the separator sites (the measurement points) to distribute the computational load of the centralised computer server to the distributed computers. In this setup, the computation layer is integrated with the field layer forming a Cyber Physical System (CPS). It has been shown in the literature (e.g. Refs.[2, 26–28]) that such an integration results in a real time computation for very large scale closed loop OR-based decision systems via parallel computation and consensus between distributed computing devices. How to develop such a CPS for the oil reservoirs with the objective of the enhancing the oil recovery factor and the oil production is an interesting research direction, which is currently under way in our research group.

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AUTHOR CONTRIBUTION

Hossein Malekpour Naghneh: Software. **Maryamparisa Amani:** Conceptualisation, Writing – review & editing. **Alireza Farhadi:** Formal analysis, Funding acquisition, Supervision, Writing – original draft. **Mohammad Taghi Isaai:** Writing – review & editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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