Applied Computing and Geosciences 16 (2022) 100103

Contents lists available at ScienceDirect

Applied Computing and Geosciences

journal homepage: www.sciencedirect.com/journal/applied-computing-and-geosciences

# Adaptive Proxy-based Robust Production Optimization with Multilayer Perceptron

Cuthbert Shang Wui Ng *, Ashkan Jahanbani Ghahfarokhi

*Department of Geoscience and Petroleum, Norwegian University of Science and Technology, Trondheim, Norway*

ARTICLE INFO

*Keywords:*
Machine learning
Data-driven modeling
Multilayer perceptron
Nature-inspired algorithms
Adaptive training
Robust production optimization

ABSTRACT

Machine learning (ML) has been a technique employed to build data-driven models that can map the relationship between the input and output data provided. ML-based data-driven models offer an alternative path to solving optimization problems, which are conventionally resolved by applying simulation models. Higher computational cost is induced if the simulation model is computationally intensive. Such a situation aptly applies to petroleum engineering, especially when different geological realizations of numerical reservoir simulation (NRS) models are considered for production optimization. Therefore, data-driven models are suggested as a substitute for NRS. In this work, we demonstrated how multilayer perceptron could be implemented to build data-driven models based on 10 realizations of the Egg Model. These models were then coupled with two nature-inspired algorithms, viz. particle swarm optimization and grey wolf optimizer to solve waterflooding optimization. These data-driven models were adaptively re-trained by applying a training database that was updated via the addition of extra samples retrieved from optimization with the proxy models. The details of the methodology will be divulged in the paper. According to the results obtained, we could deduce that the methodology generated reliable data-driven models to solve the optimization problem, as justified by the excellent performance of the ML-based proxy model (with a coefficient of determination, $R^2$ exceeding 0.98 in training, testing, and blind validation) and accurate optimization result (less than 1% error between the Expected Net Present Values optimized using NRS and proxy models). This study aids in an enhanced understanding of implementing adaptive training in tandem with optimization in ML-based proxy modeling.

## 1. Introduction

At the dawn of 21st century, energy has become an essential part of daily life due to its significant contribution and utilization in different sectors of human activities. The importance of energy had been further illustrated when the global energy demand in 2021 generally was expected to increase by 4.6%, which would exceed that of the pre-COVID-19 level, as reported by International Energy Agency (2021). Hence, meticulous planning of energy extraction and usage is required to ensure that the increasing global population can be commensurate with the availability of energy. In this aspect, petroleum is considered one of the primary sources of energy. Different technological methods, viz. enhanced oil recovery (EOR), artificial lift, hydraulic fracturing, etc., have been developed and employed to guarantee a sufficient supply of energy. Nevertheless, to produce petroleum sustainably and economically, oil and gas companies often incorporate a thorough blueprint of field development (FD) and reservoir management (RM). This is where engineering optimization plays a pivotal role.

In the domains of FD and RM, engineering optimization of decision variables has been ubiquitous and user-friendly because of the rapid development of today's technology. In petroleum engineering, these decision variables include, but are not limited to, EOR initiation time, the number of wells, well control, well placement, well trajectory, etc. In tandem with the growth of computing power, the transport of fluid flow in porous media can be modeled with ease by using numerical reservoir simulation (NRS). Thereafter, petroleum engineers can utilize NRS to perform optimization more conveniently. Moreover, the results yielded by running different cases on NRS provide additional insight for the engineers to formulate their plans for FD and RM. Despite this, NRS encounters computational issues when the reservoir modeled is geologically sophisticated. This implies that running one scenario of NRS is computationally expensive and this might cause inconvenience to obtain a fast solution for RM when plans are updated at a high frequency. Moreover, this computational challenge will be further

* Corresponding author.
*E-mail address:* cuthbert.s.w.ng@ntnu.no (C.S.W. Ng).

https://doi.org/10.1016/j.acags.2022.100103
Received 3 February 2022; Received in revised form 27 September 2022; Accepted 8 October 2022
Available online 10 October 2022

exacerbated if several geological realizations are needed for robust production optimization, which means production optimization under geological uncertainty as discussed in Hong et al. (2017). Therefore, to reduce the computational cost, proxy modeling is suggested as one of the alternative solutions.

Proxy modeling, which is also surrogate modeling or meta-modeling (Zubarev, 2009), is the development of one or more models that can be applied as a substitute for a base model (NRS). Also, proxy modeling is mostly data-driven, and its building block mainly stems from data. Therefore, data must be acquired before proceeding to the establishment of proxy models. This explains why proxy modeling can alternatively be termed data-driven modeling. Besides that, there are generally two classes implemented to establish data-driven models, namely statistics-based and machine learning-based (ML-based) methods. The use of the statistical method in proxy modeling has been extensively discussed in different petroleum-related pieces of literature and the relevant examples comprise response surface methodology (also known as polynomial regression) (Babaei and Pan, 2016; Olabode et al., 2018) and kriging (Fursov et al., 2020; Hamdi et al., 2021). Apart from data-driven methods, the reduced physics approach is another option for proxy modeling. Regarding the reduced physics approach, the capacitance resistance model, proposed by Bruce (1943), is one of the epitomes. It has been extensively investigated and employed in petroleum engineering as discussed in several works of literature (Hong et al., 2017; Yousefi et al., 2021). Albeit these approaches have demonstrated fruitful results, some literature (Mohaghegh, 2017; Zubarev, 2009) also briefed their limitations in proxy modeling. Mohaghegh (2017) expounded that the reduced physics method requires simplification of the physics and assumptions in terms of modeling an actual system. Zubarev (2009) investigated the performance of 4 different proxy modeling techniques, such as response surface method, thin-plate splines, kriging, and artificial neural network. He deduced that in terms of proxy modeling, kriging would require higher computational effort whereas the response surface method would decrease the precision of prediction.

This paper mainly sheds light on the application of ML-based methods. ML is defined as a computer algorithm that can enhance the performance of a model through experience, reflected by data (Mitchell, 1997). Examples of ML are, but are not circumscribed to, artificial neural network, gradient boosting machine, support vector machine, k-nearest neighbor, and random forest. ML has been evidenced to be useful in different domains of knowledge, including speech recognition (Nassif et al., 2019; Seehapoch and Wongthanavasu, 2013) and image analysis (Komura and Ishikawa, 2018; Poostchi et al., 2018). Furthermore, the implementation of ML has been widely generalized in different aspects of petroleum engineering, specifically reservoir and production engineering. In this context, ML has displayed successful applications in numerous pertinent areas, such as the design of well trajectory (Kristoffersen et al., 2021, 2022), $CO_2$ sequestration (Nait Amar et al., 2020a; Nait Amar and Jahanbani Ghahfarokhi, 2020; Vo Thanh et al., 2022), history matching (He et al., 2016; Jo et al., 2022), and flow assurance issue (Benamara et al., 2019; Nait Amar et al., 2021a). ML-based proxy models have also been efficiently coupled with mathematical optimization algorithms in performing production optimization. In this aspect, some articles (Guo and Reynolds, 2018; Sen et al., 2021) have illustrated the application of ML techniques in robust production optimization. Besides that, the employment of derivative-free mathematical algorithms, which are generally nature-inspired, has been studied in some works (Nait Amar et al., 2020b, 2021b; Ng et al., 2021a). These nature-inspired algorithms have broadly been used due to their ability to converge to the global optimum in solution space (Ezugwu et al., 2020; Yang, 2014).

For further details, developing or training the ML-based proxy models is considered "learning". Precisely speaking, these models are attempting to learn by discovering the pattern of the data supplied. If the database provided is not updated throughout the process of development, such training is generally termed "offline learning". Proxy models constructed from "offline learning" can occasionally yield a less optimal solution to an optimization problem due to lower prediction accuracy. Such an issue has been highlighted by Salehian et al. (2022) in which proxy models built from "online learning" are recommended as a possible improvement. According to Geng and Smith-Miles (2015), online learning shares the same definition as adaptive learning or incremental learning. This terminology expounds that this method involves a continuous update of the database. The fundamental idea lies in selecting the "useful" candidate to be added to the database used to train the data-driven model. Generally, generating this candidate involves sampling the data that fulfills predefined infill criteria (Forrester et al., 2008; Liu et al., 2012, 2018; Xu et al., 2012). The metrics of these criteria include, but are not limited to, Expected Improvement, Lower Confidence Bound, and Probability of Improvement. Adaptive proxy modeling has been a common practice exercised during the implementation of a statistical-based approach as briefed and demonstrated in some published works (Forrester et al., 2008; Li et al., 2015; Liu et al., 2018; Redouane et al., 2019). Nonetheless, as Golzari et al. (2015) pointed out, for managing higher dimensional problems, ML-based methods generally illustrate higher aptitude in handling non-linearity in terms of time-series prediction. Therefore, in this work, we choose to utilize ML-based proxy models.

The workflow presented in this paper can be considered as a variant of surrogate-based global optimization (SBGO), perceived as the simultaneous application of adaptive sampling and optimization with the aid of a global optimizer (Ye and Pan, 2019). In simpler terms, it performs as a hybridization of training and optimization. As outlined in Ye and Pan (2019), SBGO revolves around the employment of statistical approaches to develop the proxies and derivative-free algorithms as optimizers. However, we discuss and illustrate the use of ML-based proxy models here instead. Concerning this, the ML technique demonstrated in this work consists of multilayer perceptrons (MLP). Moreover, the developed proxy models aim to conduct robust production optimization under waterflooding. Therefore, these models are coupled with nature-inspired algorithms to conduct the optimization. Two examples of nature-inspired algorithms were selected, viz. particle swarm optimization (PSO) and grey wolf optimizer (GWO). As discussed in this paper (Yang, 2014), nature-inspired algorithms generally achieve a balance between exploration and exploitation over the search space. Exploration means the diversification of solutions in the search space whereas exploitation refers to a more focused search on a local region. A good combination of both, which is generally achieved by nature-inspired algorithms (considering the algorithms are optimally tuned), usually avoids the convergence to local optima. Slightly different from the general practice in SBGO, the candidate (adaptively chosen to be added to the database) is retrieved from the results of the iterative optimization with the proxy model. Concerning this, based on our studies done in this work, using these optimal results, which are obtained from the proxy model with the help of nature-inspired algorithms, to re-train the proxy model has the potential to increase its fidelity. The pertinent details will be revealed under the section of Results and Discussion.

After this introduction, the paper is formulated as shown: Section 2 briefs the basic theoretical concepts of MLP, PSO, and GWO regarding some of our previous works (Ng et al., 2021a, 2021b, 2022a, 2022b). Thereafter, section 3 provides a comprehensive explanation of the methodology applied to develop the proxy models in this work. Section 4 expounds on the results yielded and the relevant discussion. Then, the main findings are conclusively summarized.

## 2. Previous related works

The methodology presented in this work was established based on the insights gained from our previous works (Ng et al., 2021a, 2021b, 2022a, 2022b). Since this paper is considered an extension of these

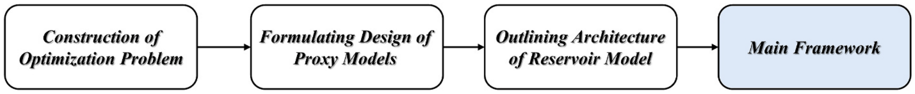


**Fig. 1.** General workflow implemented in this work.

previous works, the 3D Egg Reservoir Model that has been used in Ng et al. (2021a) was selected as the reservoir model for proxy modeling here. However, the proxy models built here consider 10 different geological realizations. With geological uncertainty (only about permeability), well control optimization is conducted under waterflooding. The methodology was developed using Python (Van Rossum and Drake, 2009). For the modeling of MLPs, they were developed with the help of the Scikit-learn package (Pedregosa et al., 2011). PSO was formulated by applying the toolkit built by James V. Miranda (2018) whereas GWO was constructed with the toolkit by Lickevic and Bartoshevic (2021).

### 2.1. Multilayer perceptron (MLP)

It is unassailable that artificial neural network (ANN) is one of the most prominent ML techniques used in a wide variety of domains (Lopez-Garcia et al., 2020; Runge and Zmeureanu, 2019). The method has demonstrated its excellent performance in learning how the input data is related to output data for any physically sophisticated process. Biological neural networks in the brain are mainly the inspiration for its formulation (Rosenblatt, 1958). MLP is one of the most widely employed variants of ANN in building data-driven models (Buduma and Locascio, 2017). In essence, MLP consists of many artificial neurons or calculating nodes. MLP also comprises three types of layers, viz. the input layer, the hidden layer, and the output layer. Each layer has its neurons in which these neurons are interconnected with the use of weights and biases. For more information about the mathematical implementation of MLP, refer to our previous works (Ng et al., 2021a, 2021b, 2022b). The training process for MLP typically involves finding the optimal values of weight and bias sets to minimize the predefined loss function, such as mean squared error (MSE) and mean absolute percentage error. MSE was selected as the loss function whereas Adam (Adaptive Moment Estimation) was applied for training. For the details of Adam, peruse the literature (Kingma and Ba, 2015).

### 2.2. Nature-Inspired Algorithms

Kennedy and Eberhart (1995) proposed PSO that attempts to simulate the behavior of flying stock of birds. A swarm of particles mathematically represents some possible solutions to an optimization problem. The status of each particle is calculated by using its position and velocity. About the mechanism of PSO, random initialization of the position and velocity of each particle is first done. Thereafter, to calculate the fitness of every particle, a cost function is required. Upon computing the fitness, the local and global best positions of a particle are determined to update the velocity at the current step. After assessing the velocity at the next iteration, the position of a particle for the next iteration is updated. As several iterations complete, each particle updates its position by minimizing the fitness value until the convergence of the optimal position occurs.

Mirjalili et al. (2014) developed GWO based on the inspiration of the leadership hierarchy and hunting behavior of grey wolves. Fundamentally, the population of grey wolves is divided into four different groups, e.g., alpha (α), beta (β), delta (δ), and omega (ω). Among all, ω wolves are the most inferior and preceded by δ, β, and α. Mathematically, a wolf population represents a set of random solutions. Thereafter, the fitness value of each solution set is evaluated by using a predefined objective function (Xu et al., 2020). According to the fitness value, the population of wolves is divided into the four previously mentioned groups. As optimization commences, the three best wolves: α, β, and δ, would gradually lead the other ω wolves towards the prey, which is treated as the global solution in the search space. This is done by iteratively updating the positions of the wolves. These algorithms are preferred in this work due to their good performance in our previous studies (Ng et al., 2021a, 2022a), where they demonstrated improved optimization results compared to the base case when they were coupled with the proxy models. For more details about the algorithms of both PSO and GWO, please peruse these articles (Kennedy and Eberhart, 1995; Mirjalili et al., 2014; Ng et al., 2021a; Xu et al., 2020).

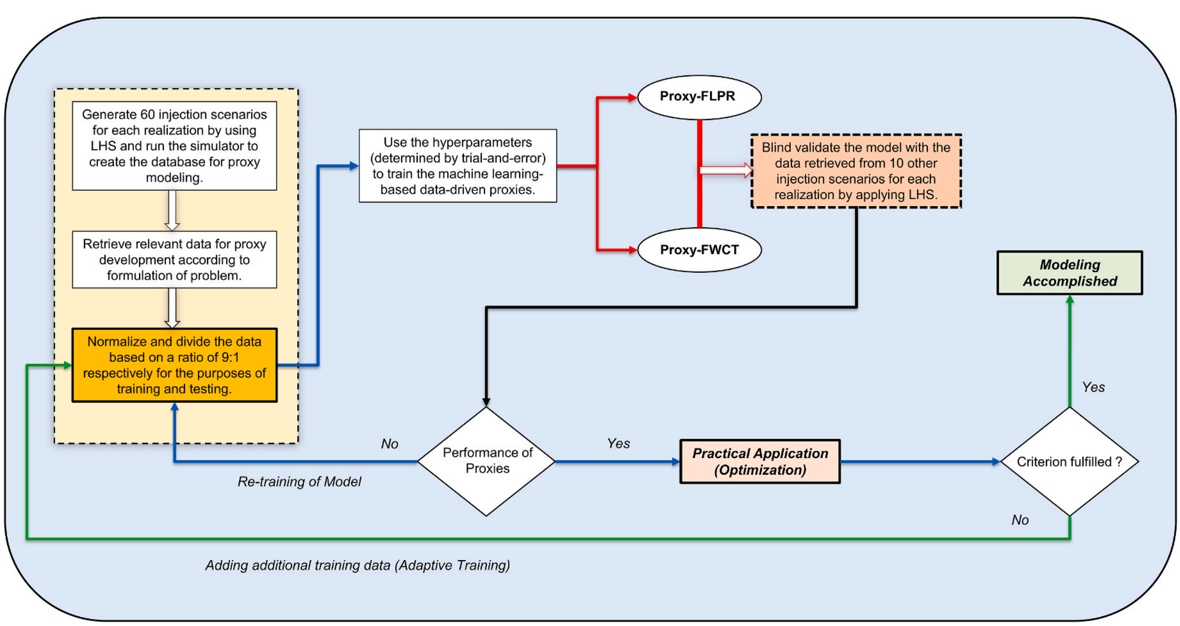


**Fig. 2.** Details of the main framework (Backbone of AP-ROpt).

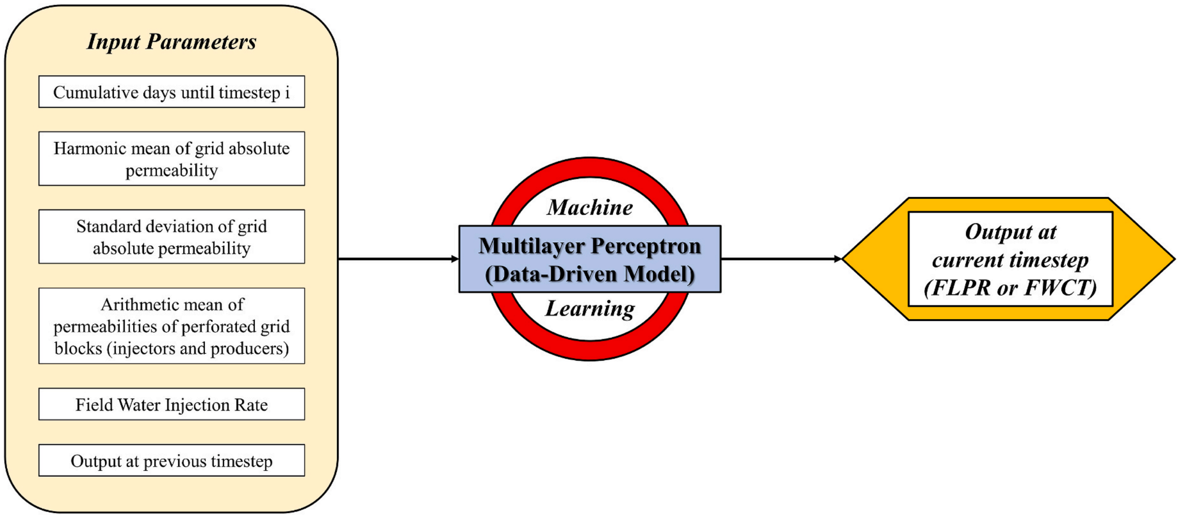


**Fig. 3.** Diagram of input and output parameters.

## 3. Methods and materials

For convenient articulation, the methodology proposed here is termed "Adaptive Proxy-based Robust Production Optimization" (AP-ROpt). The general workflow of implementing the AP-ROpt is illustrated in Fig. 1, consisting of 4 steps. The Main Framework can be further categorized into 2 parts, viz. Establishment of Proxy Models and Optimization. The details of the Main Framework are illustrated in Fig. 2.

### 3.1. Formulating the optimization problem

A database is one of the most essential elements in data-driven modeling. Before acquiring the database, it is of great importance for modelers to clarify and define the functionality of the data-driven models since data-driven proxy modeling is objective-oriented. Therefore, modelers should perceive what engineering problem is to be solved via the use of proxy models. In this paper, the engineering problem defined is the optimization of well control under waterflooding which is similar to the one discussed in Ng et al. (2021a). Thus, only the field water injection rate is considered as the control parameter. The objective function used in the optimization is the expected net present value (ENPV) as shown:

$$\mathrm{ENPV}(\mathbf{u}) = \frac{\sum_{r=1}^{n_r}\left(\sum_{i=1}^{n_{total}} \frac{\Delta t_i \times \left(Q_{i,oil}(\mathbf{u})P_{oil} - Q_{i,wat\ prod}(\mathbf{u})P_{wat\ prod} - Q_{i,wat\ inj}(\mathbf{u})P_{wat\ inj}\right)}{(1+\text{interest rate})^{t_i/365}}\right)_r}{n_r} \quad (1)$$

Based on the objective function, $n_r$ is the total number of realizations which is 10 here, $\mathbf{u}$ represents the control vector, $Q_i$ indicates the field rates of produced oil, produced and injected water at timestep i, P means the respective price. In addition, $\Delta t_i$ (unit in days) is the time difference between timestep i and previous timestep, $t_i$ (unit in days) is the cumulative time until timestep i, and the reference period for discounting cash flow is 365 days. The oil price is 440.3 USD/$m^3$, the cost of handling water produced, and water injection is 12.58 USD/$m^3$, and the interest rate is 0.10 per year.

### 3.2. Design of proxy models

Having explicitly defined the optimization problem, modelers would have better insights into what parameters can be yielded by the proxy models, directly or indirectly. More importantly, the decision variables (optimization parameters) are treated as one of the inputs of the proxy models. According to Eq. (1), the parameters required from the proxies are field oil and water production rates whereas field water injection rates act as decision variables. To attain this goal, we followed the ideas based on our previous studies and investigation in which two different proxy models were built. One of them can forecast the field liquid production rates (FLPR) at a certain timestep given a timeframe whereas another one has the same functionality in terms of field water cut prediction (FWCT). For both proxies, the input parameters comprise the cumulative days until timestep i, self-defined geological parameters, field water injection rate (decision variables), and the output at the previous timestep, $y_{i-1}$. About the self-defined geological parameters, they comprise the harmonic mean (and standard deviation) of grid absolute permeability for every reservoir layer as well as the arithmetic mean of permeabilities of perforated grid blocks (injectors and producers). This corresponds to 29 input parameters and 1 output parameter. The input parameters were selected based on our knowledge of

**Table 1**
Summary of the initial database for the development of proxy models.

| Types of Data | Number of Data Points | Maximum Value | Minimum Value | Mean Value | Standard Deviation |
|---|---|---|---|---|---|
| Static Data | | | | | |
| Cumulative days until timestep i | 1 × 60,000 | 3000 | 30 | 1515 | 865.98 |
| Harmonic mean of grid absolute permeability | 7 × 60,000 | 749.41 | 577.57 | 641.71 | 37.88 |
| Standard deviation of grid absolute permeability | 7 × 60,000 | 1701.24 | 654.44 | 1149.07 | 252.72 |
| Arithmetic mean of permeabilities of perforated grid blocks (injectors) | 8 × 60,000 | 3994.57 | 132.99 | 1109.78 | 963.85 |
| Arithmetic mean of permeabilities of perforated grid blocks (producers) | 4 × 60,000 | 5000 | 200 | 1581.12 | 1372.47 |
| Dynamic Data | | | | | |
| Field Water Injection Rate | 1 × 60,000 | 800 | 320 | 559.96 | 138.34 |
| Previous Output and Current Output (FLPR) | 2 × 60,000 | 798.67 | 0 | 557.24 | 143.43 |
| Previous Output and Current Output (FWCT) | 2 × 60,000 | 1 | 0 | 0.7067 | 0.3401 |

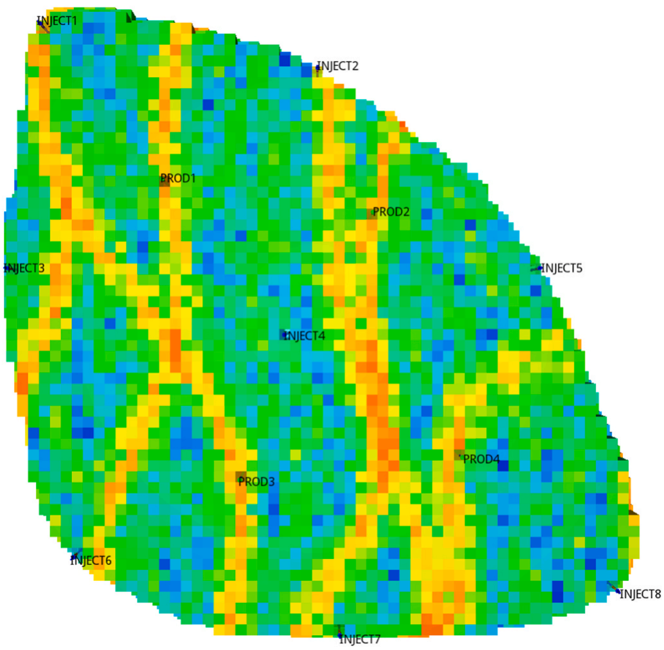


**Fig. 4.** Horizontal permeability distribution of Realization 1 of 3D Egg Model with labeled well locations. The same locations apply to all realizations. The warm color indicates higher horizontal permeability whereas the cold color implies the otherwise.

reservoir engineering and insights gained from previous studies. Refer to Fig. 3 for the diagram of input and output parameters and Table 1 for the initial database used for training. The number 60000 in Table 1 was determined by having 60 injection scenarios × 100 timesteps × 10 realizations. According to the insights gained from our previous works (Ng et al., 2021a, 2022a), 60 scenarios have been illustrated to be adequate to produce the proxy models with a good degree of accuracy. Therefore, the same number of scenarios is applied in this study. Readers are also referred to Ng et al. (2021a) for more comprehensive information about the formulation of the proxy models.

### 3.3. Outlining architecture of reservoir model

As mentioned, the reservoir model implemented in this paper is the Egg Model and the simulation was performed using the Eclipse 100 software (Schlumberger, 2019). This model is a benchmark case, developed by Jansen et al. (2014) for research purposes. The Egg Model has 7 layers, and it is built as a channelized depositional system. It also has eight injectors and four producers in which the trajectory of each well is vertical. The well configuration is shown in Fig. 4. Peruse Jansen et al. (2014) and Ng et al. (2021a) for the details of the topology of the reservoir model. Regarding the details of optimization, it involves adjustment of field water injection rates within 320 and 400 $Sm^3$/day (each injector has an equal allocation of the total rate) by having the maximum bottomhole pressure of each producer set at 395 bars. This adjustment is done every 150 days over 3000 days of the production period. This results in 20 control variables. However, the proxy models have been designed to consider a timestep of 30 days and every control variable remains the same for 5 timesteps (150 days). Therefore, during optimization, 100 variables are involved. We have considered 10 realizations in this work and the corresponding reservoir architecture of each realization is presented in Fig. 5.

### 3.4. Main Framework

#### 3.4.1. Establishment of proxy models

In the establishment of proxy models, the generation of a training database often comes first. Here, we implemented Latin Hypercube sampling (LHS) to create 60 sample sets of control rates in which one set represents one injection scenario. In this case, these 60 scenarios are the same for every realization. Peruse McKay et al. (1979) for the details of LHS. Each scenario was then sent to the reservoir simulator to produce the simulation outputs. Upon the completion of 600 simulations, the dynamic inputs were retrieved and merged with the static inputs to develop the database. Normalization of the database is a highly recommended practice before being fed into the training phase of ML models. The database was normalized between 0 and 1 according to the formula below:

$$X_{normalized} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

where $X_{normalized}$ is the normalized value of X. $X_{max}$ and $X_{min}$ correspond to the maximum and minimum values of X, respectively. It is important to note that during the adaptive training, an additional sample has been included in the training database. Therefore, the values of $X_{max}$ and $X_{min}$ also need to be updated (considering all input and output parameters) and normalization is repeated. Thereafter, the normalized database was partitioned into training and testing with a ratio of 9:1. Regarding this partition of data, only the training data is employed to establish the models. Since the package of scikit-learn was selected, within the training data, a portion of it would be extracted to conduct the validation phase. Concerning this, MLP would undergo a validation phase in which 1/9 of the 90% training data was treated as the validation set. Nevertheless, evaluation of the developed models was performed meticulously to ensure that the overfitting issues had been eluded.

Regarding the topology of proxy models and hyperparameters used in the training, the values were slightly different for both FLPR and FWCT. For FLPR, the learning rate was 0.001, the number of hidden layers was 4 (each layer had 50 hidden nodes), and tolerance was $10^{-6}$. For FWCT, the learning rate was 0.005, the number of hidden layers was 4 (each layer had 15 hidden nodes), and tolerance was $10^{-6}$. Rectified Linear Unit (ReLU) was implemented as an activation function for all layers. Considering an arbitrary function of f(x), ReLU is mathematically expressed as f(x) = max (x, 0). The maximum number of iterations for both models was defined as 1000 in which the early stopping mechanism was activated. These setting parameters were decided via a trial-and-error approach. After the training and testing phases, the data-driven proxies must be blind-validated before being practically employed. In this aspect, data of blind validation should be independent of the above-mentioned database. Hence, we implemented LHS to generate 10 other injection scenarios for each realization (a total of 100 blind validation cases) to be fed into the reservoir simulator to yield the relevant outputs, which would then be compared with the outputs predicted by the proxy models. The comparative result is a deciding factor to evaluate if the proxies should either undergo re-training or proceed to optimization. If the performance of proxies is not up to certain quality, then re-training will be done. In this paper, two statistical metrics were chosen to assess the performance of proxies, viz. coefficient of determination ($R^2$) and root mean squared error (RMSE). The formula of metrics is as follows in Eqs. (3) and (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i^{pred} - Y_i^{real}\right)^2}{\sum_{i=1}^{n}\left(Y_i^{pred} - \overline{Y}\right)^2} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i^{pred} - Y_i^{real}\right)^2}{n}} \tag{4}$$

where n represents the total number of data points, i denotes the index of data points, $Y_i$ is the corresponding output, the superscripts pred and real represent the proxy model and reservoir simulator model, respec-

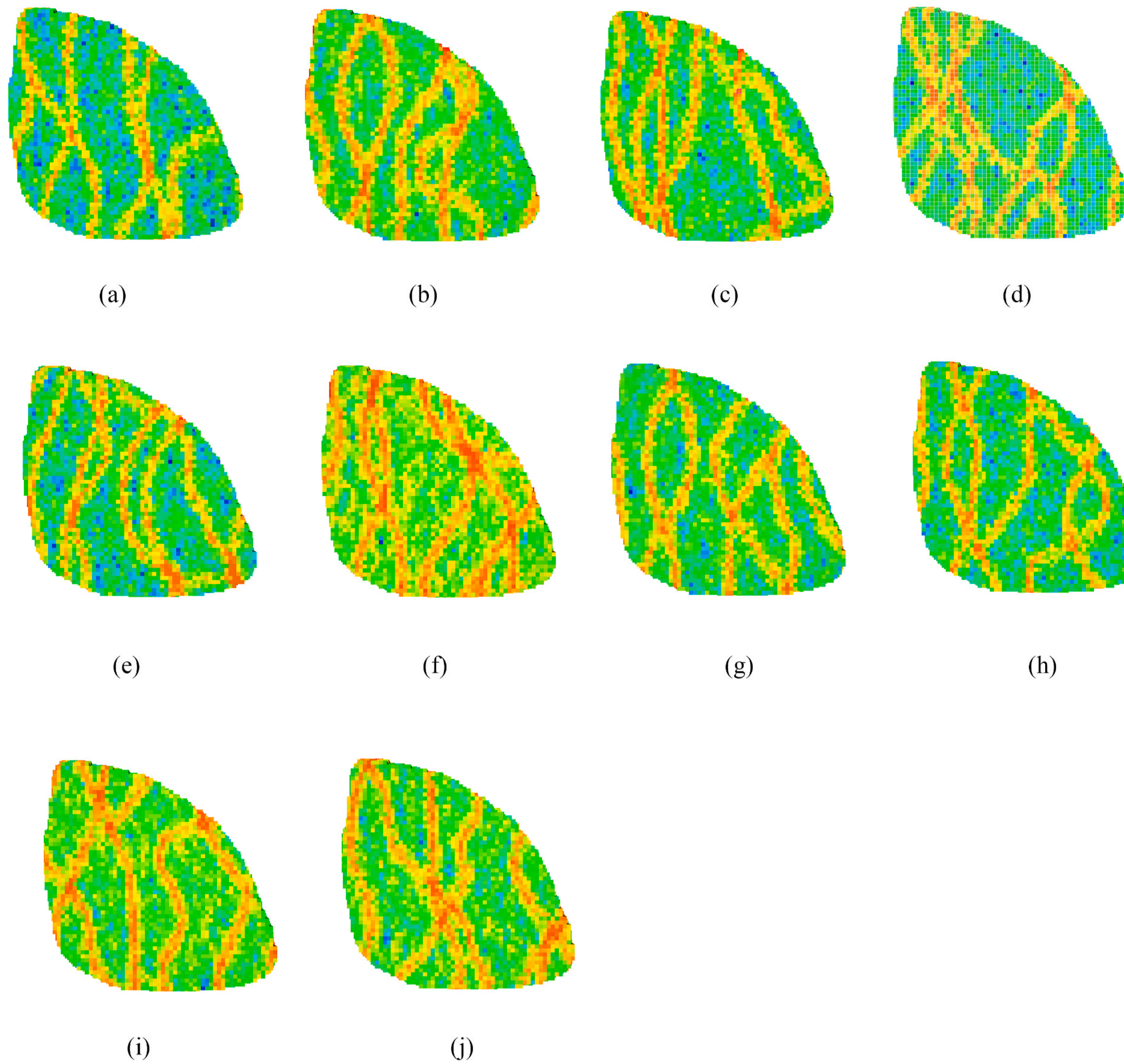


**Fig. 5.** Horizontal permeability distribution of 10 different geological realizations of the 3D Egg Model. The warm color indicates higher horizontal permeability whereas the cold color implies the otherwise. (a) to (j) respectively refer to Realization 1 to 10.

tively. Also, $\overline{Y}$ indicates the mean value of output. Re-training is only needed if the mean $R^2$ values of blind validation[1] for FLPR and FWCT are less than predefined values. In this case, the predefined values for FLPR and FWCT were decided to be 0.998 and 0.970, respectively via trial-and-error.

*3.4.2. Optimization with proxy models and reservoir simulation*

In the phase of optimization, PSO and GWO were applied to determine the optimal well control. In the case of proxy models, as the optimization iterations were completed, the proxy-optimized control would be obtained and treated as a new injection scenario to be fed into the reservoir simulator. The response of the simulator was again compared with that of the proxy. If the criterion check was satisfied, then the whole workflow was considered complete. Otherwise, the optimal control would be treated as a new dynamic input to be added to the training database. The loop of workflow would then start again. It would only cease if the criterion were fulfilled, or the number of additional simulations exceeded a predefined value. In this study, the average between the mean[2] $R^2$ of FWPR and FOPR was used as the criterion check. The predefined threshold was arbitrarily set as 0.994. About the parameters used in PSO, the inertia weight was 0.80 whereas the cognitive and social learning factors were 1.05. $r_1$ and $r_2$ were sampled from a uniform distribution of (0, 1). For GWO, the default parameters set by Lickevic and Bartoshevic (2021) were applied. For PSO (GWO), 100 iterations and 20 swarm particles (100 iterations and 20 populations) were employed. These optimization algorithms were not only implemented in this workflow for proxy models but also coupled with the reservoir simulator. The details of the results would be presented and discussed in the following section.

## 4. Results and Discussion

Before outlining a holistic discussion about the findings of this work,

[1] Mean $R^2$ of blind validation refers to the arithmetic average of 100 $R^2$ values (each calculated over 100 timesteps) as 10 blind validation scenarios are considered for each of the 10 realizations.

[2] The term "mean $R^2$" refers to the arithmetic mean of 10 values of $R^2$ as 10 realizations were used to develop the proxy models.

**Table 2**
Results of training, testing, and blind validation of the developed proxy models.

| | | ROpt- MLP-FLPR | ROpt-MLP-FWCT |
|---|---|---|---|
| Training | $R^2$ | 0.9999 | 0.9995 |
| | RMSE | 0.9288 | 0.0073 |
| Testing | $R^2$ | 0.9999 | 0.9995 |
| | RMSE | 0.9485 | 0.0074 |
| Blind Validation | $R^2$ | 0.9999 | 0.9872 |
| | RMSE | 0.9459 | 0.0328 |

we illustrate the results of the training, testing, and blind validation phases as shown in Table 2 to provide a better insight into the performance of the developed proxy models. Table 2 consists of two statistical metrics, namely $R^2$ and RMSE, that have been useful to reflect the accuracy of the proxy models built in this work. For better illustrative purposes, the cross plots between the actual and predicted data in each phase of proxy modeling are demonstrated in Fig. 6 for FLPR and in Fig. 7 for FWCT. In terms of training, testing, and blind validation, MLP-FLPR generally displays better performance than MLP-FWCT. Despite this, the results obtained by MLP-FWCT have sufficiently confirmed its reliability for further employment.

Upon completing the modeling part, these models are readily employed for adaptive learning and optimization. In this aspect, the models would be correspondingly coupled with PSO and GWO to determine the optimal field injection rates within the range as previously explained. For benchmarking, we also coupled these two algorithms with E100 software to perform the optimization with NRS models. The optimal control determined using the simulator and proxy models are correspondingly shown in Figs. 8 and 9. Though there may be low proximity between the optimal control yielded by these two approaches, we would like to emphasize that the main objective here is to create substitute models that can achieve an optimized objective function close to the "ground truth" (generated by the NRS) at much less computational cost.

Thereafter, the proxy-optimized control rates were fed back into the reservoir simulator to yield the necessary parameters for the calculation of ENPV. By acquiring the results, the ENPVs for three cases of reservoir simulator, simulator-proxies (referring to the results in which the optimal control derived from only using the proxy models, is fed back to the simulator), and proxies are computed and recorded in Table 3. Under an assumption of a base case with a maximum constant field injection rate, the ENPV of the base case is 155.76 million USD. During the optimization with the reservoir simulator, GWO resulted in a better improvement on ENPV with 3.75% as PSO only enhanced the ENPV by 2.76%. A similar outcome is also illustrated in the case of simulator-proxies. In terms of optimization, this generally shows that GWO slightly outperforms PSO in this study. For better purposes of illustration and comparison, the optimized NPVs of each realization for the cases of simulator and simulator-proxies (considering cases that involve the use of simulator) are correspondingly illustrated in Figs. 10 and 11.

Regarding the accuracy of results, it can be noted that GWO records a lower percentage error between the two ENPVs produced by simulator-proxies and dynamic proxies, which is about 0.20% whereas that of MLP-PSO is 0.90%. For both algorithms, the differences between the ENPVs of simulator and simulator-proxies are practically small. Nevertheless, GWO records ENPV of simulator-proxies that is closer to the "ground truth" (ENPV of reservoir simulator). Thus, proxy models coupled with GWO yielded slightly more accurate results than those of PSO in this work. Despite this, PSO still portrayed promising applicability due to its practically good accuracy of the result attained. This further enlightens us that the proxy models built here have sufficient capability to provide solutions for this optimization problem. For illustrative purposes, the plots of the optimized field water and oil rates for each optimization case considering 10 realizations are presented in Figs. 12 and 13, respectively.

Table 4 is displayed for closer scrutiny in both Figs. 8 and 9. These metrics are calculated by correspondingly comparing FWPR and FOPR generated by simulator-proxies and proxy models. According to Table 4,

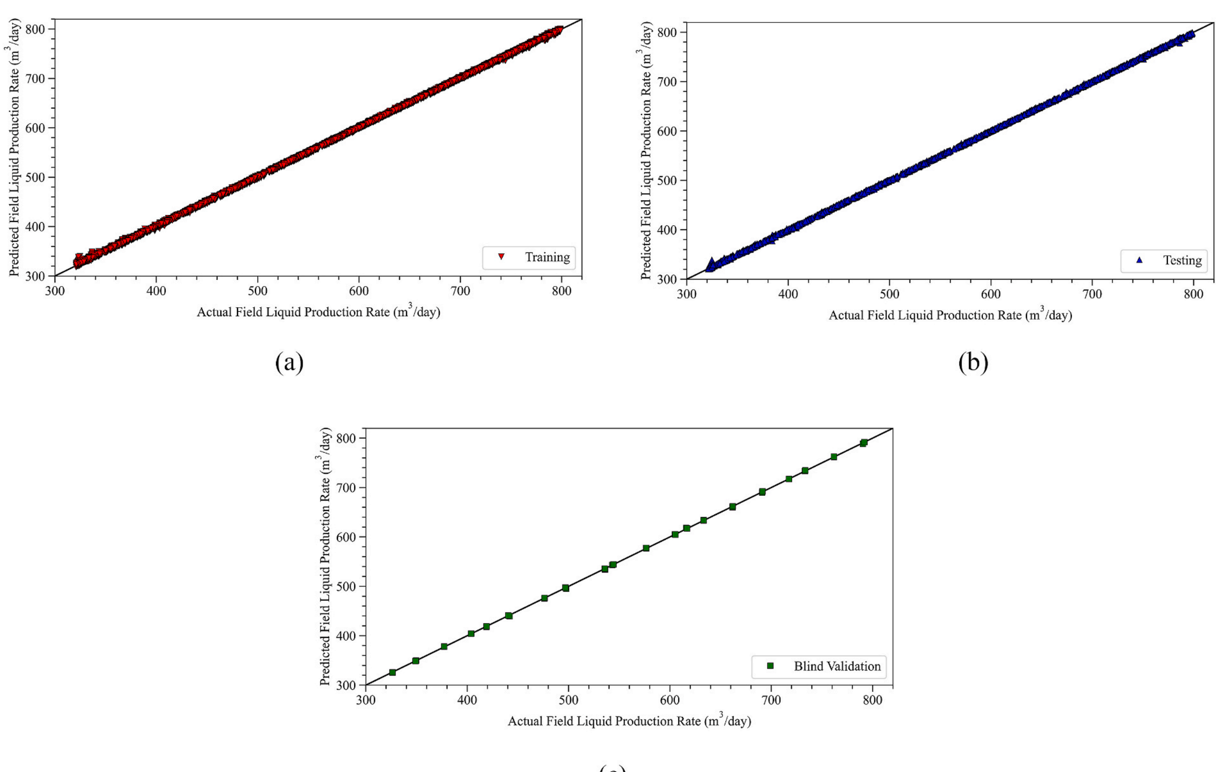


**Fig. 6.** Cross plot between the actual FLPR and FLPR predicted by the proxy model. a) Training, b) Testing, and c) Blind Validation (only illustrating 1 blind validation scenario in Realization 2).

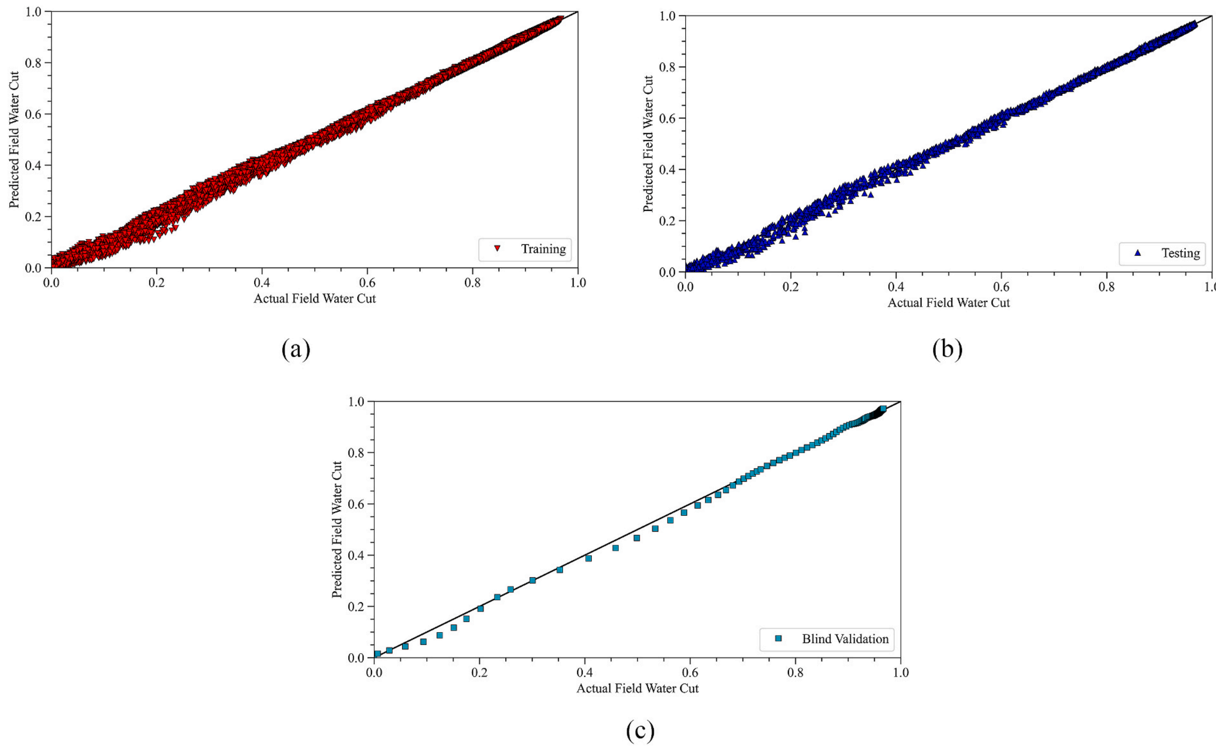


**Fig. 7.** Cross plot between the actual FWCT and FWCT predicted by the proxy model a) Training, b) Testing, and c) Blind Validation (only illustrating 1 blind validation scenario in Realization 2).

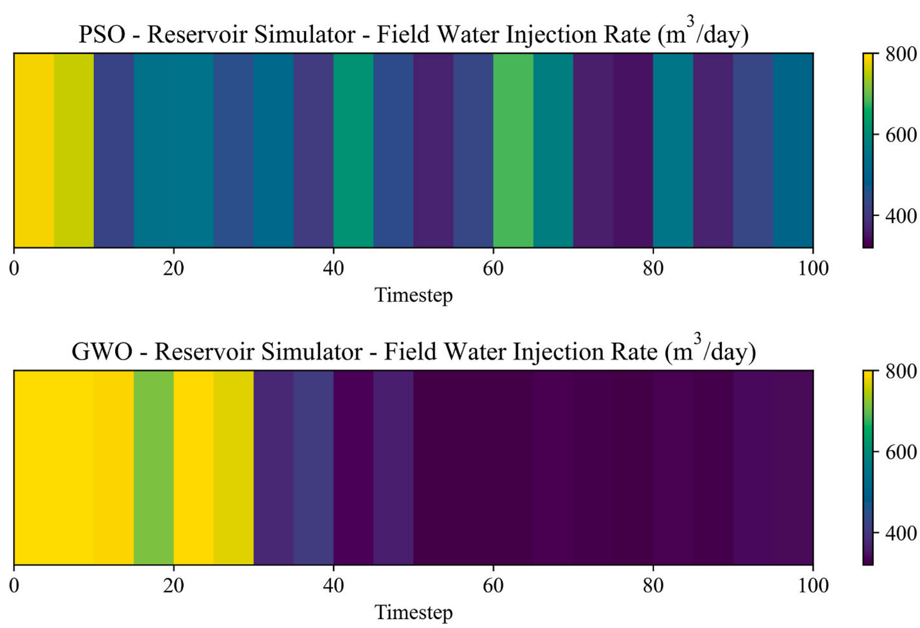


**Fig. 8.** Optimized control of Field Water Injection Rate (FWIR) resulted by coupling reservoir simulator with nature-inspired algorithms.

it can be opined that the worst performing realizations in the cases of FWPR and FOPR still produced results within a satisfactory level of accuracy. This confirmed the good applicability of the workflow proposed here. Considering all 10 realizations, Table 5 presents the mean $R^2$ and RMSE (considering 10 different geological realizations) between the optimized FWPR (and FOPR) generated by simulator-proxies and proxy models. Based on these results, MLP-GWO showed a closer approximation of the results. Also, these results proved that the developed proxy models successfully served their purpose of application.

The proxy modeling and optimization were done by using a PC with Intel® Core™ i9-9900 CPU @3.10 GHz (64.0 GB RAM) (Ng et al., 2021a). Regarding computational time, both MLP-GWO and MLP-PSO have exhibited excellent computational efficiency. In this case, MLP-GWO spent about 13 h performing adaptive training and optimization whereas MLP-PSO used about 16 h. In addition, about the number of additional simulations induced, MLP-PSO has adaptively employed 66 additional simulations for the extension of the training database. For MLP-GWO, it adaptively created 54 other simulations. For the

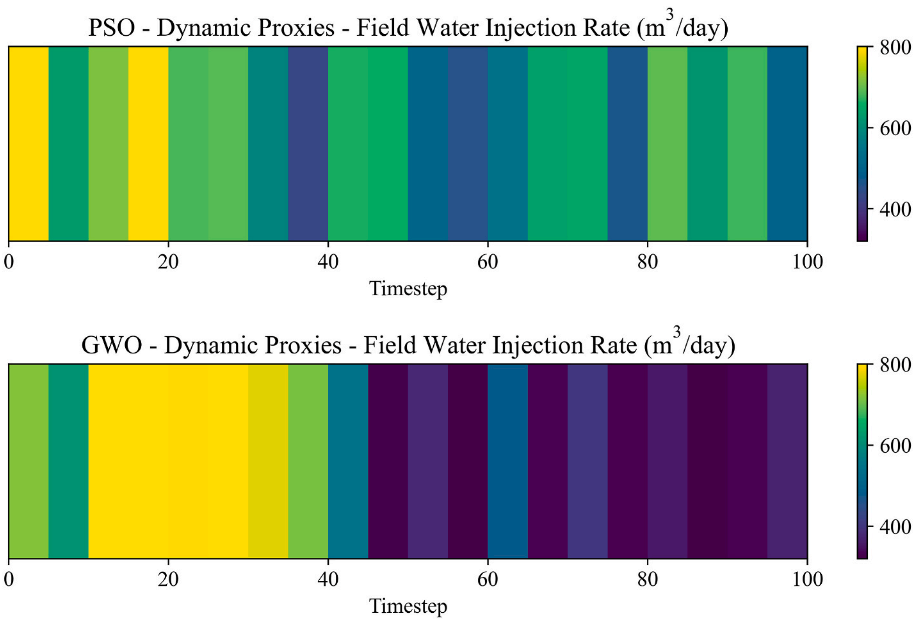


**Fig. 9.** Optimized control of Field Water Injection Rate (FWIR) resulted by coupling proxy models with nature-inspired algorithms.

**Table 3**
Optimized ENPV of three cases considering PSO and GWO (in the unit of million USD).

| Optimization Algorithm | Reservoir Simulator | Simulator-Proxies | Dynamic Proxies |
|---|---|---|---|
| PSO | 160.06 | 158.93 | 160.37 |
| GWO | 161.60 | 159.80 | 159.48 |

optimization with the simulator E100, PSO required 159 h and GWO needed 238 h. Based upon this, GWO generally reflects a more significant added value of the application of proxy models in this work.

We would like to reiterate that the primary aim of the established proxy models is to locate the optimal solution to the waterflooding optimization problem. In this case, the optimal solution provided by these data-driven models results in an objective function that is close to the one obtained by applying only the reservoir simulator. We also fathom that there are a few limitations regarding the workflow proposed here. Hyperparameter (topology of MLP) optimization is one of them. During adaptive training, when additional data is retrieved from additional simulation and added to the training database for proxy modeling, there is a possibility that the predefined hyperparameters are less reliable in achieving more accurate training results. However, integrating hyperparameter optimization can certainly induce higher computational effort. Despite having excellent results in this work, achieving a good trade-off between accuracy and computational time (considering hyperparameter optimization) certainly needs to be researched to increase the applicability of this methodology. Besides that, another shortcoming concerns the tuning parameters of the algorithms. These parameters were decided via a trial-and-error approach which could be subject to a degree of limited sensitivity. There is also another discussion about the impact of random number generators on the whole

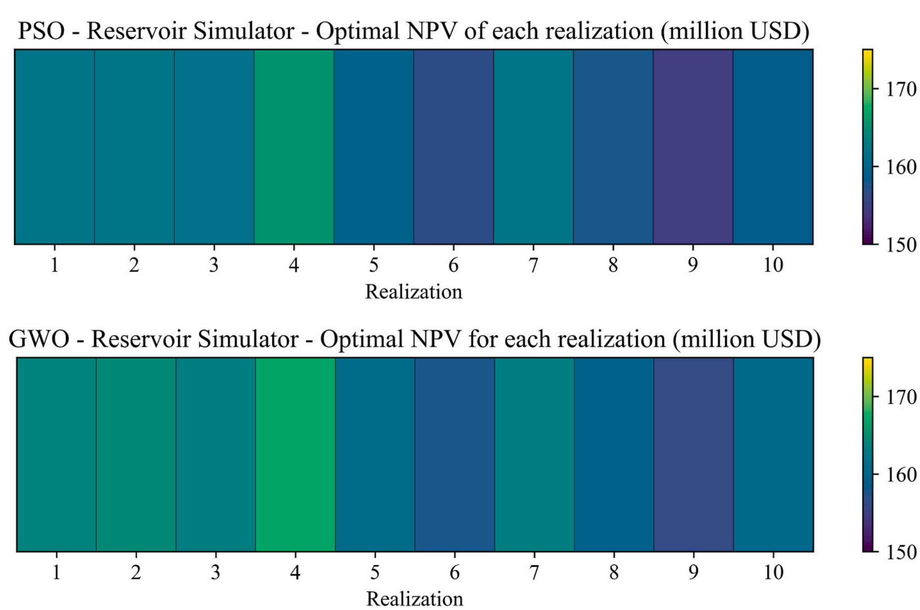


**Fig. 10.** Optimized NPV of each realization (reservoir simulator).

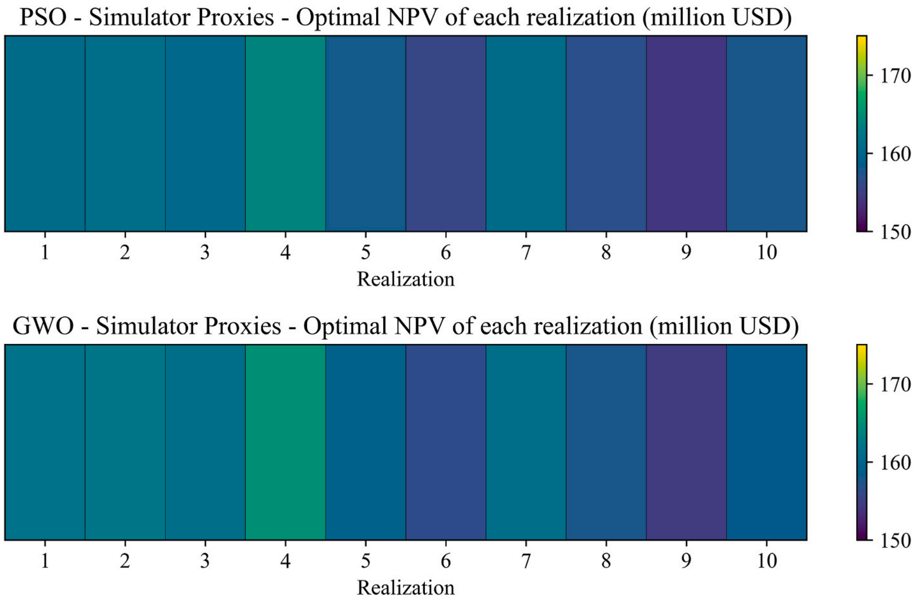


**Fig. 11.** Optimized NPV of each realization (simulator-proxies).

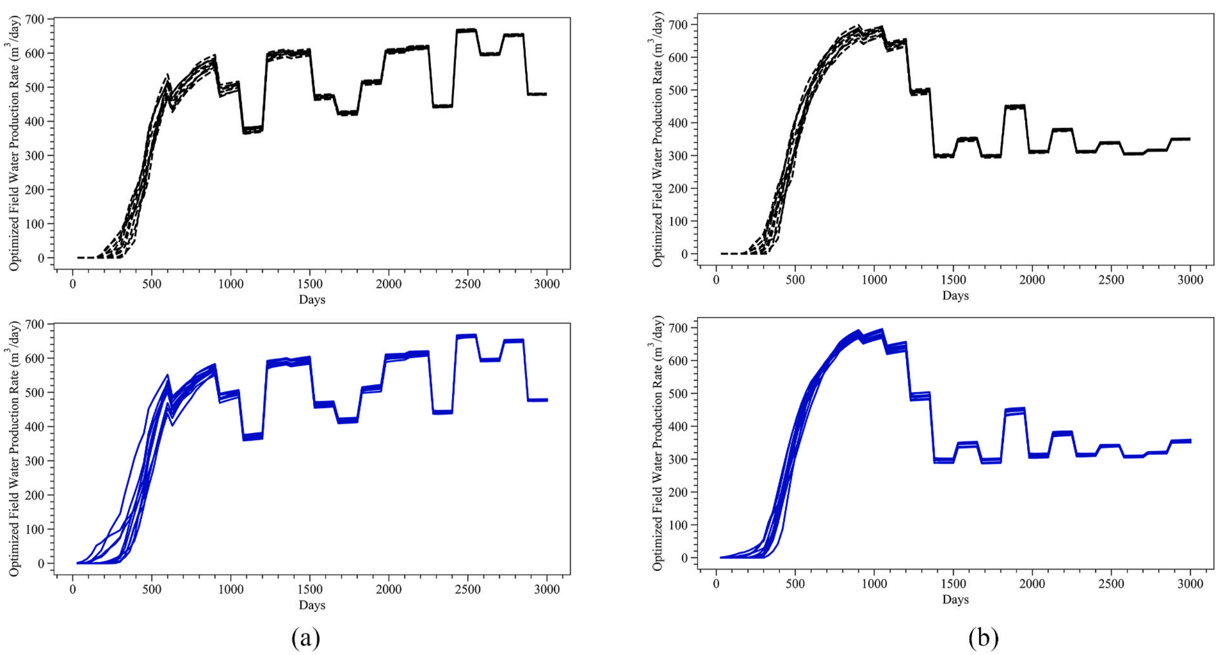


**Fig. 12.** Plots of the optimized FWPR considering 10 realizations. The black dashed lines indicate the case of simulator-proxies whereas the blue lines imply the cases of proxy models. a) PSO and b) GWO.

framework. Therefore, an in-depth study on tuning parameters and random number generators is needed to further reinforce the maturity of the workflow discussed here.

Apart from these, we only considered 10 realizations in this work since there is an apparent computational challenge arisen when more realizations are included in the methodology of the workflow. Hence, integrating the dimensionality reduction technique (for instance, as proposed in this paper (Salehian et al., 2021) through the selection of representative realization via clustering method) into the workflow proposed here is another domain that can be pondered upon in the future. Also, the additional training data is generated "online" via optimization with proxy models. Albeit this additional data is gotten through nature-inspired algorithms, the accuracy of proxy models might cause premature convergence to local optima. The accuracy of proxy models is influenced by the complexity of the optimization problem being solved. Thus, this subject is upon consideration for further research when it comes to more sophisticated real-life applications. Furthermore, proxy models are often case-dependent and hence, the models built here can only be implemented to solve the optimization problem discussed here. Hence, modifications of the methodology are likely inevitable and require further investigation to instill higher confidence in application in future studies. In short, through this study, we aimed at developing a methodology that serves as a foundation for further enhancement in the future.

## 5. Summary and Conclusions

In this paper, we implemented the AP-ROpt that adaptively retrieved

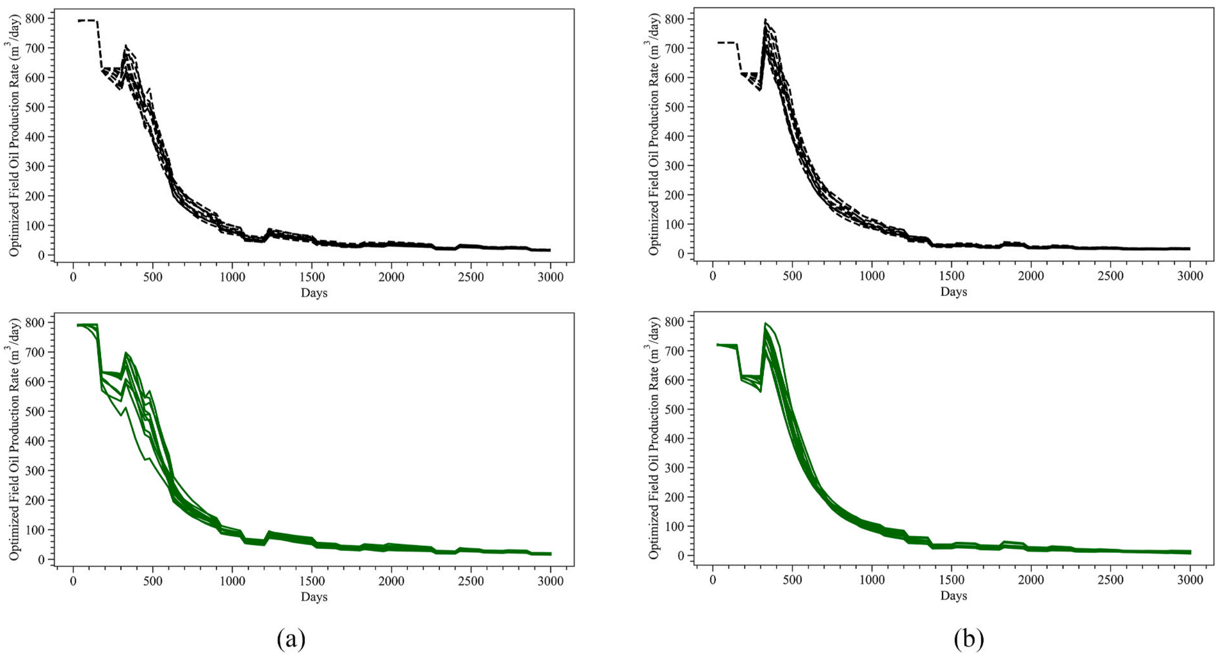


**Fig. 13.** Plots of the optimized FOPR considering 10 realizations. The black dashed lines indicate the cases of simulator-proxies whereas the green lines imply the cases of proxy models. a) PSO and b) GWO.

**Table 4**
Performance metrics of the best and worst performing realizations of FWPR and FOPR under the case of proxy models along with PSO and GWO.

| | | $R^2$ | RMSE |
|---|---|---|---|
| MLP-PSO (FWPR) | *Best Realization: 6* | 0.9983 | 7.44 |
| | *Worst Realization: 5* | 0.9651 | 34.63 |
| MLP-PSO (FOPR) | *Best Realization: 7* | 0.9995 | 5.42 |
| | *Worst Realization: 5* | 0.9756 | 34.64 |
| MLP-GWO (FWPR) | *Best Realization: 8* | 0.9989 | 6.30 |
| | *Worst Realization: 9* | 0.9898 | 18.67 |
| MLP-GWO (FOPR) | *Best Realization: 8* | 0.9992 | 6.12 |
| | *Worst Realization: 9* | 0.9930 | 18.66 |

**Table 5**
Mean $R^2$ and RMSE of optimized FWPR (and FOPR) generated by comparing the results of simulator-proxies and proxy models.

| | | ROpt-FWPR | ROpt-FOPR |
|---|---|---|---|
| MLP-PSO | Mean $R^2$ | 0.9932 | 0.9954 |
| | Mean RMSE | 13.59 | 13.11 |
| MLP-GWO | Mean $R^2$ | 0.9956 | 0.9972 |
| | Mean RMSE | 11.21 | 11.31 |

the optimal control (resulted from optimization with the established proxy models) and added it to the training database to further enhance the performance of the proxy models. This methodology is inspired by some of our previous works. The whole workflow of the methodology was performed in a closed-loop manner. Regarding this, by using 10 different realizations of the 3D Egg Model as the reservoir model, we employed MLP, an ML technique, to build two different proxy models which respectively forecast FLPR and FWCT. Then, they were coupled with PSO and GWO to optimize ENPV through the adjustment of FWIR.

We first implemented a trial-and-error approach to determine the optimal topology of these proxy models. Based on the training, testing, and blind validation results, the performance of these models was validated to be apt for further application. After the execution of the methodology, the results confirmed that a near-optimal solution (as compared with the solution from optimization with only reservoir simulation) could be achieved with much less computational demand. For PSO, the computation was improved by nearly 10 times whereas for GWO, it has become about 18 times faster. High reduction in computational efforts is the main advantage attained in this work. Nevertheless, we are still cognizant of the limitations of this methodology, including consideration of only geological uncertainty, integration of hyperparameter optimization, and limited applicability to other optimization problems, viz. $CO_2$ sequestration and history matching.

With this, we would like to summarize that a fundamental methodology has been built upon which further improvement can be maneuvered, and this highlights the benefit garnered from this work. Also, the proxy models established here have sufficiently achieved their goal of the application. About this, integrating adaptive training with optimization, which yields an excellent result of proxy modeling under geological uncertainty, is considered the key finding here. We hereby opine that this workflow can be practically useful to improve any developed data-driven model that yields optimization results with a low satisfying level of accuracy. Nonetheless, refinements can still be done when dealing with more real-life applications.

## Authors' contributions

Cuthbert Shang Wui Ng: Conceptualization, Methodology, Modeling, Programming, Coding, Data Preparation and Analysis, Investigation, Writing, Editing. Ashkan Jahanbani Ghahfarokhi: Supervising, Methodology, Writing, Reviewing and Editing.

## Declaration of competing interest

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

The authors are unable or have chosen not to specify which data has been used.

## Acknowledgment

This research is a part of BRU21 – NTNU Research and Innovation Program on Digital Automation Solutions for the Oil and Gas Industry (www.ntnu.edu/bru21).

## References

Babaei, M., Pan, I., 2016. Performance comparison of several response surface surrogate models and ensemble methods for water injection optimization under uncertainty. Comput. Geosci. https://doi.org/10.1016/j.cageo.2016.02.022.
Benamara, C., Nait Amar, M., Gharbi, K., Hamada, B., 2019. Modeling Wax Disappearance Temperature Using Advanced Intelligent Frameworks. Energy and Fuels. https://doi.org/10.1021/acs.energyfuels.9b03296.
Bruce, W.A., 1943. An electrical device for analyzing oil-reservoir behavior. Trans. AIME. https://doi.org/10.2118/943112-g.
Buduma, N., Locascio, N., 2017. Fundamentals of Deep Learning : Designing Next-Generation Machine Intelligence Algorithms, Designing Next-Generation Machine Intelligence Algorithms.
Ezugwu, A.E., Adeleke, O.J., Akinyelu, A.A., Viriri, S., 2020. A conceptual comparison of several metaheuristic algorithms on continuous optimisation problems. Neural Comput. Appl. 32 https://doi.org/10.1007/s00521-019-04132-w.
Forrester, A.I.J., Sóbester, A., Keane, A.J., 2008. Engineering Design via Surrogate Modelling : a Practical Guide. J. Wiley.
Fursov, I., Christie, M., Lord, G., 2020. Applying kriging proxies for Markov chain Monte Carlo in reservoir simulation. Comput. Geosci. 24 https://doi.org/10.1007/s10596-020-09968-z.
Geng, X., Smith-Miles, K., 2015. Incremental learning. In: Li, S.Z., Jain, A.K. (Eds.), Encyclopedia of Biometrics. Springer US, Boston, MA, pp. 912–917. https://doi.org/10.1007/978-1-4899-7488-4_304.
Golzari, A., Haghighat Sefat, M., Jamshidi, S., 2015. Development of an adaptive surrogate model for production optimization. J. Pet. Sci. Eng. https://doi.org/10.1016/j.petrol.2015.07.012.
Guo, Z., Reynolds, A.C., 2018. Robust life-cycle production optimization with a support-vector-regression proxy. SPE J. https://doi.org/10.2118/191378-PA.
Hamdi, H., Clarkson, C.R., Esmail, A., Sousa, M.C., 2021. Optimizing the Huff "n" Puff gas injection performance in shale reservoirs considering the uncertainty: a duvernay shale example. In: SPE Reservoir Evaluation and Engineering. https://doi.org/10.2118/195438-PA.
He, Q., Mohaghegh, S.D., Liu, Z., 2016. Reservoir simulation using smart proxy in SACROC unit - case study. In: SPE Eastern Regional Meeting. https://doi.org/10.2118/184069-MS.
Hong, A.J., Bratvold, R.B., Nævdal, G., 2017. Robust production optimization with capacitance-resistance model as precursor. Comput. Geosci. https://doi.org/10.1007/s10596-017-9666-8.
International Energy Agency, 2021. Global Energy Review 2021, Global Energy Review 2020.
James, V., Miranda, L., 2018. PySwarms: a research toolkit for particle swarm optimization in Python. J. Open Source Softw. 3 https://doi.org/10.21105/joss.00433.
Jansen, J.D., Fonseca, R.M., Kahrobaei, S., Siraj, M.M., Van Essen, G.M., Van den Hof, P. M.J., 2014. The egg model - a geological ensemble for reservoir simulation. Geosci. Data J. https://doi.org/10.1002/gdj3.21.
Jo, S., Jeong, H., Min, B., Park, C., Kim, Y., Kwon, S., Sun, A., 2022. Efficient deep-learning-based history matching for fluvial channel reservoirs. J. Pet. Sci. Eng. 208 https://doi.org/10.1016/j.petrol.2021.109247.
Kennedy, J., Eberhart, R., 1995. Particle swarm optimization. In: IEEE International Conference on Neural Networks - Conference Proceedings. https://doi.org/10.4018/ijmfmp.2015010104.
Kingma, D.P., Ba, J.L., 2015. Adam: a method for stochastic optimization. In: 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings.
Komura, D., Ishikawa, S., 2018. Machine learning methods for histopathological image analysis. Comput. Struct. Biotechnol. J. https://doi.org/10.1016/j.csbj.2018.01.001.
Kristoffersen, B.S., Silva, T.L., Bellout, M.C., Berg, C.F., 2021. Efficient well placement optimization under uncertainty using a virtual drilling procedure. Comput. Geosci. https://doi.org/10.1007/s10596-021-10097-4.
Kristoffersen, B.S., Bellout, M.C., Silva, T.L., Berg, C.F., 2022. Reduced well path parameterization for optimization problems through machine learning. J. Pet. Sci. Eng. 208 https://doi.org/10.1016/j.petrol.2021.109523.
Li, W., Zhang, D., Lin, G., 2015. A surrogate-based adaptive sampling approach for history matching and uncertainty quantification. In: Society of Petroleum Engineers - SPE Reservoir Simulation Symposium. https://doi.org/10.2118/173298-ms, 2015.
Lickevic, V., Bartoshevic, P., 2021. SwarmPackagePy.
Liu, J., Han, Z., Song, W., 2012. Comparison of infill sampling criteria in kriging-based aerodynamic optimization. In: 28th Congress of the International Council of the Aeronautical Sciences 2012. ICAS 2012.
Liu, H., Ong, Y.S., Cai, J., 2018. A survey of adaptive sampling for global metamodeling in support of simulation-based complex engineering design. Struct. Multidiscip. Optim. https://doi.org/10.1007/s00158-017-1739-8.
Lopez-Garcia, T.B., Coronado-Mendoza, A., Domínguez-Navarro, J.A., 2020. Artificial neural networks in microgrids: a review. Eng. Appl. Artif. Intell. 95 https://doi.org/10.1016/j.engappai.2020.103894.
McKay, M.D., Beckman, R.J., Conover, W.J., 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics. https://doi.org/10.2307/1268522.
Mirjalili, S., Mirjalili, S.M., Lewis, A., 2014. Grey wolf optimizer. Adv. Eng. Software. https://doi.org/10.1016/j.advengsoft.2013.12.007.
Mitchell, Tom, 1997. Machine Learning Textbook. McGraw Hill.
Mohaghegh, S.D., 2017. Data-Driven Reservoir Modeling. Society of Petroleum Engineers.
Nait Amar, M., Jahanbani Ghahfarokhi, A., 2020. Prediction of CO2 diffusivity in brine using white-box machine learning. J. Pet. Sci. Eng. https://doi.org/10.1016/j.petrol.2020.107037.
Nait Amar, M., Jahanbani Ghahfarokhi, A., Zeraibi, N., 2020a. Predicting thermal conductivity of carbon dioxide using group of data-driven models. J. Taiwan Inst. Chem. Eng. https://doi.org/10.1016/j.jtice.2020.08.001.
Nait Amar, M., Zeraibi, N., Jahanbani Ghahfarokhi, A., 2020b. Applying hybrid support vector regression and genetic algorithm to water alternating CO2 gas EOR. Greenh. Gases Sci. Technol. https://doi.org/10.1002/ghg.1982.
Nait Amar, M., Jahanbani Ghahfarokhi, A., Ng, C.S.W., 2021a. Predicting wax deposition using robust machine learning techniques. Petroleum. https://doi.org/10.1016/j.petlm.2021.07.005.
Nait Amar, M., Jahanbani Ghahfarokhi, A., Ng, C.S.W., Zeraibi, N., 2021b. Optimization of WAG in real geological field using rigorous soft computing techniques and nature-inspired algorithms. J. Pet. Sci. Eng. 109038. https://doi.org/10.1016/j.petrol.2021.109038.
Nassif, A.B., Shahin, I., Attili, I., Azzeh, M., Shaalan, K., 2019. Speech recognition using deep neural networks: a systematic review. IEEE Access 7. https://doi.org/10.1109/ACCESS.2019.2896880.
Ng, C.S.W., Jahanbani Ghahfarokhi, A., Nait Amar, M., 2021a. Application of nature-inspired algorithms and artificial neural network in waterflooding well control optimization. J. Pet. Explor. Prod. Technol. https://doi.org/10.1007/s13202-021-01199-x.
Ng, C.S.W., Jahanbani Ghahfarokhi, A., Nait Amar, M., Torsæter, O., 2021b. Smart proxy modeling of a fractured reservoir model for production optimization: implementation of metaheuristic algorithm and probabilistic application. Nat. Resour. Res. 30, 2431–2462. https://doi.org/10.1007/s11053-021-09844-2.
Ng, C.S.W., Ghahfarokhi, A.J., Nait Amar, M., 2022a. Production optimization under waterflooding with Long Short-Term Memory and metaheuristic algorithm. Petroleum. https://doi.org/10.1016/J.PETLM.2021.12.008.
Ng, C.S.W., Jahanbani Ghahfarokhi, A., Nait Amar, M., 2022b. Well production forecast in Volve field: application of rigorous machine learning techniques and metaheuristic algorithm. J. Pet. Sci. Eng. 208, 109468 https://doi.org/10.1016/J.PETROL.2021.109468.
Olabode, O.A., Orodu, O.D., Isehunwa, S.O., Mamudu, A., Rotimi, O.J., 2018. Effect of foam and WAG (water alternating gas) injection on performance of thin oil rim reservoirs. J. Pet. Sci. Eng. 171 https://doi.org/10.1016/j.petrol.2018.07.043.
Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., 2011. Scikit-learn: machine learning in Python. J. Mach. Learn. Res. 12.
Poostchi, M., Silamut, K., Maude, R.J., Jaeger, S., Thoma, G., 2018. Image analysis and machine learning for detecting malaria. Transl. Res. https://doi.org/10.1016/j.trsl.2017.12.004.
Redouane, K., Zeraibi, N., Nait Amar, M., 2019. Adaptive surrogate modeling with evolutionary algorithm for well placement optimization in fractured reservoirs. Appl. Soft Comput. J. https://doi.org/10.1016/j.asoc.2019.03.022.
Rosenblatt, F., 1958. The perceptron: a probabilistic model for information storage and organization in the brain. Psychol. Rev. 65 https://doi.org/10.1037/h0042519.
Runge, J., Zmeureanu, R., 2019. Forecasting energy use in buildings using artificial neural networks: a review. Energies. https://doi.org/10.3390/en12173254.
Salehian, M., Sefat, M.H., Muradov, K., 2021. A robust, multi-solution framework for well placement and control optimization. Comput. Geosci. https://doi.org/10.1007/s10596-021-10099-2.
Salehian, M., Haghighat Sefat, M., Muradov, K., 2022. Multi-solution well placement optimization using ensemble learning of surrogate models. J. Pet. Sci. Eng. 210, 110076 https://doi.org/10.1016/J.PETROL.2021.110076.
Schlumberger, 2019. Eclipse Reservoir Simulation Software Reference Manual. schlumberger.
Seehapoch, T., Wongthanavasu, S., 2013. Speech emotion recognition using support vector machines. In: Proceedings of the 2013 5th International Conference on Knowledge and Smart Technology. KST. https://doi.org/10.1109/KST.2013.6512793, 2013.
Sen, D., Chen, H., Datta-Gupta, A., Kwon, J., Mishra, S., 2021. Machine learning based rate optimization under geologic uncertainty. J. Pet. Sci. Eng. 207, 109116 https://doi.org/10.1016/J.PETROL.2021.109116.
Van Rossum, G., Drake, F.L., 2009. Python 3 Reference Manual. CreateSpace, Scotts Valley, CA.
Vo Thanh, H., Yasin, Q., Al-Mudhafar, W.J., Lee, K.-K., 2022. Knowledge-based machine learning techniques for accurate prediction of CO2 storage performance in underground saline aquifers. Appl. Energy 314, 118985. https://doi.org/10.1016/J.APENERGY.2022.118985.
Xu, Q., Wehrle, E., Baier, H., 2012. Adaptive surrogate-based design optimization with expected improvement used as infill criterion. Optimization 61. https://doi.org/10.1080/02331934.2011.644286.
Xu, C., Nait Amar, M., Ghriga, M.A., Ouaer, H., Zhang, X., Hasanipanah, M., 2020. Evolving support vector regression using Grey Wolf optimization; forecasting the

geomechanical properties of rock. Eng. Comput. https://doi.org/10.1007/s00366-020-01131-7.

Yang, X.-S., 2014. Chapter 1 - introduction to algorithms. In: Yang, X.-S. (Ed.), Nature-Inspired Optimization Algorithms. Elsevier, Oxford, pp. 1–21. https://doi.org/10.1016/B978-0-12-416743-8.00001-4.

Ye, P., Pan, G., 2019. Surrogate-based global optimization methods for expensive black-box problems: recent advances and future challenges. In: Proceedings - 2019 2nd International Conference of Intelligent Robotic and Control Engineering. IRCE. https://doi.org/10.1109/IRCE.2019.00026, 2019.

Yousefi, S.H., Rashidi, F., Sharifi, M., Soroush, M., Ghahfarokhi, A.J., 2021. Interwell connectivity identification in immiscible gas-oil systems using statistical method and modified capacitance-resistance model: a comparative study. J. Pet. Sci. Eng. 198, 108175 https://doi.org/10.1016/J.PETROL.2020.108175.

Zubarev, D.I., 2009. Pros and cons of applying proxy-models as a substitute for full reservoir simulations. In: Proceedings - SPE Annual Technical Conference and Exhibition. https://doi.org/10.2118/124815-ms.