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Evolving Well Stimulation Optimization Tool with OliFANT: A Pilot Machine Learning Project to Boost National Oil and Gas Production

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Abstract

In Indonesia, for a half-decade, the decrease in oil and gas production from 2016 is 4.23% and 3.53%, respectively (ESDM, 2021). This production decrease has a domino effect on the investment loss. According to the International Trade Administration, investment in Indonesia's oil and gas industry in 2019 reached around USD 12 billion, which decreased from around USD 16 billion in 2016. Such loss is a serious disaster; thus, applying digital transformation such as machine learning to the most-used method, well-stimulation, is immediately needed. Unfortunately, the implemented well stimulations nowadays are prone to short-lived effects due to unreliable selection methods, as they do not have any integrated database. As the pilot project, this research focuses on field data collected in West Indonesia from sandstone and carbonate lithologies, and the type of stimulation used is acidizing. This tool, OliFANT, defines the success of inspiration based on the productivity index before and after stimulation. The method uses geostatistical approaches and optimizing decline curve analysis for analysing and modelling spatially correlated data. The model's accuracy is validated at a minimum of 75%, showing its high reliability. It can also forecast the duration effect of the stimulation. Additionally, it provides the estimation of profit scenarios. The proposed machine learning model adopts an empirical working principle by utilizing reservoir parameters and test data of stimulation, which are inputted into a user-friendly interface after filling in a comprehensive database. In conclusion, the main benefits of using this tool are cutting evaluation time and achieving higher cost-efficiency. This software can be continuously improved by adding more data to widen the variety of the methods. Considering that each field has different types of properties, this tool is built to be adaptable to every reservoir condition. Over and above that, this tool can be implemented for other stimulated wells and be modified for different methods and operations, such as drilling and workover. In the future, it can be a one-stop solution for stimulation plan validation, where data-driven solutions pave the way for success.

Keywords:
digitalization, geostatistical approaches, machine learning, production rate, well stimulation

1. Introduction

1.1 Background of the Study

Indonesia's oil and gas industry has been facing multiple challenges in recent years. With the aim of producing one million barrels of lifting oil per day by 2030, the government is relying heavily on oil and gas exploration, especially in the unexplored basins, as reports show there are 68 unexplored ones, mostly located in the eastern part of Indonesia (ESDM, 2020). However, due to the lack of new oil field exploration and ageing oil fields, the country's oil production has been declining by 11% per year (International Trade Administration, 2021). To achieve the 2030 target, it is imperative to maximize the production capacity of current wells, especially since more than 60% of oil production and 30% of gas production in Indonesia come from late-life-cycle resources (Dolya et al., 2017). However, one of the major problems in mature fields is the production rate decrease caused by formation damage, which results in a production decrease in the aftermath.

For a half-decade, the decrease in oil and gas production from 2016 is 4.23% and 3.53%, respectively (ESDM, 2021). Over the past few years, the decline in oil and gas production has had a domino effect on investment loss in the industry. According to the International Trade Administration, investment in Indonesia's oil and gas industry in 2019 reached around USD 12 billion, which decreased from around USD 16 billion in 2016. Moreover, despite Indonesia's potential, foreign contractors are leaving due to weak legal certainty, unattractive incentives, and complicated bureaucracy (Handoyo, 2023). However, there is still hope, but a maneuver is required. Engineers have been working on well stimulation as the most feasible solution for increasing oil and gas production. Considering, as stated earlier, that most of the hydrocarbon production in Indonesia comes from late-life-cycle resources, exploitation optimization is more impactful in the near time than relying on new exploration and well drilling.

For example, to maximize the production at Kruh Block, Indonesia Energy Corporation is in the process of conducting a workover of the existing Kruh-21 well, which was drilled in 2015 (Indonesia Energy Corporation Limited, 2023). There are more mature wells that need to be evaluated, like Kruh-21, such as the Sanga-Sanga Block in Indonesia, which has reached a mature life stage, with 364 wells drilled and production continuing to decline (Fedriando et al., 2019). Fitnawan et al. (2021) also added regarding drilling infill wells to improve recovery factor in maturing fields, as infill wells in mature fields are usually associated with many drilling challenges such as depleted reservoir pressure, uneven reservoir pressure along reservoir section, formation compaction or subsidence, and other geomechanical problems. Knowing Indonesia has become a net oil importer since 2004 as the growing internal demand exceeds the country's oil production (Fitnawan et al., 2021), and 2030 is getting closer, this target of national oil and gas production boost must not be let into illusion. A "quick win" is needed, and it is achievable through well stimulation, taking the 2023 program of SKK Migas to reactivate 1086 idle wells through workover and well services as a concrete instance (Hakim, 2023).

Concisely, a turning point is mandatory, but manual predictions regarding the plan's compatibility with manual reality may not always be precise. This is where machine learning comes in, and humans are going beyond borders to be limitless. Machine learning can help identify controlling factors and optimize well-stimulation design by finding implicit rules from a large amount of data and expressing them with high-dimensional nonlinear algorithms. While it is seldom used in reservoir stimulation, it has the potential to revolutionize the industry and help Indonesia reach its 2030 target. This research provides a tool to predict the outcomes of an operation, specifically stimulation acidizing, and perform production forecasting after the process using a geostatistical method. With the aid of machine learning through OliFANT, Indonesia can overcome the challenges in its oil and gas industry and become a leading energy provider in the region.

1.2 Objective of the Study

The main objectives of this research are to:
1. Define the success or failure of the stimulation.
2. Develop a machine learning model to predict the results of acid stimulation.
3. Predict the duration of the stimulation effect.

1.3 Basic Theory

1.3.1 Acid Stimulation

Acid stimulation or acidizing is a well stimulation technique to improve the productivity of oil and gas reservoirs by injecting acid into the wellbore and the surrounding formation to dissolve or remove materials that impede the flow of hydrocarbons. There are three methods of acid treatments, namely, acid washing, matrix acidizing, and fracture acidizing. Acid washing is a stimulation treatment that focuses on wellbore cleaning to clean out the scale and other debris restricting flow in the well. Matrix acidizing is a stimulation treatment that injects the fluid below the fracturing pressure of the formation. This treatment can be applied in both carbonate and sandstone formations. Last, distinct from matrix acidification, fracture acidizing injects fluid above fracture stresses and is generally applied for carbonate formation (Kalfayan, 2008).

The type of acid used is generally mineral acid, such as mud acid (HCl-HF) for sandstone formations and HCl for carbonate formations. Besides mineral acids, there are organic acids, powdered acids, acid mixtures, and retarded acid systems. Organic acids are used in high-temperature conditions and require a low level of corrosivity. The organic acids commonly used are acetic and formic acids. Acid mixture is a mixture of different types of acids, usually a mixture of organic acids. Then retarded acid is used to slow down the rate of reaction. By gelling the acid, oil-wetting the formation of solids, or emulsifying the acid with oil, the rate of acid reaction can be slowed (Williams et al., 1979).

The main purpose of acid stimulation is to increase production, but in fact, acid stimulation can fail or not experience a significant increase in production. This is due to several factors, such as the treatment of high-skin wells with no damage, use of incorrect acid, use of incorrect volumes or concentrations, additive overuse or misuse, and shutting in the acid treatment too long. As stated in the Schlumberger Energy Glossary, skin is a dimensionless factor calculated to determine the production efficiency of a well by comparing actual conditions with theoretical or ideal conditions. A positive skin value indicates some damage or influences that are impairing well productivity. A negative skin value indicates enhanced productivity, typically resulting from stimulation. It is, therefore, necessary for the approach to acid work to be reproducible so that potential controllable causes of failure can be addressed and eliminated. Thus, it can increase the chances of success from acid stimulation treatment.

Table 1. Well stimulation and EOR comparison.

	Well Stimulation (IOR)	**Enhanced Oil Recovery (EOR)**
Definition	Forms of intervention to improve hydrocarbon flows from the reservoir to the well.	Fluids injection into the reservoir to increase oil production.
Common Methods	Hydraulic fracturing and acidizing	Steam injection, gas injection, and chemical injection.
General Purposes	Improving flow capacity near the well, either by creating new flow paths or cleaning well perforations.	Increasing oil production through various methods.
Implementation Baseline	Non-stimulated, naturally flowing vertical production wells.	Incremental production after primary and secondary production.
Scope Specificity	Applicable to be implemented into a small scope such as certain specific well only.	Basically, planned to be implemented into a large scope such as a field.

As additional information, considering the intended well stimulation here does not affect or even change the reservoir properties, it needs to be mentioned that the classification of this stimulation is improved oil recovery or IOR. The comparison between this well stimulation and enhanced oil recovery can be seen in the following table (King, 2023). For more details, as an information enrichment towards hydraulic fracturing general process and matrix acidizing impact on wells, please refer to Figure 10 and Figure 11 in the Appendices.

1.3.2 SARIMA

ARIMA is an acronym for auto-regressive integrated moving average; it is a class of models used for analyzing and forecasting time series data sets (Brownlee, 2020). ARIMA model extension that considers the seasonal component is famously known as SARIMA. The components that make up the model of ARIMA are expounded as follows.

Auto Regressive (AR)

Auto-regressive is a model where the evolving variable of interest or, is regressed on its own lagged values. AR Model is usually symbolized by the variable *p*. It basically utilizes the dependence between present-time observation and observations over the previous period. In a mathematical model, it can be expressed as follows:

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \ldots + \emptyset_p y_{t-p} + \in_t \quad (1)$$

Integrated (I)

Integrated means the usage of raw observation differencing, which is subtracting an observation from an observation at the previous time step in order to make the time series stationary. Integration is usually symbolized by the variable d. Thus, this model indicates that the data values have been replaced with the difference between their values and the previous values.

Moving Average (MA)

Moving average is a model where the evolving variable of interest, or, is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past. MA model is usually symbolized by the variable q. This model uses the dependency between an observation and a residual error from a moving average model applied to lagged observations. In a mathematical model, it can be expressed as follows:

$$y_t = \in_t + \theta_1 \in_{t-1} + \theta_2 \in_{t-2} + \cdots + \theta_q \in_{t-q} \quad (2)$$

1.3.3 Decline Curve Analysis

Decline curve analysis, also known as DCA, is defined as an empirical reservoir engineering technique that extrapolates trends in the production data from oil and gas wells (IHS Energy, 2020). There are several purposes for conducting DCA, such as determining the expected ultimate recoverable, or EUR, value and forecasting future production rates. One of the most important field data to be analyzed is the production rate. Production rate from a reservoir will always naturally decline due to some factors, which include:

1. Reservoir pressure depletion
2. Relative permeability altercation
3. Increase in water cut or gas-oil ratio
4. Formation damage (usually caused by production activities)
5. Fluid cross flow
6. Combination of the above factors.

Furthermore, the DCA technique basically relies on the concept of extrapolating the trends of the observed data in order to predict future production performance (Permadi, 2016). The historical production rate data is usually fitted by a predictive model on which the forecasting of the future production rate performance is based. DCA techniques are applicable for several conditions as follows:

1. Reservoirs with declining pressure
2. Reservoirs showing an increase in water cut or producing gas-oil ratio
3. Reservoir with gravity drainage.

On the other hand, besides the applicability as above, there are several conditions in which DCA will not be applicable, which are as follows:

1. Reservoirs with strong water drive or gas cap drive because the production rate is mainly controlled by an external force, and it usually experiences minimal pressure depletion.
2. At the beginning phase of tight reservoir depletion, the production rate is mainly affected by infinite-acting reservoir conditions.
3. Reservoirs whose wells are under mechanical restrictions, such as the usage of choke.

DCA has been widely used due to its accuracy, reliability, and cost efficiency. Just like everything in this world, the DCA technique surely has a flaw. One of its notable weaknesses is the fact that a fit of the historical data with an equation of line represents only a mathematical relationship. Therefore, in most cases, the shape of the curve does not accurately represent the reservoir character quantitatively. Throughout time, experts from all over the world have proposed several DCA methods. However, up until this current moment, the one proposed by J. J. Arps in 1945 is still the most used DCA technique in the oil and gas industry. Figure 8 illustrates the concept of the DCA technique proposed by J. J. Arps. This method consists of 3 decline models, which are exponential, hyperbolic, and harmonic. Exponential decline is also famously known as the 'pessimist' forecast. Meanwhile, harmonic decline is the 'optimist' forecast. The empirical equation for each of those 3 decline models is written below.

1. Exponential Decline (b = 0)

$$q_t(t) = q_i e^{-Dt} \tag{3}$$

$$N_p(t) = \frac{q_i}{D}(1 - e^{-Dt}) \tag{4}$$

$$N_p(q) = \frac{(q_i - q_t)}{D} \tag{5}$$

2. Hyperbolic Decline (0 < b < 1)

$$q_t(t) = q_i(1 + bD_i t)^{-\frac{1}{b}} \tag{6}$$

$$N_p(t) = \frac{q_i}{(b-1)D_i}\left[(1 + bD_i t)^{\frac{b-1}{b}} - 1\right] \tag{7}$$

$$N_p(q) = \frac{q_i}{(b-1)D_i}\left[\left(\frac{q_i}{q_t}\right)^{b-1} - 1\right] \tag{8}$$

4. Harmonic Decline (b = 1)

$$q_t(t) = q_i(1 + bD_i t)^{-\frac{1}{b}} \tag{9}$$

$$N_p(t) = \frac{q_i}{D_i} ln(1 + D_i t) \tag{10}$$

$$N_p(q) = \frac{q_i}{D_i} ln\left(\frac{q_i}{q_t}\right) \tag{11}$$

1.3.4 SciPy

SciPy module is a comprehensive library for scientific computing in Python, featuring an optimization module that offers a variety of algorithms for finding the minimum or maximum of a function. This module is useful for solving optimization problems, from curve fitting to complex parameter estimation for machine learning models. Curve fitting is a process that involves finding a mathematical function that accurately describes the relationship between independent and dependent variables. This is accomplished by choosing a mathematical function and adjusting its parameters to minimize the difference between the function and the data points using an optimization algorithm such as the least-squares method. The resulting parameter values can be used to plot the curve and assess the quality of the fit using statistical measures.

1.3.5 Root Mean Square Error (RMSE)

The square root of the mean of the square of all of the errors is the root mean square error, also known as RMSE. It is considered a general error metric for quantitative calculations.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y})^2} \tag{12}$$

To obtain a percentage error for the validation data, divide the RMSE value by the mean of the target variable in Equation (12). To verify experimental results, root mean square error is frequently used in climatology, forecasting, and regression analysis.

1.3.6 Machine Learning

Machine learning is a subset of artificial intelligence that uses mathematical approaches for large-scale data regression, classification, and grouping. Machine learning algorithms use statistical approaches to train data to create classifications or predictions. Machine learning can be taught to execute tasks using computer systems rather than being explicitly programmed to do so (Kühl et al., 2022). There are two types of machine learning algorithms: supervised machine learning algorithms and unsupervised machine learning algorithms. Supervised machine learning labels data sets in order to train computers to correctly classify data or predict outcomes. Unsupervised learning, on the other hand, is used to analyze and cluster unlabeled datasets. The machine learning category employed in this work is supervised machine learning, which uses this method to label data and predict an outcome. To categorize data, supervised learning methods such as XG-Boost, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Gradient-Boosted Tree, and Random Forest. These methods are explained below.

1. XG-Boost
   XG-Boost is a machine learning algorithm that combines learning methods and variances of gradient boosting based on a decision tree. Boosting is a common ensemble learning technique that combines sequentially weak learners to produce a powerful final learner. Each base learning algorithm learns from its previous base learner and reduces its error. XG-boost is good at finding the relationship in any type of training but struggles to generalize well on unseen data (Kühl et al., 2022).
2. K-Nearest Neighbors
   K-Nearest Neighbors is a machine learning model that classifies the datasets by assuming the similarity of new data compared to existing data or classifies the data to the group with similar features. This model determines the class or value of a new data point based on its proximity to

the nearest k data points in the training dataset. When a new, unlabeled data point needs to be classified or predicted, the algorithm calculates the distance between that data point and all the data points in the training dataset. The algorithm then selects the k nearest data points based on the calculated distances.

3. Support Vector Machine
   Support Vector Machine algorithm is used to find a hyperplane that categorizes data points in an N-dimensional space. Hyperplanes are decision boundaries that help the classification of data points, and their dimension is determined by the number of features. To determine the optimum hyperplane, SVM optimizes the margin between the hyperplane and the nearest points from each class, known as support vectors. SVM seeks the hyperplane with the biggest margin or the distance between the hyperplane and the support vectors.
4. Gradient Boosted Tree
   Gradient Boosted Tree is a type of algorithm that works as a classification model or as a regression model, subject to the type of response variable. The algorithm starts by building a single decision tree and the predicted outputs of this tree are compared with the actual outputs, and the differences between the two are used to train the next tree. The new tree is designed to predict the remaining errors of the previous tree. This process is repeated until the desired level of accuracy is achieved.
5. Random Forest
   Random Forest algorithm is a supervised machine-learning technique built on decision tree algorithms. This algorithm's goal is to address regression and classification problems. This technique employs a large number of classifiers to solve complicated issues. A random forest algorithm is made up of several decision trees that have been trained using bagging or bootstrap aggregation. The result of predictions is based on the average or mean of the output from various trees.

1.3.7 SMOTE

SMOTE, an acronym for synthetic minority oversampling approach, is an oversampling approach in which one class has a large amount of data while another class has a small number of data, also known as imbalance datasets. Imbalanced datasets make it difficult for machine learning algorithms to infer good classifiers since they degrade model performance and can lead to overfitting. SMOTE employs an oversampling strategy in which the minority class is oversampled by creating "synthetic" samples until the amount of minority data is balanced with the amount of majority data. The minority class is oversampled by using each sample of the minority class and adding synthetic examples along the line segments linking any/all the minority class's k nearest neighbours (Chawla et al., 2002).

2. Methodology

This study is conducted based on the workflow in Figure 5 and Figure 6, with the main 7 steps expounded as follows:

Data Acquisition

The data comes from the stimulation project from 2018 until 2022, with a total of 224 stimulation jobs of 157 wells. The data collected includes the date of stimulation, data rate and pressure before and after stimulation, reservoir permeability and porosity, bubble point pressure, reservoir pressure, reservoir temperature, stimulation type, formation type, treatment volume, perforation interval, acid type, depth of penetration, and stimulation costs.

Data Preparation

All required data are gathered in one file and need to be filtered before processed. At this step, data cleaning is carried out and filling in the data that is still empty. But it cannot be denied that there are also blank data so that data must be eliminated. Furthermore, because the classification type in this data is category, it is necessary to convert the data into numeric data because machine learning can only read numeric data. Use the "factorize" feature in pandas to encode categorical variables as integer arrays without changing their values.

Calculate Well Productivity Index

The well's productivity index is calculated to see the results of the simulation work. If the well's productivity index after stimulation is greater than the well's productivity index before stimulation, then the stimulation label is successful. Conversely, the stimulation will be labelled as failed if the well's productivity index after stimulation is smaller or equal to the well's productivity index before stimulation.

Data Oversampling

Data needs to be balanced between successful and failed stimulation data to prevent overfitting. Besides that, the small data also affects the accuracy of the model, so the data needs to be over-sampled using SMOTE. The amount of initial data after filtering was 130 data, with the results of successful stimulation jobs being 95 and failed stimulation jobs being 35. By using SMOTE, the data was over-sampled to 190 data with a data balance between failed simulation data and successful stimulation in each of the 95 jobs.

Machine Learning Method Selection

After the data is prepared, split the data into training and testing data sets. In this research, the training data size is set at 70%, and the testing data size is set at 30%. Parameter selection in the model uses the correlation method, which is displayed using a heatmap in Figure 9. The parameter selection results that most influence the stimulation results are formation type, rate before stimulation, predicted bottomhole pressure before stimulation, reservoir temperature, static bottomhole pressure, perforation interval, treatment injection volume, acid penetration depth, and stimulation type. Work. Then, classification models are built and evaluated by using many algorithms such as XG-Boost, Random Forest, Support Vector Machine, K-Nearest Neighbors, and Gradient Boosted Tree. The algorithm is selected based on the results of the highest accuracy using the evaluation of the confusion matrix. After that, parameter tuning using cross-validation is used to select the best hyperparameters for a machine-learning model. Cross-validation is used to evaluate the performance of a model on a dataset by splitting the dataset into multiple subsets or folds, training the model on some folds, and then evaluating the performance of the model on the remaining folds. This model uses 5 folds to train the model.

Model Prediction

In this step, the algorithm has been selected, and the prediction model is created. The model will be used to predict the failure or success of the simulation results. The selected algorithm for this model is XG-Boost, with a model accuracy of 75.93%.

Production Rate Forecasting

In this final step, there are a scope of 2 forecasting models to be covered, and those models are as follows:

- SARIMA
  To run a SARIMA model, at least 50 data points of production rate and well test date need to be inputted. A model is constructed to fit the training dataset and is checked with the testing dataset. The prediction or forecast generated from the training dataset is then evaluated with the original testing dataset to determine the acceptability of the model. If the model is accepted, it is re-fitted on the entire dataset to predict or forecast future data. This step ensures that the model is ready to be used for forecasting purposes.

- DCA
  To perform DCA analysis, you need to input at least 2 data points consisting of production rate and well test date. Then, by running DCA code with SciPy optimization and curve-fitting features, the type of DCA curve, either exponential, harmonic, or hyperbolic, can be defined. Input the target rate, which is the rate before stimulation, and determine the stimulation duration as the time between the stimulation date and the point of intersection between the DCA curve and the target rate line.

3. Results and Discussions

The following presents some examples of how the Author(s) could write his research results. If needed, the Author(s) may use Subsections to present his results.

3.1 Results

From the available data, there are 7 types of acid stimulation, which are acid wash, carbonate matrix, foam acid, gelled acid, organic acid, sandstone matrix, and temperature control viscosity acid. Then, it is necessary to evaluate the use of the type of acid that is successful in stimulation in terms of reservoir properties. The determination of the success of stimulation is assessed based on the increase in productivity index before and after stimulation. The results obtained from the data were 95 successful stimulation jobs, and 35 failed stimulation jobs. Because there is unbalanced data between successful and failed stimulation jobs, the data needs to be oversampled to reduce over-fitting. Besides SMOTE, the hyperparameter tuning method using cross-validation is also used to reduce overfitting. The data is split into 70% and 80% train data; the results show that splitting data into 70% train data and 30% test data provides higher accuracy (Table 3). Using 5 machine learning algorithms, namely XG-boost, Random Forest, KNN, Gradient Boosted Tree, and SVM, the accuracy results are shown in Table 4. The best algorithm for predicting the success of the stimulation is XG-Boost, with an accuracy of 75.93%. After predicting the simulation results, the successful stimulation work is then forecasted using SARIMA and DCA methods. In this field, the productivity index stabilized 3 weeks after stimulation. Therefore, the data used for the forecast are data from 3 weeks after the stimulation. The data required for the SARIMA method does not meet the minimum amount of data required, 50 data. Thus, the rate cannot be predicted by using the SARIMA method. On the other hand, by using the DCA model, the maximum error is 10%, which concludes as a highly accurate forecasting.

As the application of forecasting with the DCA model, after creating the database of the acidizing stimulations that have been conducted by Company X, there are 2 real cases from Company X that will be run.

3.1.1 Case 1: Forecasting for "Stimulation Plan A"

Well A is located in the Sunda Basin and is part of the Batu Raja formation. Prior to stimulation, the well had a predicted stimulation bottomhole pressure or PBHP of 160 psi and a temperature of 179.5 °F. The static bottomhole pressure, or SBHP, was measured at 381 psi. The stimulation plan for Well A includes treating a 52-foot interval with a volume of 94 gallons per foot. The depth penetration of the stimulation is expected to be 4 feet, the production rate before stimulation is 1372 BFPD, and the type of job is carbonate matrix acidizing. From the success-or-fail prediction, the results show that the stimulation plan will be successful. Hence, the rate after stimulation will be predicted with the DCA model by using SciPy optimization for curve fitting.

Based on Figure 1, the intersection between the curve and the target rate, which is the rate before stimulation, shows the predicted duration of the stimulation effect. Therefore, the duration of the stimulation effect is 222 days. However, due to the error that might happen, the range of the stimulation effect is between 199 and 245 days, with an error percentage of 10%. As the data above are acquired from a real case in Company X, here is also the comparison between the forecast data and the actual data after the stimulation.

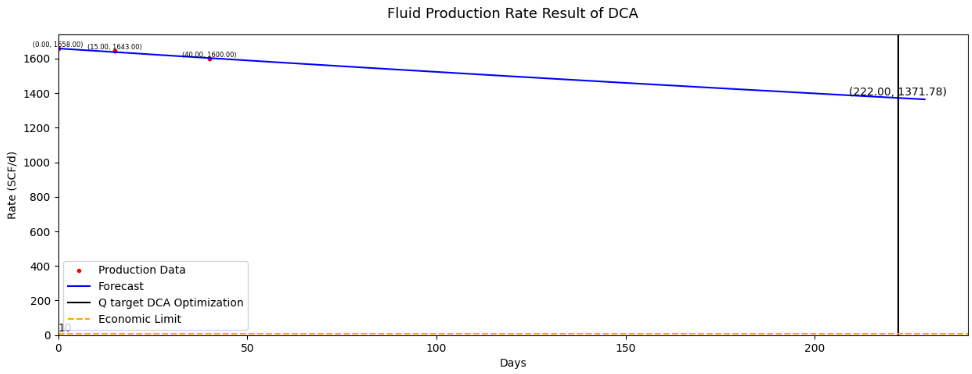

Figure 1. DCA result to well A production rate prediction.

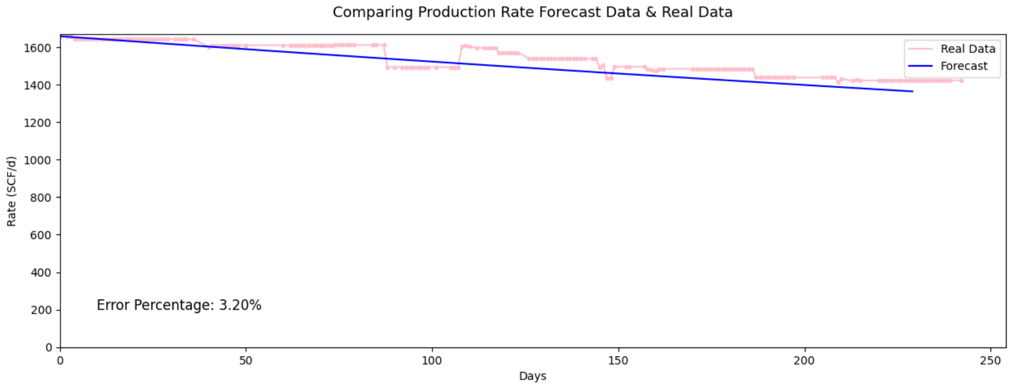

Figure 2. Comparison of forecast data to actual data after stimulation.

Figure 2 shows this DCA forecasting method is reliable due to its low error percentage, 3.2%, which is even lower than a 10% error. The error from the figure above is calculated with the RMSE percentage.

3.1.2 Case 2: Forecasting for "Stimulation Plan B"

Well B is located in the Sunda Basin and belongs to the Batu Raja formation. The initial properties of Well B before stimulation include a PBHP of 109 psi and a temperature of 213 degrees. The SBHP recorded was 245 psi. For the stimulation plan, a 105-foot interval will be treated with a volume of 55 gallons per foot. The depth penetration of the stimulation is 3.5 feet, and the selected type of job is foam acid stimulation.

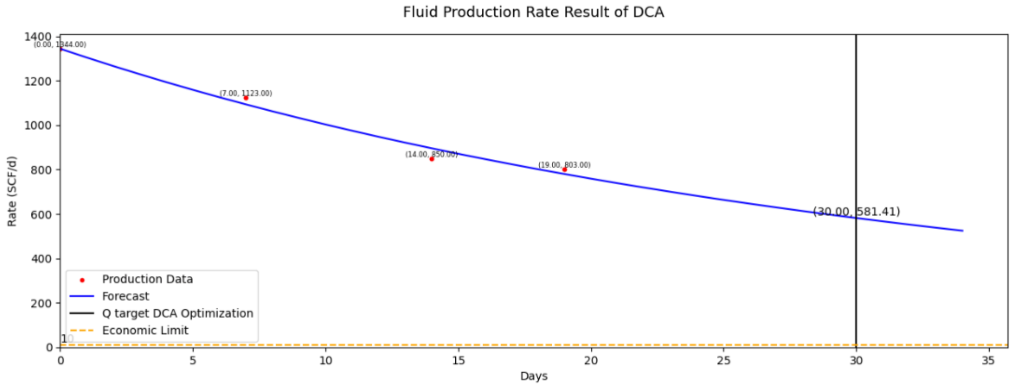

Figure 3. DCA result to well B production rate prediction.

Figure 3 shows the DCA result to Well B production rate prediction, with the range of predicted duration of the stimulation effect between 27 to 33 days. Meanwhile, the comparison of the forecast to the actual data can be seen in the following chart.

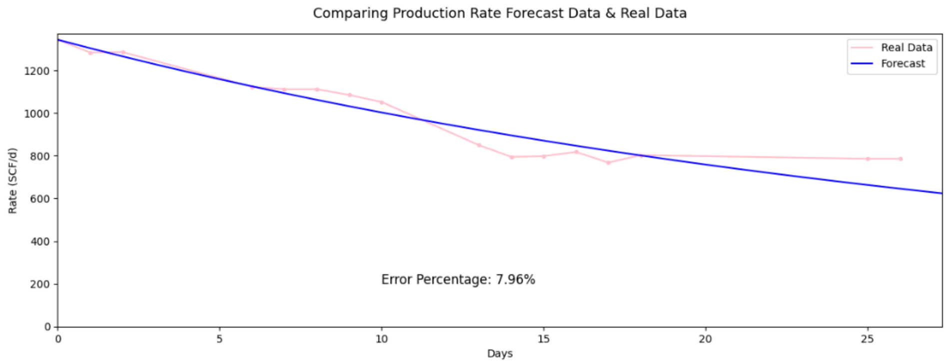

Figure 4. Comparison of forecast data to actual data with an error or 7.96%.

In the end, based on these 2 case studies, with the performed comparison between production rate forecast data and real data, both acquired error percentages are below 10%. In other words, it can be categorized as definitely acceptable and reliable.

Table 2. Summary for case study 1 and case study 2 error rate results.

Case Study 1	Case Study 2
3.20% (Stimulation effect between 199 to 245 days)	7.96% (Stimulation effect between 27 to 33 days)

3.2 Discussion

The results of this study present a tool called OLIFANT, which serves the purpose of predicting outcomes in acidizing stimulation jobs. In addition to stimulation outcome predictions, OLIFANT also enables production forecasting post-stimulation. With a remarkable accuracy rate of 75.93%, OLIFANT proves to be capable of reducing evaluation time and saving company costs.

This tool has the potential for further development in conjunction with stimulation work. The more data available, the higher the predictive model's accuracy will be. OLIFANT is not limited to stimulation jobs; it can also be applied to other operations such as drilling, well intervention, or production operations. The condition for using this tool is that the job or operation should not change the reservoir's properties.

Based on Figure 7, machine learning needs a minimal 50 data points to be run. In this case, the SARIMA method could not be utilized due to a lack of production data. However, if more than 50 data points are available, the SARIMA method can be employed alongside OLIFANT.

4. Conclusion

The conclusions that can be learnt from this study are as follows:

1. The success of stimulation was observed through the increase in productivity index before and after the stimulation process. Of the analysed 130 stimulation jobs, 95 were classified as successful and 35 as failed.
2. A comprehensive database was created using the collected data to develop a prediction model utilising machine learning. The XG-Boost algorithm was selected, yielding an accuracy rate of 75.93%. The input parameters, such as reservoir parameters, basin characteristics, reservoir pressure, reservoir temperature, perforation interval, treatment volume, depth penetration, and stimulation type, were carefully considered due to their significant impact on stimulation outcomes.
3. The forecast of successful stimulation outcomes was conducted to evaluate the decline in stimulation effects, employing DCA and SARIMA methods. DCA method showed a maximum error of 10%, indicating the model's high accuracy in forecasting simulation results.

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Nomenclature

$\boldsymbol{b}$	Decline Rate Exponent	-
$\boldsymbol{D}$	Nominal Decline Rate	%
$\boldsymbol{n}$	Number of Observations or Rows	-
$\boldsymbol{N_p}$	Cumulative Oil Production	STB
$\boldsymbol{q}$	Fluid Flow Rate	STBD
$\boldsymbol{q_i}$	Initial Production Rate	STBD
$\boldsymbol{q_t}$	Production Rate at Time *t*	STBD
RMSE	Root Mean Square Error	-
$\boldsymbol{t}$	Real Time	Days, Months, or Years (Adjusted to unit of q, q_i, or q_t)
$\boldsymbol{yi}$	Actual Value	-
$\boldsymbol{\hat{y}}$	Predicted Value	-

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Appendices

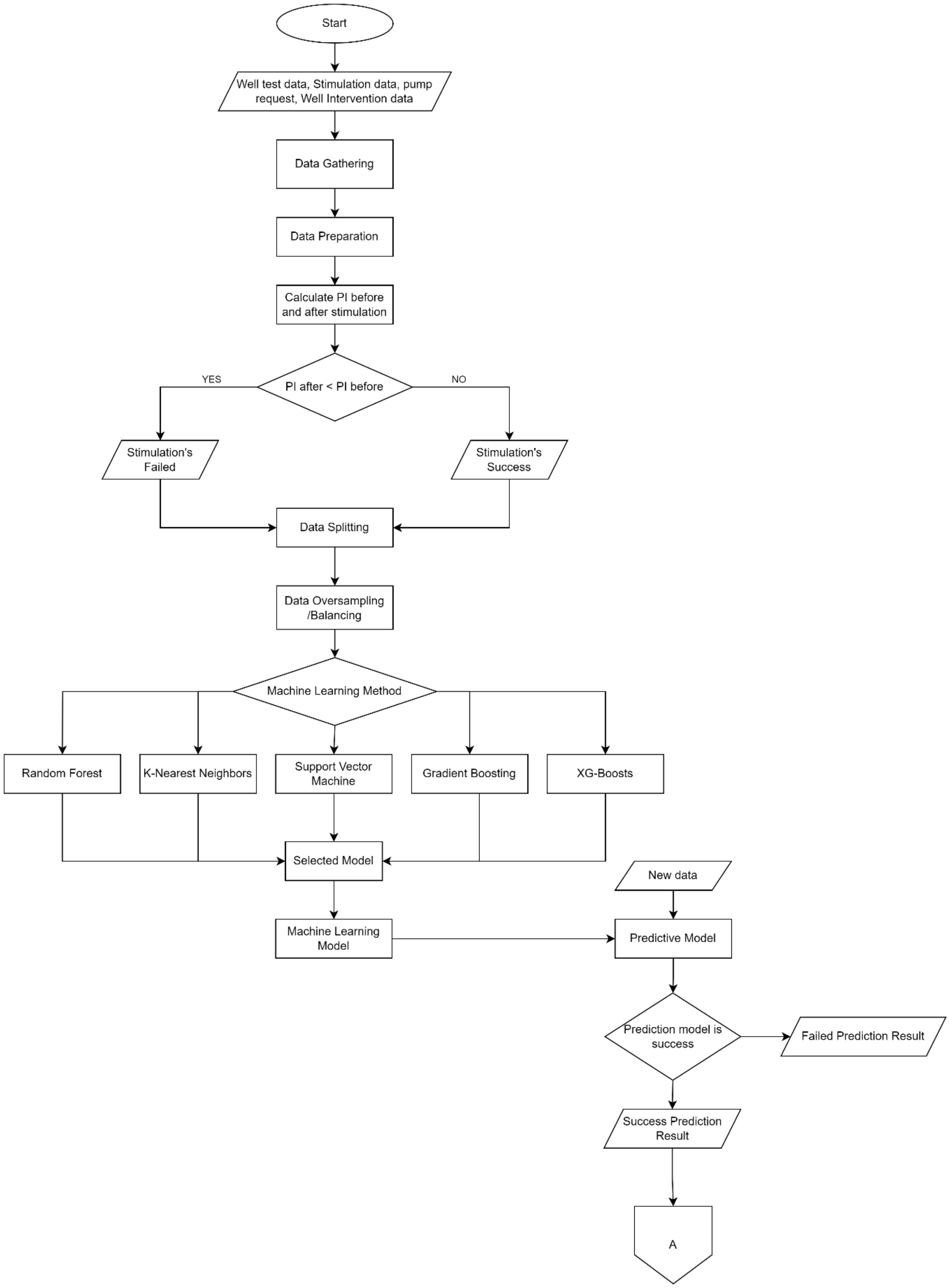

Figure 1. Study workflow part 1.

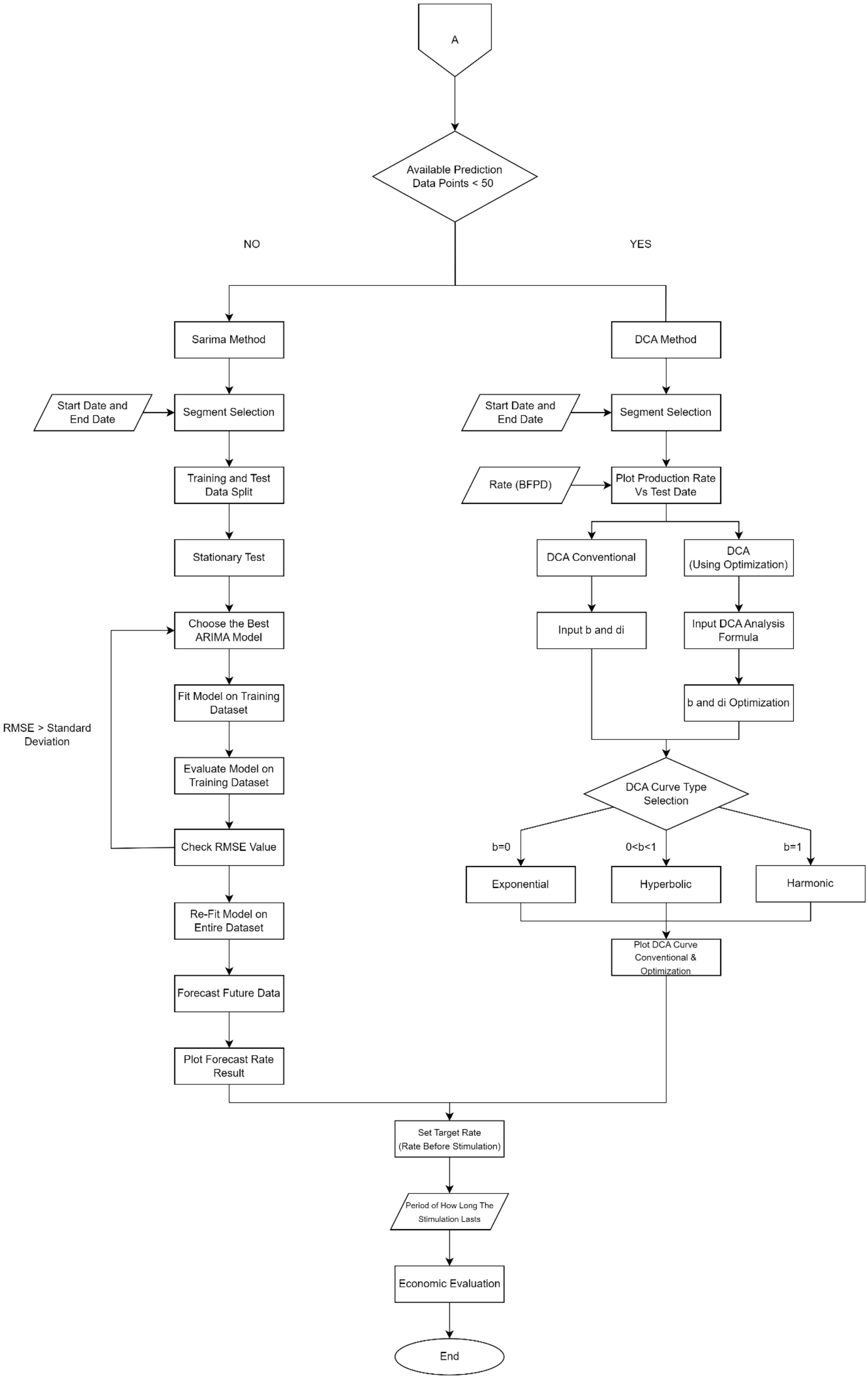

Figure 6. Study workflow part 2.

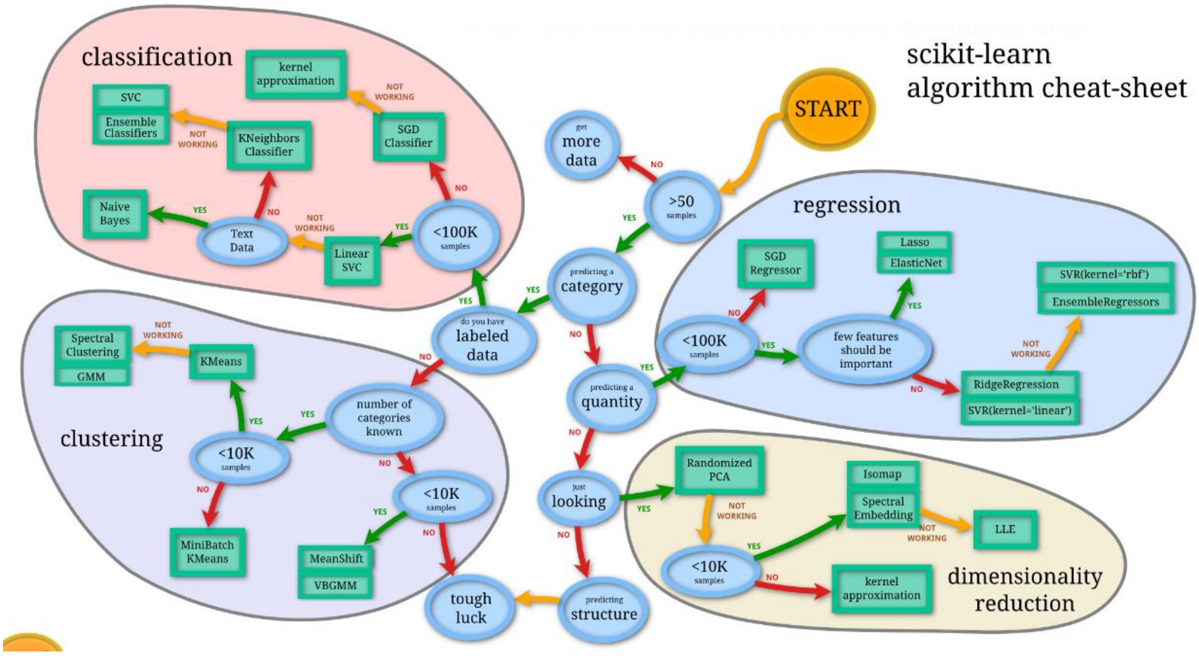

Figure 7. Machine learning data selection (Scikit-Learn, 2022).

Loss Ratio:

$$D = -\frac{dq/dt}{q} \quad (1)$$

Derivative of the Loss Ratio:

$$b = \frac{d}{dt}\left(-\frac{1}{D}\right) \quad (2)$$

Arps equation:

$$q(t) = \frac{qi}{(1 + bDit)^{1/b}}$$

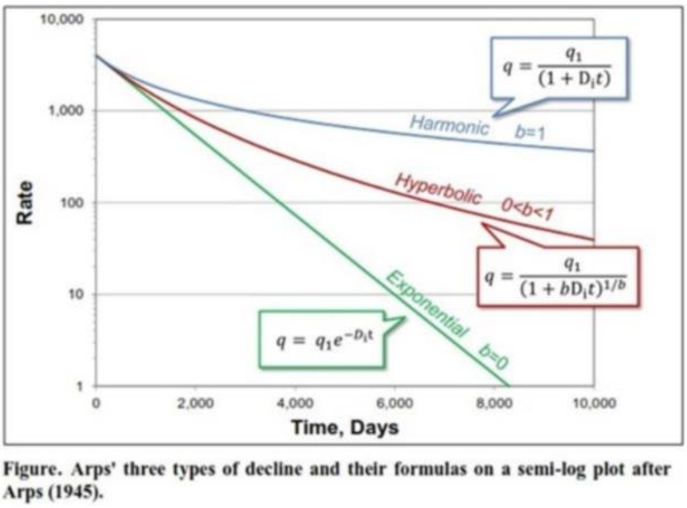

Figure 8. Concept of DCA equation (Arps, 1945).

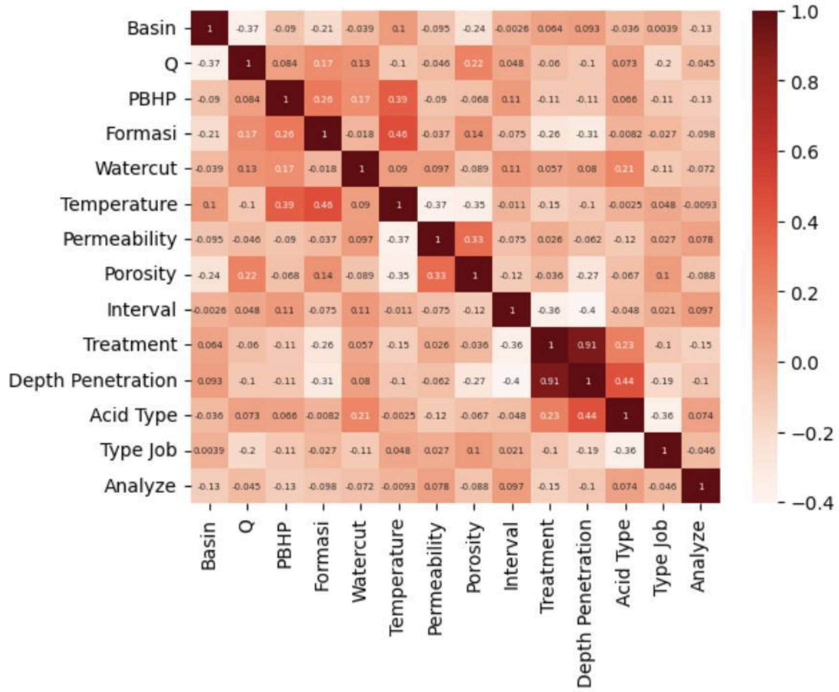

Figure 2. Heatmap parameter correlation.

Table 3. Comparison of splitting data 70% and 80% train data.

Model	Data Train 80%	Data train 70%
XG-Boost	69.44 %	75.93 %
Random Forest	71.65 %	71.44 %
Gradient Boosted Tree	65.22 %	63.51 %
KNN	64.53 %	62.65 %
SVM	58.32 %	60.34 %

Table 4. Algorithm evaluation.

Model	Best Accuracy	Precision	Recall	F1-Score	Specificity
XG-Boost	75.93 %	73.33 %	81.48 %	77.19 %	70.37 %
Random Forest	71.45 %	67.86 %	70.37 %	69.09 %	66.67 %
KNN	62.65 %	76.92 %	74.07 %	75.47 %	77.78 %
Gradient Boosted Tree	63.51 %	76 %	70.37 %	73.08 %	77.78 %
SVM	60.34 %	57.69 %	55.56 %	56.6 %	59.26 %

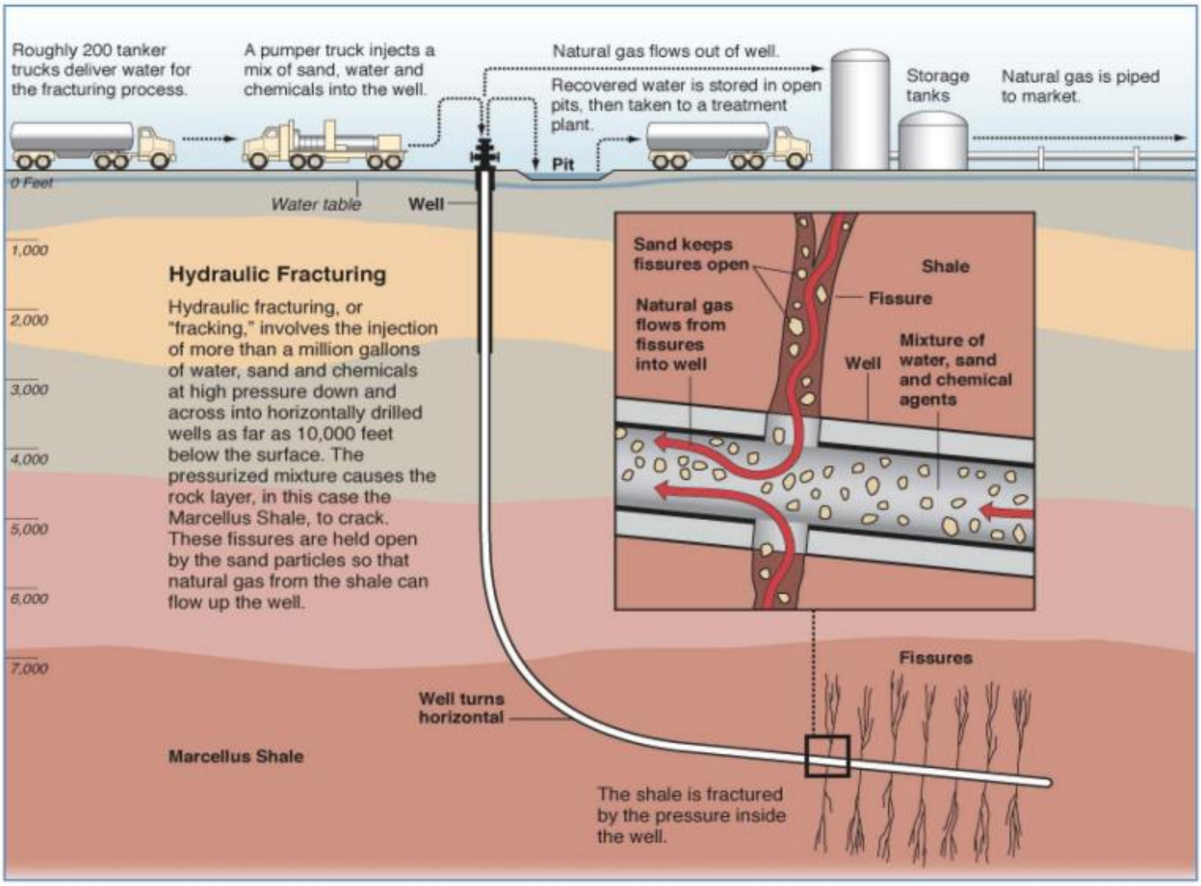

Figure 10. Overall general process of hydraulic fracturing (Yegin et al., 2017).

Figure 11. Illustration of matrix acidizing impact on the well (Dong et al., 2020).

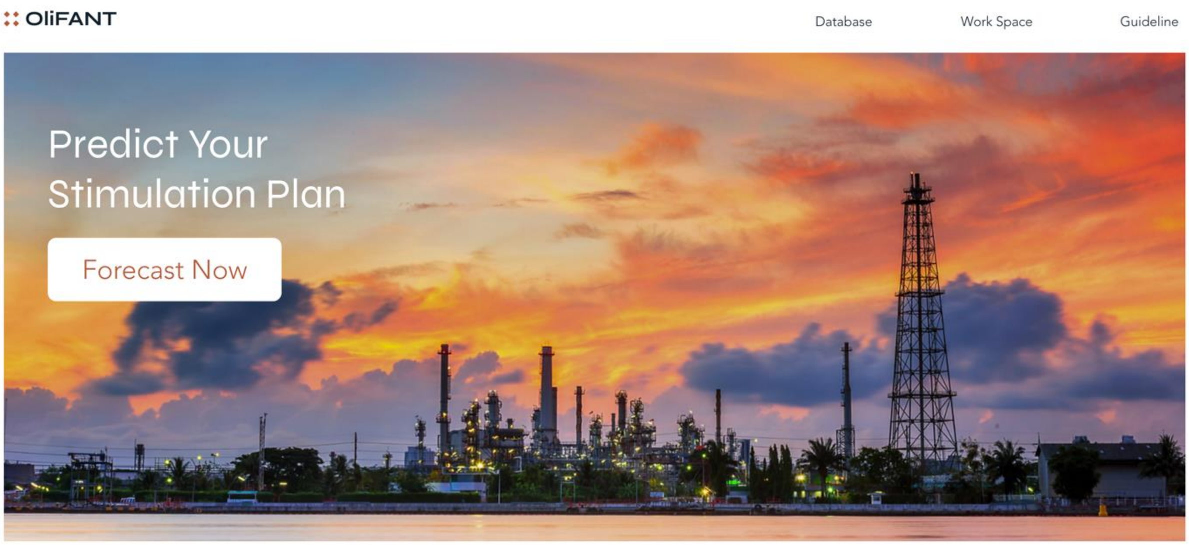

Figure 12. Planned user interface – introduction dashboard.

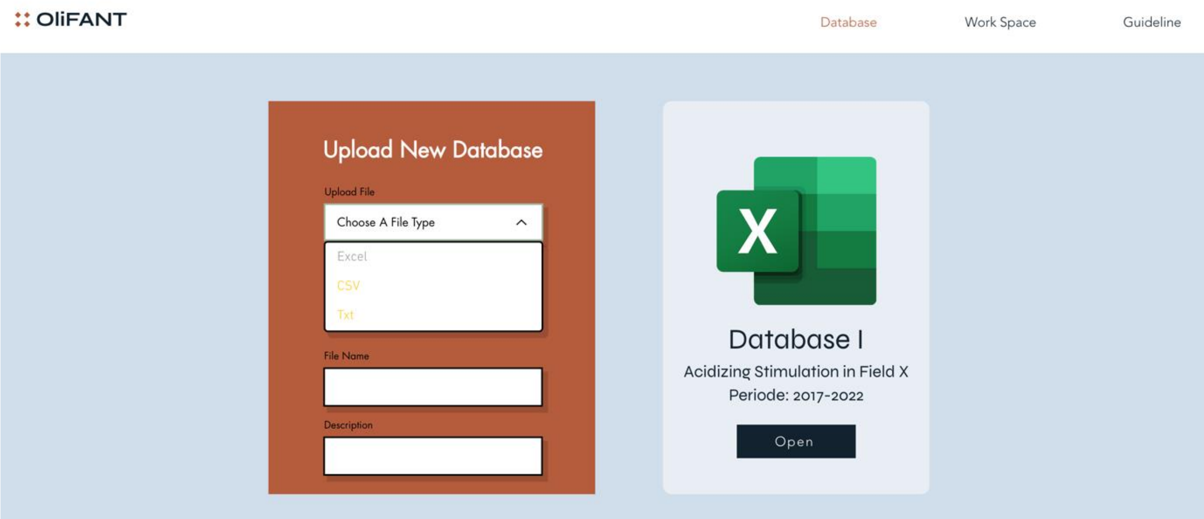

Figure 13. Planned user interface – database uploading dashboard.

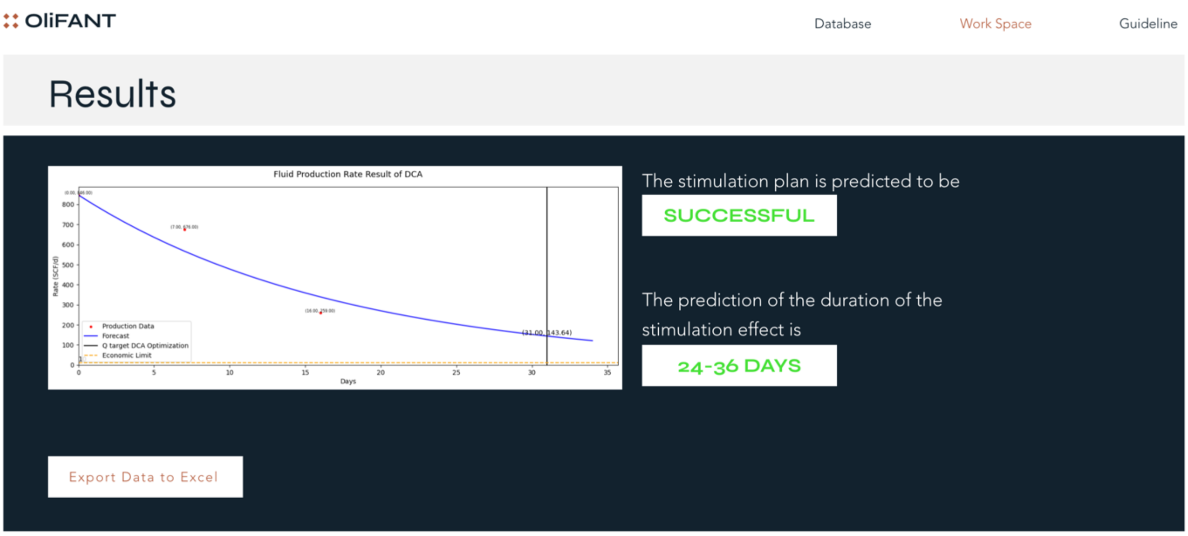

Figure 14. Planned user interface – program result and follow-up dashboard.

Figure 15. Planned user interface – stimulation plan input dashboard.