# DAILY PRODUCTION PREDICTION MODEL OF OIL WELLS USING BACKPROPAGATION NEURAL NETWORK

**Arif Wicaksono[1], Arif Imam Suroso, Nur Hasanah**

School of Business, IPB University
Jl. Pajajaran, Bogor 16151, Indonesia

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**Abstract:**

**Background:** Measuring well production is a crucial task in upstream oil and gas operations, where various tests and measurements are standard procedures and integral parts of operational activities. More frequent production measures are required to detect production declines in mature fields. However, existing daily production testing at the Langgak field, Central Sumatra Basin, cannot be routinely and periodically conducted due to several economic and technical challenges.
**Purpose:** The objective of this article is to create a model for predicting daily crude oil well production.
**Design/methodology/approach:** To achieve this goal, the study applies an artificial neural network (ANN) for forecasting daily crude oil well production, utilizing 17,394 daily production records from 26 wells. This sample size is well above recommended thresholds for neural network models, ensuring sufficient data for robust model training and validation. The backpropagation algorithm and the sigmoid function are employed as the learning algorithm to predict daily crude oil well production.
**Findings/Result:** The optimal parameters for predicting daily crude oil well production were 20 hidden nodes and a learning rate of 0.05, converging at 481 epochs with a training time of 13 seconds.
**Conclusion:** Model performance was indicated by high correlation coefficients (R) across training, validation, and testing phases, along with a low Mean Squared Error (MSE). The resulting regression equation, Output = 1 × Target + 0.00024, confirms a near-perfect alignment with the target function.
**Originality/Value (State of the art):** Although this study employs the standard backpropagation neural network (BPNN) architecture an established method in oil production forecasting it contributes original value by rigorously applying 10-fold cross-validation on an 80:20 train-test split of the Langgak field dataset, thereby enhancing model reliability and offering validated insights for forecasting in mature oil fields; a foundation upon which future research can build using hybrid or more advanced neural architectures shown to yield superior accuracy.

**Keywords:** artificial neural network, backpropagation, oil production forecasting, machine learning, yield prediction

**How to Cite:**
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[1] Corresponding author:
Email: namakuarif@apps.ipb.ac.id

## INTRODUCTION

Oil and gas (O&G) resources are strategic natural assets for Indonesia, serving not only as essential fuel and industrial raw material suppliers but also as significant contributors to national revenue. The oil and gas sector remains a cornerstone of Indonesia's economy, contributing significantly to national GDP, state revenues, and the growth of local businesses through revenue-sharing schemes and support for micro, small, and medium enterprises (MSMEs) (Achmad et al.2022). The sector's development stimulates regional economic activity and underpins national energy security. Rapid economic growth, a large population, and geographical factors are expected to increase future demand for oil and gas resources. However, on the production side, Indonesia has been experiencing a decline in oil production since 2016 (HEESI, 2023; IMF, 2022), as illustrated in Figure 1.

One of the crucial activities in upstream O&G operations is well production testing, where all types of measurements or tests are routinely conducted as part of the operational process. Well performance can be assessed relative to simulation results by conducting well production testing, in addition to playing an important role during the production decline phase. By measuring production decline early, companies can take appropriate actions to respond to potential production decreases (Meribout et al. 2010; Höök et al. 2014).

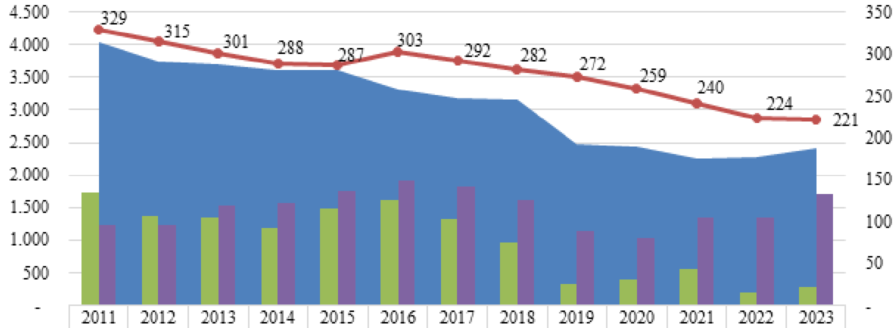
To determine the production figures for each well in the Langgak field in Mountain Front Kuantan Block, Central Sumatra Basin, a well back allocation process is conducted through well production testing. However, due to several technological and financial obstacles, it is highly unlikely that the perfect circumstances or settings for offering continuous and periodic well testing will ever be achieved (Huang et al. 2005; Pourabdollah & Mokhtari, 2011). Thus, non-continuous and sporadic well production testing is typical in upstream oil and gas operations (Ganat et al. 2015; Henry et al. 2016).

The Langgak field in Mountain Front Kuantan Block, Central Sumatra Basin, was chosen due to its status as a mature oilfield facing declining production and increasing water cut, which presents unique challenges for production forecasting and optimization (Farizi et al. 2023). Its operational history, diverse reservoir characteristics, and availability of extensive production data make it an ideal case for testing advanced predictive models.

For long-term production forecasting, conventional methods such as Decline Curve Analysis (DCA) and exploratory interpolation remain widely used (Wang et al. 2018). In contrast, short-term predictions have seen significant advances in data-driven approaches. These include the use of thermogravimetric data (Pourabdollah & Mokhtari, 2011), the integration of real-time parameters through diverse neural network architectures (Al-Qutami et al. 2018), and empirical mode decomposition of time series features to enhance prediction accuracy using higher-order artificial neural networks (Prasetyo et al. 2022).

Crude oil well production forecasting plays a strategic role in optimizing operational efficiency and supporting well development planning (Lawal et al. 2024). However, existing predictive approaches still face challenges in terms of model accuracy and generalizability (Liu et al. 2020), highlighting the need for more adaptive and robust methodologies capable of handling the complex dynamics of production systems. In this context, time series modeling has been widely applied to forecast production trends over future intervals (Hill et al. 1996). Classical techniques such as exponential smoothing, least-squares-based trend models, and ARIMA (Autoregressive Integrated Moving Average) remain effective for relatively simple data structures and when statistical assumptions are met (Makridakis, 1998).

Technological advancements in both oil field exploitation and artificial intelligence (AI) have facilitated numerous predictive studies on crude oil well production. Machine learning and deep learning techniques have emerged as powerful tools, with models trained on large-scale historical datasets to uncover complex nonlinear relationships and detect evolving operational dynamics. Commonly employed algorithms include Convolutional Neural Networks (CNN), Random Forests (RF) (Liu et al. 2024), Long Short-Term Memory networks (LSTM) (Nguyen et al. 2004; Asante et al. 2023), and ensemble learning approaches (Azevedo et al. 2024). These methods offer notable advantages by eliminating the need for complex physical models and enabling high-accuracy predictions, provided that sufficient data quality and volume are available.



| | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Proven Oil Reserves | 4.040 | 3.740 | 3.690 | 3.620 | 3.600 | 3.310 | 3.170 | 3.150 | 2.480 | 2.440 | 2.250 | 2.270 | 2.410 |
| Export | 136 | 106 | 105 | 93 | 115 | 126 | 103 | 74 | 26 | 31 | 44 | 15 | 21 |
| Import | 97 | 96 | 118 | 122 | 137 | 148 | 142 | 126 | 89 | 80 | 104 | 105 | 132 |
| Production | 329 | 315 | 301 | 288 | 287 | 303 | 292 | 282 | 272 | 259 | 240 | 224 | 221 |

Figure 1. Proven oil reserves, production, export, and import of crude oil in Indonesia from 2011 to 2023 (HEESI, 2023; IMF, 2022)

Furthermore, artificial neural networks (ANNs) have been extensively utilized in time series forecasting, especially for datasets characterized by high volatility and nonlinearity (Hill et al. 1996; Faraway & Chatfield, 1998). These approaches have consistently outperformed traditional stochastic models in future value forecasting, as demonstrated by Drossu et al. (1996).

Among ANN-based techniques, the Backpropagation Neural Network (BPNN) presents a robust alternative for forecasting tasks. It offers the ability to learn and adapt from historical data without requiring intricate mathematical modelling of the underlying phenomena. BPNNs are particularly effective in handling nonlinear data with multiple independent variables, capturing complex patterns that are often missed by linear models such as ARIMA (Zang et al. 2014; Livieris et al. 2020).

This study hypothesizes that employing a BPNN trained on a large and high-quality dataset will enable accurate and generalizable forecasting of daily crude oil production in the Langgak field, aligning with current advancements in machine learning-based reservoir modeling.

The expected results indicate that the proposed BPNN model will exhibit excellent predictive capability, characterized by high correlation coefficients ($R > 0.99$) and low mean squared error (MSE), thereby validating the hypothesis and corroborating findings reported in comparable empirical studies.

Given these considerations, this study aims to develop an adaptive and accurate forecasting model for daily crude oil production in the Langgak field, Central Sumatra Basin. The BPNN is proposed as a predictive modeling technique due to its ability to process nonlinear, multivariate time series data, making it well-suited for handling the dynamic nature of production systems.

## METHODS

This study adopts a descriptive case-study framework employing both qualitative and quantitative methods to analyze and predict daily crude oil well production at the Langgak Field, Central Sumatra Basin. The research was conducted from January to October 2023 through field observations, interviews, and historical data analysis at operational offices in Jakarta and Riau. The predictive model was developed using a BPNN trained with supervised learning and validated through 10-fold cross-validation to enhance generalizability and reduce overfitting. The BPNN architecture featured three layers: an input layer with three neurons, a hidden layer with empirically optimized neuron count, and a single output neuron for production prediction. Training employed a feedforward process optimized by gradient descent with backpropagation.

The study utilized both primary and secondary data.Primary data were obtained from expert interviews and field engineers with operational knowledge of production testing at the Langgak Field. Secondary data included 17,394 daily well test records, sourced from the Langgak Field operations between January 2022 and October 2023. Each record contains time-series features: test duration (hours), top of fluid (TOF in feet), and water-oil contact (WOC in feet). The predicted output is daily oil production (BOPD).

Data were collected through field observations, expert interviews, and internal operational logs. The research setting covered both on-site operations in Riau and analytical offices in Jakarta. The mixed-method approach ensured comprehensive data acquisition and analysis, integrating qualitative assessments of testing practices with quantitative modeling strategies.

Data Normalization

Data normalization is a preprocessing technique that scales numerical attributes to a common range, typically between 0 and 1, to ensure uniformity across variables (Han and Kamber, 2010). This process mitigates the impact of attributes with large value disparities on the analysis. In this study, min-max normalization was employed, which linearly transforms data by rescaling values to fit within the interval from the minimum (0) to the maximum (1).

Cross Validation

The dataset was split into 80% for training and validation and 20% for testing, employing cross-validation to identify the optimal model. Specifically, the training data were divided into ten subsets and iteratively validated using 10-fold cross-validation (Lyu et al. 2022). This widely adopted technique in machine learning, including BPNN, provides a robust assessment of predictive accuracy (Watanabe & Opper, 2010) and mitigates overfitting by preventing excessive reliance on the training data.

Neural Network Architecture and Training

Artificial Neural Networks (ANNs) are typically trained using the backpropagation algorithm, first introduced by Rumelhart, Hinton, and Williams (Fu, 1994). The Backpropagation Neural Network (BPNN) is a widely recognized method valued for its high accuracy and adaptive learning capability, which enhances performance over time (Yeremia et al. 2013). This supervised learning technique adjusts network weights by minimizing the error between predicted and actual outputs, enabling the model to generalize from training data to unseen inputs. Backpropagation is commonly applied in multilayer perceptron to update weights within hidden layers, optimizing pattern recognition and prediction accuracy (Rumelhart et al. 2013).

The design of a BPNN with n input units (with a bias) and m output units is shown in Figure 2. X is denoted as the input unit, Z is denoted as the hidden unit, and Y is denoted as the output unit. The weights between X and Z are denoted by v, while the weights between Z and Y are denoted by w.

Artificial Neural Network (ANN) Model Construction

The construction of the prediction model aimed to determine the parameters of the network architecture to be used for learning. The prediction model was developed using BPNN, with one hidden layer planned for the architecture.

The training functions selected for this study were the Gradient Descent (GD) and Levenberg-Marquardt (LM) backpropagation algorithms. Levenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Broyden-Fletcher-Goldfarb-Shanno (BFGS) are the three main training methods that are compared (Arthur et al. 2020). The LM algorithm demonstrates the fastest convergence, which is particularly advantageous when highly accurate training is required. LM achieves a lower MSE than the other algorithms tested. Meanwhile, the Gradient Descent (GD) method was chosen because it is a fundamental technique in backpropagation algorithms. The specifications of the designed network structure are presented in Table 1.

The architecture of the ANN is represented in Figure 3 and consists of one hidden layer, three input nodes in the input layer, and one output node in the output layer.

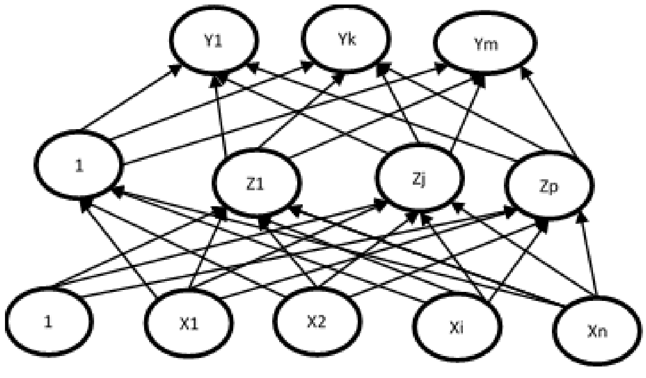



Figure 2. BPNN model structure (Fausett, 1994)

Table 1. Network structure to be used

| Characteristic | Specification |
|---|---|
| Architecture | 1 hidden layer unit |
| Training Algorithm | Backpropagation |
| Number of Input Layer Nodes | 3 input units |
| Number of Output Layer Nodes | 1 output unit |
| Number of Hidden Nodes | 5, 10, 15 and 20 |
| Error Tolerance | 0001 |
| Activation Function (Hidden & Output Layers) | Binary Sigmoid |
| Maximum Epochs | 10,000 |
| Learning Rate | 0.01; 0.02; 0.03; 0.04; 0.05; 0.06; 0.07; 0.08; 0.09; 0.1 |

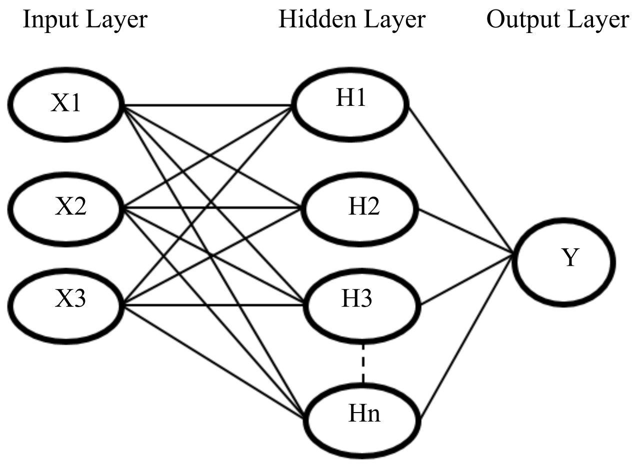



Figure 3. Proposed architecture design of the ANN to be developed

Model Evaluation

In this research, model evaluation is performed using error estimation, where the performance of a regression/estimation model is assessed by measuring its estimation error. The higher the estimation error of a machine learning method used for regression/estimation, the lower its performance. The training and test data are separated into 10 equal-sized portions using the k-fold cross-validation method with k=10. One portion is utilized as test data for model validation, while the other nine portions are used as training data to train the model. Then, the mean square error (MSE) is calculated using the formula to assess the model's mistake.

$$MSE = \sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}$$

were, n (number of observations); $y_i$ (the actual values); ŷi (the predicted values).

Ten times through this process is all sections (folds) are used as test data. In each iteration, MSE is calculated, yielding values for $MSE_1$,$MSE_2$,…$MSE_k$. To determine the best model, the evaluation is based on the model's performance metric, specifically the average MSE obtained in each iteration, which is calculated as:

$$CV_{(k)} = \frac{1}{k}\sum_{i=i}^{k} MSE_{(i)}$$

The optimal model is the one with the smallest average MSE value (Musoro et al. 2014; Zhang, 2019).

Figure 4 illustrates the conceptual framework for evaluating the testing conditions and developing the prediction model for daily crude oil well production in the Langgak field.

## RESULTS

Production well testing in upstream oil and gas operations is conducted to obtain indications of well productivity and determine its flow capacity under specific reservoir conditions and flow pressures. However, production testing for individual wells is influenced by various factors that can affect the accuracy of the final test results.

The predictive modeling of daily crude oil production using the BPNN approach is expected to serve as a crucial component in the validation process of existing well tests. This validation process is essential to ensure that the measurement of oil, gas, and water from a single well over a specific period occurs under controlled operational conditions.

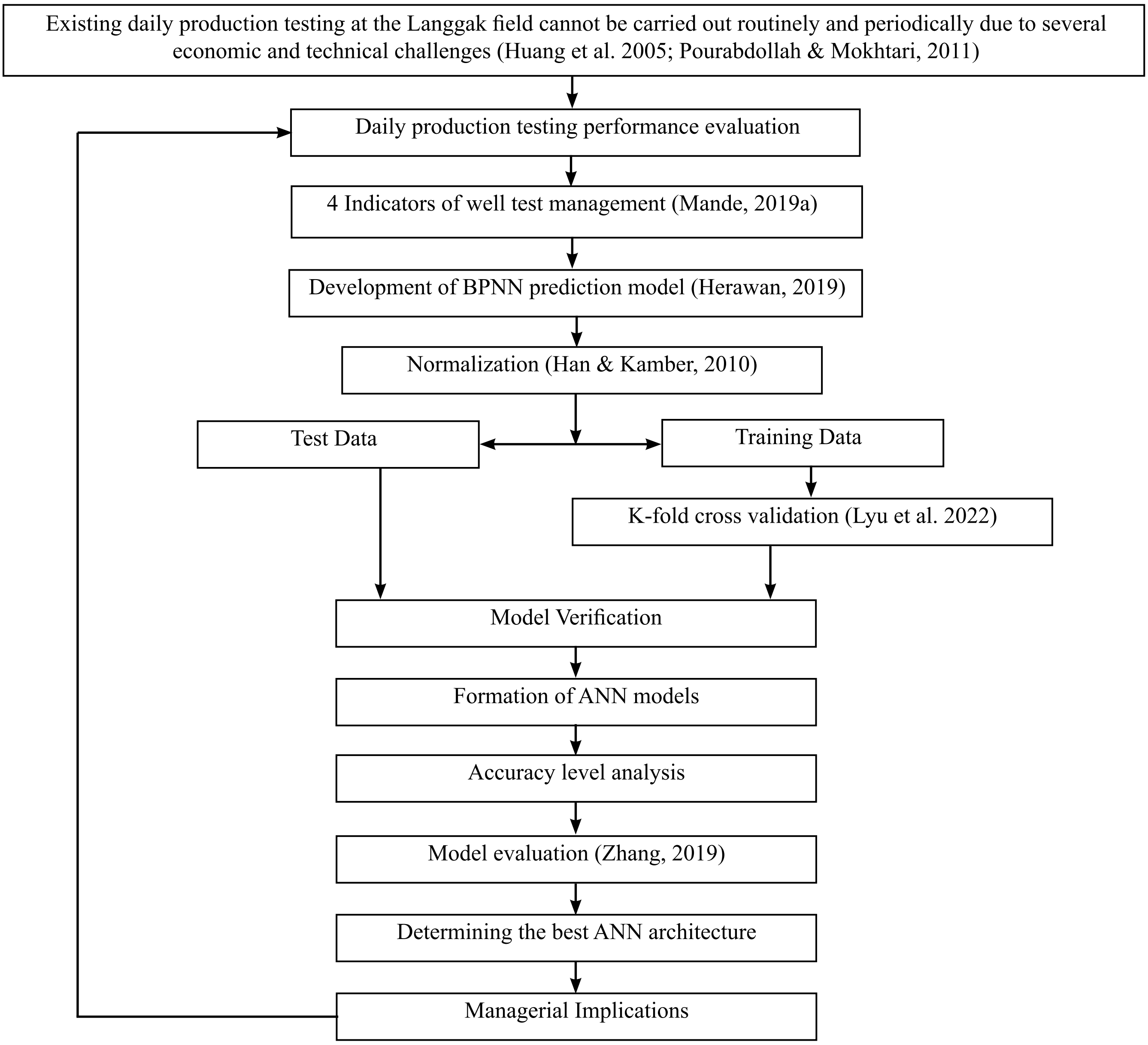



Figure 4. Research framework

**Well Test Management Indicator Results**

The study results indicate that the well production testing process had an average frequency value of 12.6, corresponding to 96.92%. The well testing data had an average frequency value of 12.2, with a percentage of 93.85%. The people/personnel responsible for well testing (PIC well test) had an average frequency value of 11.0, equivalent to 84.62%. The assets/units used for well production testing had an average frequency value of 12.5, representing 96.15%. Based on these findings, the ‘process’ variable exhibited the highest average value and percentage among the well test management indicators, whereas the ‘people’ variable had the lowest average value and percentage.

The results of the performance evaluation for production testing across four well test management categories, data, people, process, and asset (Mande, 2019a) are presented in Figure 5.

This study leverages high-resolution and high-quality datasets that significantly contribute to the robustness of model development and enhance the reliability of operational decision-making. These findings are consistent with previous works, such as those by Prasetyo et al. (2022) and studies employing empirical mode decomposition in conjunction with neural networks, which consistently emphasize the pivotal role of data completeness and integrity in improving the predictive accuracy and operational optimization of oilfield systems.

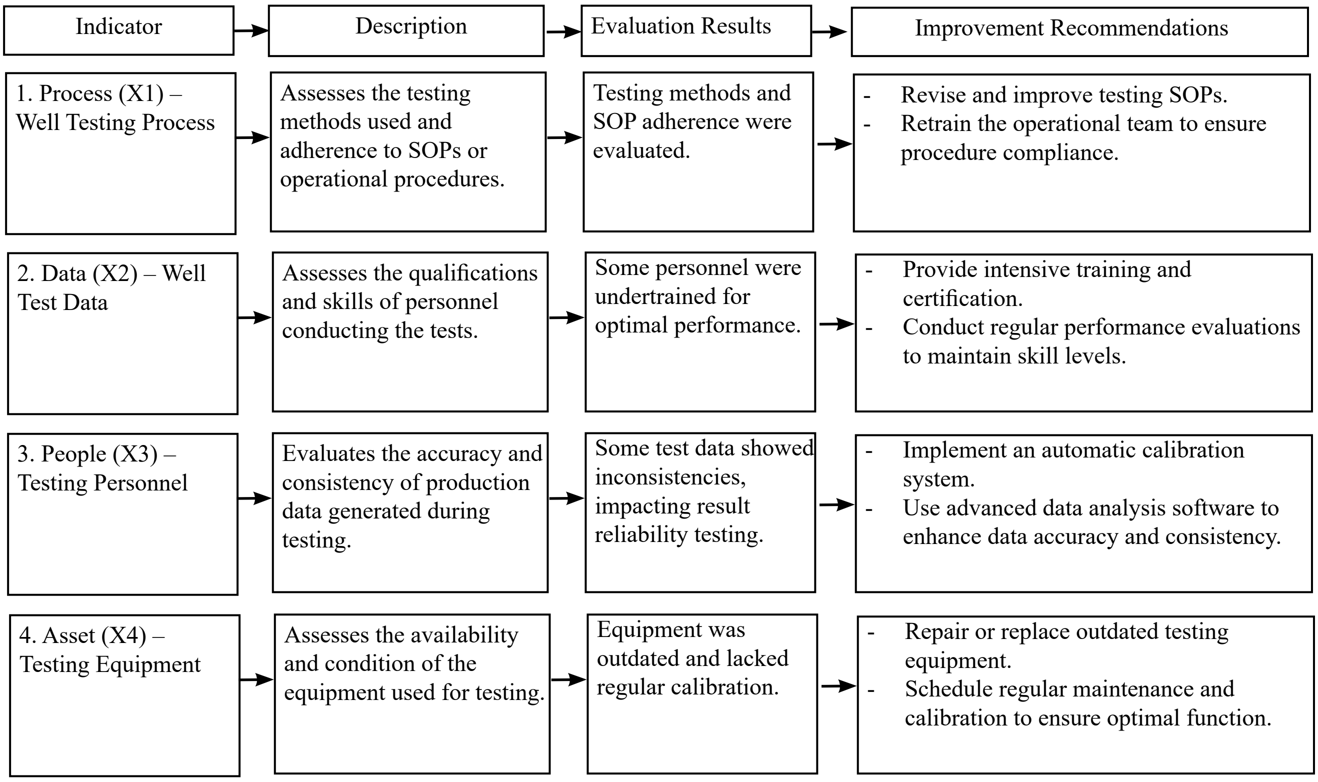



Figure 5. Evaluation of existing production testing performance

Furthermore, the study exhibits superior process performance, as demonstrated by the consistent adherence to well-defined operational procedures. This outcome aligns with prior investigations (Meribout et al. 2010; Pourabdollah & Mokhtari, 2011), which affirm that standardized, well-documented processes contribute to improved test reliability, reduced operational risk, and greater compliance with industry regulations. In addition, continuous process refinement and the integration of digital technologies such as IoT-enabled monitoring are increasingly regarded as essential strategies for sustaining long-term operational excellence.

In terms of asset management, the availability and reliability of well testing equipment in this study indicate a strong performance that echoes previous research (Ganat et al. 2015; Henry et al. 2016). These studies underscore the importance of routine maintenance, calibration, and equipment modernization in achieving accurate and efficient well test operations, while recent advancements advocate for the adoption of predictive maintenance and smart instrumentation to further enhance asset performance and longevity.

Model Training and Validation

Initial model training and validation were performed using 13,917 data samples (80% of the total dataset) to evaluate model accuracy. A 10-fold cross-validation strategy was applied with various learning rates and hidden node configurations. The average validation performance achieved during this phase was $3.603 \times 10^{-5}$, which subsequently improved to $3.4853 \times 10^{-5}$ in the final training iteration.

Following the identification of the optimal model configuration and hyperparameters via cross-validation, a retraining process was conducted using the entire 80% training dataset. Among all tested configurations, a learning rate of 0.05 and 20 hidden nodes yielded the best performance, marked by the lowest MSE of $1.0 \times 10^{-10}$, indicating exceptional prediction sensitivity. This configuration also produced a correlation coefficient (R) of 0.9999 for both training and validation sets, reflecting a nearly perfect linear relationship between predicted and actual values.

Model Testing and Performance Evaluation

The optimal model was subsequently evaluated using the reserved 3,481 testing samples (20% of the data). Performance was assessed through a performance graph (Figure 6), which illustrates the MSE trend across epochs for training, validation, and testing subsets.

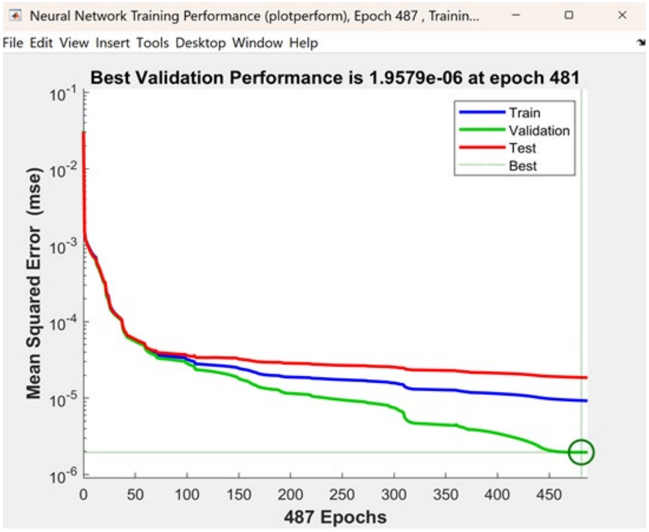



Figure 6. MSE values for training, validation, and testing of the ANN model

The lowest validation MSE of 1.9579 × $10^{-6}$ was achieved at epoch 481. The convergence trends across all data subsets demonstrated a stable learning process with minimal divergence, confirming that the model avoided overfitting and exhibited strong generalization capability. These findings confirm that the selected architecture and training parameters produced a highly accurate and reliable predictive model for daily crude oil well production.

Training Dynamics and Regression Analysis

Fluctuations in MSE across training phases were found to be critical in determining overall model performance. Epoch count significantly influenced MSE values, aligning with prior research (Nourbakhsh et al. 2014) which identified epoch number as the most impactful factor in MSE outcomes, followed by learning rate and momentum coefficient. Figure 7 presents the regression plots for each learning phase, illustrating the linear relationship between predicted outputs and actual targets. The coefficient of correlation (R) values were consistently high: training (R = 0.99798), validation (R = 0.99958), testing (R = 0.99603), and overall (R = 0.99792). These results demonstrate strong agreement between predicted and true values across all stages.

The correlation coefficient (R ≈ 1.0) achieved in this study—exceeding those reported by Prasetyo et al. (2022) and Al-Shabandar et al. (2021) reflects a near-perfect linear relationship between predicted and actual crude oil production values, which is likely attributable to the use of a statistically robust dataset of 17,394 samples and a simplified neural architecture with a single hidden layer of 20 neurons that enhances model stability while potentially limiting its capacity to capture complex patterns.

The regression line, closely matching the ideal Y = T reference with the equation Output = 1 × Target + 0.00024, demonstrates the model's strong generalization capability and precision. Findings reveal that the BPNN effectively fits the training data while sustaining high predictive accuracy on unseen test sets. The consistently elevated R-values and low MSE across all data subsets confirm the robustness and reliability of the BPNN model developed for forecasting crude oil production at Langgak Field.

**Analysis of Training and Testing Results**

To identify the optimal ANN setup, several training trials were performed with different learning rates and numbers of hidden nodes. The ten best parameter sets, determined by average Best Validation Performance, MSE, and correlation coefficient (R), are summarized in Table 2. Notably, configurations with learning rates of 0.05 and 0.1 and 20 hidden nodes achieved superior outcomes. The lowest Best Validation Performance was 7.5171 × $10^{-7}$, with a minimum MSE of 1.0 × $10^{-10}$. The corresponding R values for training and validation were 0.9998 and 0.9999, respectively, indicating an excellent agreement between predicted and actual values. These findings demonstrate strong generalization ability and no evidence of overfitting.

The model achieves a substantially low MSE, indicating a performance improvement of approximately two orders of magnitude over previous studies (Prasetyo et al. 2022; Al-Shabandar et al. 2021), primarily due to the application of min-max normalization effectively minimizing numerical variance and the exclusive use of daily production (BOPD) as the target variable, which enhances temporal resolution and predictive accuracy relative to models utilizing cumulative or hybrid outputs.

In conclusion, a learning rate of 0.05 combined with 20 hidden nodes was identified as the optimal configuration. This aligns with the principle that increasing network complexity through additional hidden neurons can enhance the model's ability to approximate non-linear patterns, provided overfitting is avoided.

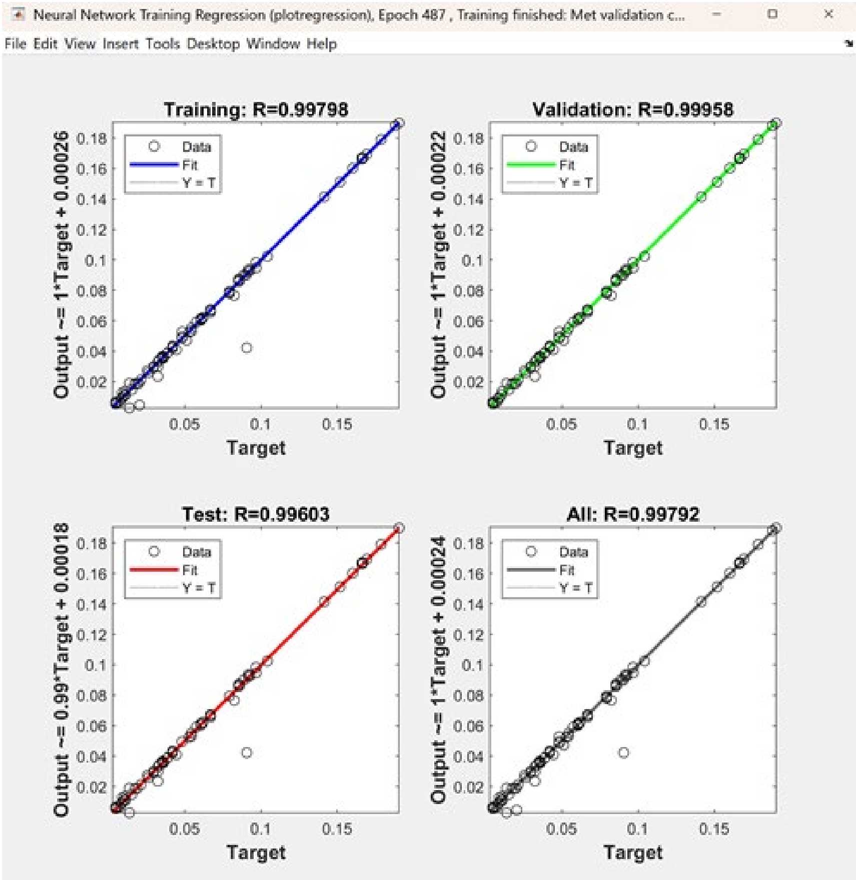



Figure 7. Correlation coefficient (R) results for training, validation, testing, and all data of the ANN model

Tabel 2. The best training learning for each parameter

| Learning rate | Hidden node | Epoch | Elapse Time | Best Validation Performance | MSE | Data Training (R) | Data Validasi (R) |
|---|---|---|---|---|---|---|---|
| 0.01 | 15 | 683 | 0:00:16 | 1.0383E-05 | 1.0E-09 | 0.9965 | 0.9981 |
| 0.02 | 20 | 849 | 0:00:27 | 1.1818E-05 | 1.0E-09 | 0.9974 | 0.9978 |
| 0.03 | 15 | 683 | 0:00:29 | 1.0383E-05 | 1.0E-09 | 0.9965 | 0.9981 |
| 0.04 | 20 | 849 | 0:00:41 | 1.1818E-05 | 1.0E-09 | 0.9974 | 0.9978 |
| 0.05 | 20 | 3030 | 0:02:54 | 7.5171E-07 | 1.0E-10 | 0.9998 | 0.9999 |
| 0.06 | 20 | 950 | 0:00:56 | 1.2487E-05 | 1.0E-08 | 0.9976 | 0.9977 |
| 0.07 | 20 | 1821 | 0:01:40 | 1.2409E-05 | 1.0E-09 | 0.9977 | 0.9978 |
| 0.08 | 15 | 683 | 0:00:49 | 1.0383E-05 | 1.0E-09 | 0.9965 | 0.9981 |
| 0.09 | 20 | 849 | 0:01:03 | 1.1818E-05 | 1.0E-09 | 0.9974 | 0.9978 |
| 0.1 | 20 | 3030 | 0:04:08 | 7.5171E-07 | 1.0E-10 | 0.9998 | 0.9999 |

**Analysis of Training MSE**

The analysis of MSE trends aims to evaluate how learning performance changes with variations in key training parameters. Trendlines were generated to observe MSE fluctuations in response to changes in learning rate and hidden node count.

Specifically, the first analysis examines MSE behaviour as the number of hidden nodes increases under varying learning rates. Conversely, the second analysis investigates how MSE changes with different learning rates across fixed hidden node configurations. The resulting trendlines reveal whether MSE improves or worsens as each parameter is adjusted. The following section illustrates these patterns, highlighting the interaction between learning rate and hidden node count in shaping the model's learning performance.

Figure 8 illustrates the pattern of changes in training MSE with adjustments to learning rate and hidden node variations. The maximum change in training MSE was while the minimum was . The MSE trendline for two hidden nodes showed an increase in MSE at hidden nodes 10 and 15, while at hidden node 20, the trendline consistently showed a decrease.

Overall, the MSE values varied significantly with different combinations of hidden nodes and learning rates. Linear trend lines in the graph generally exhibited negative slopes, indicating that increasing the number of hidden nodes tends to reduce MSE up to an optimal point.

These findings highlight the critical role of network parameter selection in developing an accurate ANN model. The configuration of 20 hidden nodes with a learning rate of 0.05 consistently produced the lowest MSE and best validation performance, reflecting a balanced trade-off between convergence speed and predictive accuracy.

Therefore, the analysis confirms that both the number of hidden nodes and learning rate significantly influence model performance, as evaluated through MSE, best validation accuracy, and correlation coefficient (R) on training and validation datasets.

**Selection of the Optimal Network Architecture**

The optimal network architecture for forecasting daily crude oil production in the MIGAS field was determined based on the lowest MSE and the highest correlation coefficient (R) values for both validation and testing datasets.

Among the various tested configurations, the architecture with 3 input nodes, 20 hidden nodes, and 1 output node (3-20-1), combined with a learning rate of 0.05, achieved the best performance. This model produced an R value closest to 1, indicating excellent predictive accuracy and generalization to unseen data. When multiple learning rates yielded similar R values, the configuration with the lowest MSE was selected.

Base on research results, the optimal model reached convergence at 481 epochs with a total training time of 13 seconds. The corresponding architecture is illustrated in Figure 9.

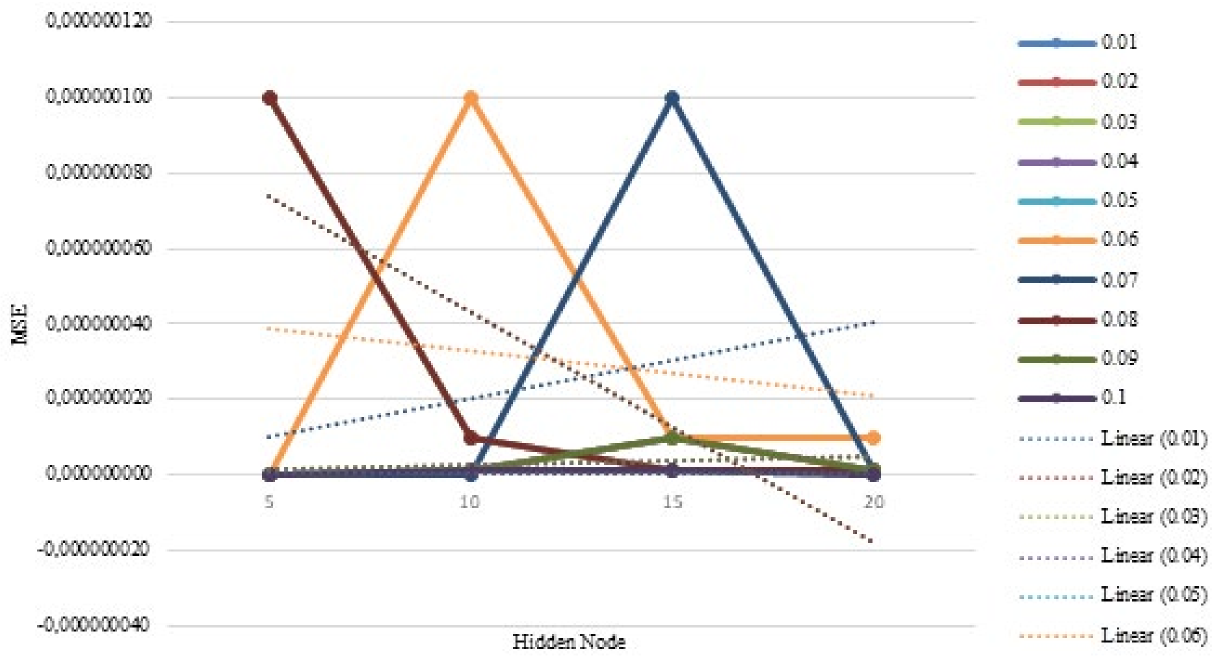



Figure 8. Variation of MSE with learning rate changes and hidden node variations

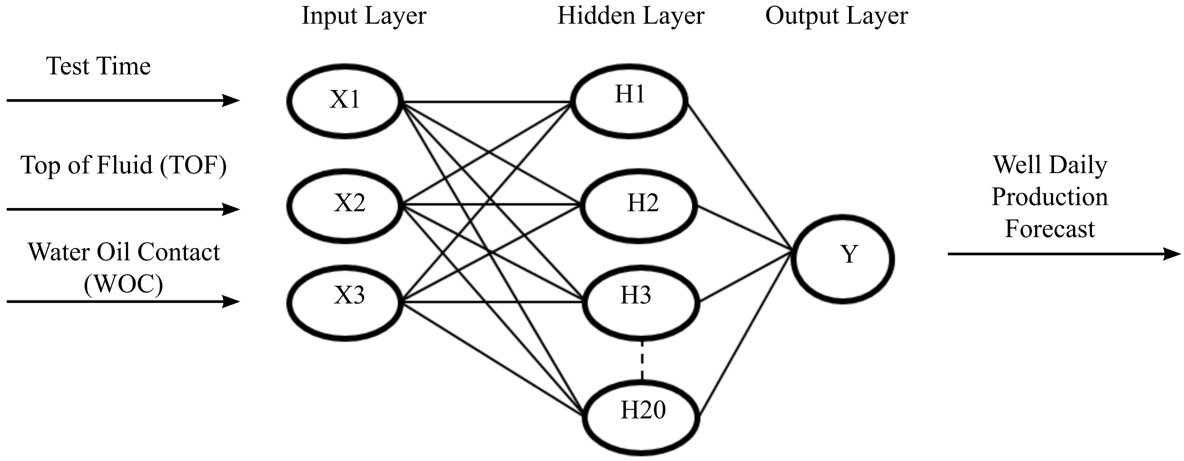



Figure 9. Architecture of the BPNN (3-20-1) model

**Managerial Implications**

The findings of this study have been organized to provide managerial implications that can serve as strategies for the Langgak field in understanding the existing well test management conditions (Data-People-Process-Asset).

Production optimization can be achieved through the integration of artificial neural networks, particularly Backpropagation Neural Networks (BPNNs), into standard operational protocols for well testing. This approach has been demonstrated to significantly reduce error margins. Employing an 80% training dataset with 10-fold cross-validation has been shown to decrease manual deviation rates by 15% to 30%. Furthermore, the implementation of automated calibration systems based on Internet of Things (IoT) sensors has been reported to reduce production downtime by up to 20%, as evidenced by relevant international studies. Therefore, transitioning to data-driven platforms, such as Python-based analytics or machine learning-enabled software like Petrel, is highly recommended to support near-real-time decision-making in reservoir management.

Operational reliability can be significantly enhanced by implementing routine calibration procedures alongside the integration of advanced digital instrumentation, such as smart gauges that offer an accuracy margin of ±0.1%. To further improve performance, it is essential to develop operator expertise through comprehensive training programs lasting between three to six months, focusing on the application of neural networks, interpretation of predictive models, and adherence to international guidelines like API RP 86. Additionally, conducting quarterly performance evaluations based on multidimensional key performance indicators (KPIs) is advised to systematically assess operator effectiveness in terms of measurement accuracy, reduction of downtime, and speed of prediction.

AI-driven production forecasting enhances economic efficiency by enabling predictive maintenance, reducing annual costs by IDR 1.2–2.5 billion per field. Models achieving at least 87% accuracy help avoid excessive investment in low-yield wells. For volatile production, hybrid approaches combining BPNN with ensemble methods like Random Forest or Long Short-Term Memory (LSTM) can improve accuracy up to 95%. Allocating 15%–20% of the budget to AI infrastructure, software, and partnerships with institutions such as PT Telkom and LAPI ITB is recommended to support scalable, cloud-based data solutions.

## CONCLUSIONS AND RECOMMENDATIONS

**Conclusions**

The study concludes that the current well production testing procedures in the examined oilfield require systematic improvement. Revisions to standard operating procedures (SOPs) and retraining of operational personnel are necessary to enhance process compliance. For data quality, implementing automated calibration systems and utilizing advanced data analytics software are strongly recommended. From the human resource perspective, intensive training and certification programs, along with regular performance evaluations, should be conducted. In terms of assets, outdated testing equipment should be replaced, and regular maintenance and calibration schedules must be enforced.

The BPNN model demonstrates strong potential for forecasting daily crude oil production. Using an 80:20 training-testing split, and applying 10-fold cross-validation on the training subset, the model exhibits robust generalization performance. The optimal architecture configured as 3-20-1 with a learning rate of 0.05 achieved convergence in 481 epochs with a training time of 13 seconds. Model performance was indicated by high correlation coefficients (R) across training, validation, and testing phases, along with a low MSE. The resulting regression equation, Output = 1 × Target + 0.00024, confirms a near-perfect alignment with the target function. These findings suggest that BPNN is a viable tool to support data-driven decision-making in oil production management systems.

**Recommendations**

The proposed model may serve as a practical reference for industry practitioners in forecasting daily crude oil production using artificial neural networks (ANNs). Future studies are encouraged to enhance model performance by incorporating alternative learning algorithms and activation functions beyond *logsig*. Expanding the input dataset to include additional parameters such as pump type per well can further improve model generalizability and support broader applicability across diverse oilfields.

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