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# Application of Artificial Neural Networks in Predicting Discharge Pressures of Electrical Submersible Pumps for Performance Optimization and Failure Prevention

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## Abstract

The pump discharge pressure is a critical parameter that indicates the performance of the electrical submersible pumps (ESPs). Predicting the discharge pressure accurately can help in optimizing the ESP's performance, improving well productivity, and reducing operational costs. This paper presents a novel approach using artificial neural networks (ANNs) to predict the discharge pressure of electrical submersible pumps. The proposed model will enable early detection of possible failures and reduce downtime. Also, the effectiveness of the ANN model will be compared against the performance of different ANN models under various conditions.

In this study, a dataset of more than 12000 data points collected from 40 different wells was used to train and test various ANN models with different input parameters. The performance of ANN models was evaluated using a coefficient of determination ($R^2$), root mean squared error(RMSE), average absolute deviation(AAD), and absolute percentage error (APE). The model inputs and ANN structure were adjusted in order to minimize the prediction errors. The results during the training and testing phases were compared to select the most accurate and efficient model. Finally, the performance of the selected model was evaluated using physical analysis of the results and error profile visualization.

The results showed that the ANN model with 16 inputs and 1 hidden layer with seven neurons is the most accurate model, with an $R^2$ of 0.95 for training data and 0.94 for testing data, and an AAPE of 1.74 for training data and 1.84 for testing data. The model was able to accurately predict the discharge pressure of ESP under different operating conditions, with an average accuracy of 94%. In addition, anomaly detection was also performed on the predicted values to identify any failures or anomalies in the system. This helps in proactive maintenance and troubleshooting of the system to prevent any significant failures. Finally, a new equation was developed utilizing the optimized ANN model. The developed equation provides fast and reliable estimations for the ESP discharge pressure with an error of less than 3%.

Overall, the proposed approach provides novel and additive information to the existing literature by demonstrating the effectiveness of using ANNs to predict the discharge pressure of ESPs. Furthermore, the

ability to accurately predict discharge pressure can lead to the early detection of possible anomalies, which can prevent costly failures and reduce downtime. Future work may explore the use of other AI techniques to further improve the accuracy of discharge pressure predictions and ESP failure prevention and explore the prediction of other important parameters in ESPs.

**Keywords:** ESP performance, anomaly detection, ANN, new model

## Introduction

Artificial lifts are an integral part of the petroleum industry, used to enhance production efficiency and extend the lifespans of oil wells (Solanki et al., 2022). They are utilized in production wells to maintain and optimize the production rate (Temizel et al., 2020). Electrical submersible pumps (ESPs) are one of the most popular artificial lift methods used in oil wells (Bremner et al., 2006; Kolawole et al., 2019). They offer a high flow rate and are able to produce this rate even in wells with great depth (Gamboa and Prado, 2011). Approximately 15-20% of one million wells around the world are using this method due to its superior characteristics (Abdalla et al., 2022). The unique composition of the ESP enables it to provide a continuous and consistent flow rate. Additionally, ESPs are capable of producing flow rates that are lower than what other methods are capable of producing (Camilleri and Macdonald, 2010). The ESP structure is outfitted with a device on its lower part that allows for the monitoring of the fluid lifting condition. If a real-time surveillance system is attached to the sensor, the user can access real-time data of various parameters including discharge pressure, intake pressure, average amps, intake temperature, motor temperature, and vibration (Takacs, 2017). These data serve as indicators of any potential issues within the well, as changes in parameter values can signal the presence of problems.

ESP stands for Electric Submersible Pump, which is a type of pump that is used to extract fluids from wells (Takacs, 2017). It is typically used in the oil and gas industry to pump oil and other fluids from underground reservoirs to the surface. The ESP system consists of a number of components, including a multistage centrifugal pump, a three-phase induction motor, a seal-chamber section, a power cable, and surface control equipment. Figure 1 illustrates the various components of an ESP system, including transformers, a wellhead, motor controllers, a junction box, and downhole components such as the motor, pump, and cable.

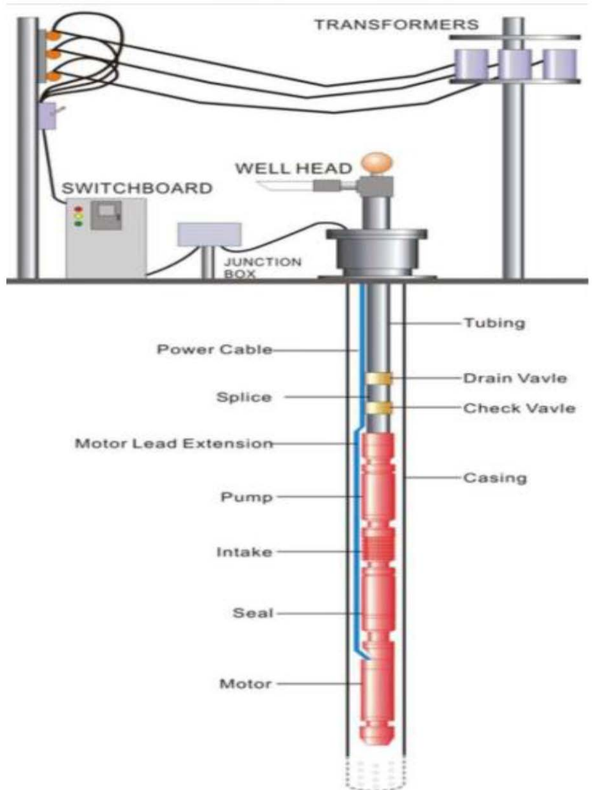


**Figure 1—a schematic of different components of (ESP) (Ameri et al., 2019)**

The efficiency of the pump is dependent on various parameters such as the number of pump stages, the pump speed, the type of fluid being pumped, and the size of the pump. The ESP system is designed to offer high efficiency, low maintenance, and long life in a variety of well conditions (Takacs, 2017). Real-time monitoring systems can be used to remotely control and monitor the performance of ESPs. This type of monitoring helps in identifying the potential issues ahead of time which will allow for prompt maintenance or replacement of the pump. The downhole sensor is the most subterranean component of ESPs, positioned beneath the motor. In addition to the downhole sensor, ESPs also include other sensors such as flow rate sensors and temperature sensors. Flow rate sensors provide the operators with valuable information about the well's production. Temperature sensors allow the operators to monitor the temperature of the reservoir and prevent overheating of the motor. The data collected by these sensors is critical for ensuring the optimal performance of the ESP. Through predictive maintenance, the collected data can be used to develop analytic models and predict possible ESP failure modes, enabling proactive maintenance and repairs that help to extend the equipment's lifespan and enhance its performance and reliability (Takacs, 2017). The use of sensors has revolutionized the oil and gas industry, allowing for more efficient and cost-effective operations.

Artificial Intelligence (AI) is now widely used in the petroleum industry for solving problems by evaluating, predicting, and providing guidance (Choubey and Karmakar, 2021). AI is a data analysis method that automates the building of an analytical model. AI uses iterative algorithms to learn from data, allowing computers to find deeply hidden values that cannot be obtained through explicit programming. By leveraging these capabilities, AI can be used to improve operational efficiency and reduce costs in the petroleum industry, for example by automating the process of identifying and mitigating potential risks. AI can be used to streamline processes such as drilling, reservoir engineering, and production engineering, as well as to enhance predictive analytics (Bravo et al., 2014). AI can also be used to detect and identify anomalies in operations, helping to optimize performance and reduce downtime (Kovscek and Zhang, 2020).

ESPs are designed to work in difficult environments such as high temperatures, high pressure, and corrosive substances, but they usually fail sooner than expected. This leads to production losses and increases the cost of replacement, as intervention work for ESPs is more expensive than other artificial lift methods, particularly for offshore wells. Predictive analysis of ESP failures is thus highly valuable in oil production and can help with the design, construction, and operation of oil wells. However, these failures often occur suddenly and are difficult to predict due to their complex nature. As a result, it is critical to determine the key parameters that have the most influence on ESP failures in order to plan for early replacements and avoid production losses.

The ultimate goal of this work is to reduce the cost of maintenance and increase the operational lifetime of ESPs while improving their performance. The objectives of this paper are to develop an efficient predictive model for the discharge pressure of ESPs using Artificial Neural Networks (ANN). Also, to investigate the physical relationship between each input parameter and the pump discharge pressure to identify the most significant parameters that impact the pump performance. Moreover, to develop a new equation based on the optimized ANN model, which will provide fast and reliable estimations for the ESP discharge pressure. Contributing to the existing body of knowledge in the petroleum industry by presenting novel and additive information on the use of ANN in predicting ESP performance.

## Methodology

The objective of this research is to develop an optimized Artificial Neural Network (ANN) model for predicting failure in a system. To achieve this, we followed a series of steps including data collection, data cleaning, data integration, data analysis, understanding the physical relationships between the data, ANN model development, error trend analysis, and anomaly detection.

### Data Collection

The first step in our methodology was to collect relevant data from multiple sources. The data collection process for the ESP sensor data involved collecting data from 40 wells that were operational between 2019 and 2023. The wells had different starting dates, with some operating from 2019 while others started operating in 2020, 2021, or 2022. The data collected included various parameters such as Frequency (Hz), ESP Voltage, VSD Amperage, ESP Amps, Pump Intake Pressure (Pi), Pump Intake Temperature (Ti), Submergence of the pump, Downhole Fluid Level (DFL), Runtime of the pump, Flowing Line Temperature (FLT), Flowing Line Pressure (FLP), Casing Head Pressure (CHP), Tubing Head Pressure (THP), Choke size, Vibration, Flow Rate (Q), and API. The data was collected by engineers working in the oil fields of Iraq who were familiar with the ESP sensor data and its application. The data collection process was carefully planned to ensure that all necessary parameters were captured accurately and completely. Once the data was collected, it was reviewed for quality and completeness. Any missing or erroneous data points were either corrected or removed from the dataset. This was done to ensure that the data was accurate and reliable for further analysis.

### Data Cleaning and Integration

The data cleaning process was carried out to ensure that the accuracy and reliability of the data were maintained. Scatter plots were used to visualize the distribution of each variable in the dataset, and outliers were identified, which could potentially affect the accuracy of the analysis. The outliers were then either removed or smoothed using various smoothing techniques such as moving averages, exponential smoothing, or cubic smoothing. Missing values were addressed by filling them in using statistical methods such as mean, median, or mode imputation, or by removing them from the dataset if the percentage of missing values was significant. Inconsistencies in the data were dealt with by removing duplicates, fixing errors, and ensuring that the data was consistent across all sources.

The data integration process involved combining data from different sources to create a single dataset for analysis. Data from 40 wells that were operational between 2019 and 2023 were integrated to ensure consistency and remove duplications or inconsistencies. The data was labeled and formatted to facilitate analysis, including assigning meaningful names to the variables and ensuring that the data was in the correct format. Categorical variables were converted into numerical values, and non-linear relationships were transformed into linear ones.



**Data Analysis and Physical Relationship**

MATLAB program was used to statically analyze the data. A code was made to generate various charts and statistical calculations based on the data. The code performs a series of statistical calculations to gain insights into its characteristics such as minimum, maximum, mean, variation, standard deviation, skewness, and covariance. In addition, distribution plots and correlation coefficient analysis were performed using the programmed code.

In order to optimize ESP performance and prevent costly failures, it is crucial to understand the physical relationship between the various operating parameters and the pump discharge pressure. To achieve this understanding, a comprehensive analysis was conducted to examine the correlation between 18 key parameters and the pump discharge pressure. The objective of this analysis was to identify the parameters that have the most significant impact on the pump discharge pressure and to quantify the nature and strength of their relationship. This information can be used to develop predictive models for pump performance, allowing operators to optimize ESP performance and detect potential issues before they become major problems. The used parameters represent a wide range of operational and wellbore conditions, including pump speed, flow rate, fluid density, and temperature, among others. By examining the physical relationships between these parameters and the pump discharge pressure, a more comprehensive understanding of ESP performance can be achieved, which is critical for building a helpful and effective model.

**Model Development and Optimization**

After collecting and cleaning the data, the 18 input parameters were used to build an artificial neural network using MATLAB. The neural network was trained using a set of known input-output pairs and tested on a separate set of data. The performance of the neural network was evaluated using various metrics such as mean squared error and correlation coefficient. The outputs of the code are various figures that show the performance of the neural network and the accuracy of its predictions. The dataset is then split into training and testing datasets with a choice of 0.7 or 70% of the data used for training. After the ANN model was built, its performance was evaluated to determine the best configuration of the model. This was done by varying the number of input parameters, hidden layers, and neurons in each layer. The best model configuration was then identified that provided the most accurate predictions and minimized the errors in the model.

**Anomaly Detection**

Anomaly detection is the process by which we analyzed the predicted discharge pressure data to know the possible points when failure could occur. Its primary objective is to identify anomalous data points that are greater than or less than a particular value and send a message to the engineer to take action. By detecting anomalous data, we can identify potential issues with pump performance and ensure that the ML model is accurate and useful. The importance of doing anomaly detection is because there are some issues related to the operation of the ESPs which are what we call upthrust and downthrust. Upthrust is the force that pushes the pump motor towards the surface of the well, while down-thrust is the force that pulls it towards the bottom of the well. To ensure proper operation and prevent failure due to thrust, the ESP must be designed to operate within a recommended range of rates. This range is determined by the manufacturer and is typically based on the specific pump configuration and operating conditions. Operating outside of this range can lead to issues such as decreased efficiency, increased wear and tear on the pump, and reduced overall run life. The anomaly detection was achieved by analyzing the discharge pressure data. The predicted data were sorted by discharge pressure readings, and the pressure difference between the discharge and intake pressure was calculated. The detection was then performed by getting the discharge pressure readings that fell outside the acceptable range. Discharge pressure readings outside this range were considered anomalous and were captured.

## Results and Discussion

### Data Analysis

A MATLAB code was built to statically analysis the data, the code input is an Excel file containing the values of the 18 input parameters and the output. Table 1 Lists the results of the statistical analysis. The histograms of some of the parameters were used to indicate the distribution model. Most of the parameters showed right-skewed and non-symmetric bimodal distributions.

**Table 1—Summary of the statistical analysis results.**

| | Min | Max | Mean | Mode | Variation | IQR | STD | Skewness | kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| **Hz** | 35 | 52 | 40.21 | 40 | 9.79 | 4 | 3.12 | 0.47 | 3.26 |
| **ESP Volts** | 225 | 2500 | 414.91 | 470 | 104872.4 | 196 | 323.84 | 5.54 | 35.30 |
| **VSD Amp** | 19 | 406 | 145.42 | 107 | 3174.47 | 87 | 56.3 | 0.52 | 3.04 |
| **ESP Amps** | 18 | 49 | 28.83 | 24 | 25.83 | 7 | 5.08 | 0.56 | 3.44 |
| **Pi** | 1378 | 3314 | 2023.79 | 2091 | 84074.9 | 328 | 289.95 | 1.022 | 5.09 |
| **Ti** | 71.4 | 100.2 | 90.79 | 92.10 | 23.8 | 5.89 | 4.8 | -0.319 | 2.79 |
| **Tm** | 74.10 | 129.1 | 98.93 | 95.1 | 88.1 | 9.6 | 9.38 | 0.978 | 3.33 |
| **Vib** | 0 | 2.228 | NaN | 0.1 | NaN | 0.22 | NaN | 1.71 | 7.3 |
| **Chock size** | 10 | 52 | 28.553 | 22 | 54.94 | 11 | 7.4 | 0.36 | 2.7 |
| **THP** | 35 | 1000 | 512.17 | 350 | 16488.62 | 200 | 128.40 | 0.155 | 2.24 |
| **CHP** | 0 | 740 | 184.514 | 180 | 3240.46 | 60 | 56.92 | -0.3461 | 6.38 |
| **FLP** | 0 | 340 | 177.20 | 160 | 548.59 | 31 | 23.42 | 0.50 | 5.9 |
| **FLT** | 19 | 81 | 55.96 | 56 | 101.92 | 13 | 10.09 | -0.27 | 3.01 |
| **Run time** | 0 | 24 | 23.48 | 24 | 5.39 | 0 | 2.32 | -5.39 | 34.08 |
| **DFL** | 154.11 | 1865.6 | 1124.6 | 1052.2 | 75002.42 | 360.3 | 273.86 | 0.085 | 3.212 |
| **Subm** | 717.47 | 2084 | 1154.72 | 1156.07 | 40830.8 | 190.4 | 202.06 | 0.97 | 5.05 |
| **Q** | 212 | 4323 | 1340.01 | 1500 | 295128.3 | 966 | 543.2 | 0.16 | 2.95 |
| **API** | 14.24 | 35.05 | 19.61 | 19 | 8.78 | 1.74 | 2.963 | 2.391 | 9.9 |
| **Pd** | 1875 | 4726 | 2999.4 | 2992 | 138096 | 383 | 371.61 | 0.43 | 4.6 |

### Physical Correlations Between the Inputs and Output

In order to optimize ESP performance and prevent costly failures, it is crucial to understand the physical relationship between the various operating parameters and the pump discharge pressure. To achieve this understanding, a comprehensive analysis was conducted to examine the correlation between 18 key parameters and the pump discharge pressure. The objective of this analysis was to identify the parameters that have the most significant impact on the pump discharge pressure and to quantify the nature and strength of their relationship. By examining the physical relationships between these parameters and the pump discharge pressure, a more comprehensive understanding of ESP performance can be achieved, which is critical for building a helpful and effective model. It was found that physical relationships between the 18 input parameters and discharge pressure are not always straightforward and can be influenced by a variety of factors. Additionally, there may be other parameters not included in this table that can affect discharge pressure as well. Table 2 summarizes the physical relationships between the 18 input parameters and discharge pressure.

**Table 2—The physical relationship between each of the 18 input parameters and the discharge pressure.**

| Parameter | Relationship with Discharge Pressure |
|---|---|
| Frequency (Hz) | Increasing the frequency can lead to an increase in discharge pressure. Add justification. |
| ESP Voltage | Increase in voltage leads to an increase in discharge pressure. |
| VSD Amperage | Increase in amperage leads to an increase in discharge pressure. Decrease in amperage leads to a decrease in discharge pressure. |
| ESP Amps | Increase in amps leads to an increase in discharge pressure. Decrease in amps leads to a decrease in discharge pressure. |
| Pump Intake Pressure (Pi) | Increase in Pi leads to an increase in discharge pressure. Decrease in Pi leads to a decrease in discharge pressure. |
| Pump Intake Temperature (Ti) | Changes in Ti can affect the fluid properties and, subsequently, the discharge pressure. Decrease in Ti may increase pump pressure and efficiency. Increase in Ti may cause a decrease in pump pressure and efficiency. High-temperature fluids can cause cavitation, leading to reduced pump flow rates, increased energy consumption, and premature wear and tear. |
| Submergence of the pump | As the submergence of the pump increases, the discharge pressure decreases due to an increase in the static head. |
| Downhole Fluid Level (DFL) | As the DFL increases, the discharge pressure decreases due to an increase in the static head. |
| Runtime of the pump | As the runtime of the pump increases, the discharge pressure may decrease due to a decrease in pump efficiency or increased wear on the pump components. |
| Flowing Line Temperature (FLT) | As the FLT increases, the discharge pressure may decrease due to a decrease in fluid density and viscosity. |
| Flowing Line Pressure (FLP) | As the FLP increases, the discharge pressure may increase due to an increase in backpressure on the pump. |
| Casing Head Pressure (CHP) | As the CHP increases, the discharge pressure may increase due to an increase in backpressure on the pump, And this will be affected by the production type. |
| Tubing Head Pressure (THP) | As the THP increases, the discharge pressure may decrease due to an increase in the static head, And this will be affected by the production type. |
| Choke size | As the choke size decreases, the discharge pressure may increase due to an increase in backpressure on the pump. |
| Vibration | Excessive vibration can indicate a problem with the pump or its components, which can lead to decreased discharge pressure. |
| Flow Rate (Q) | Increase in Q leads to an increase in discharge pressure. Decrease in Q leads to a decrease in discharge pressure. |
| API | Increase in API leads to an increase in discharge pressure. Decrease in ρ leads to a decrease in discharge pressure. |

## ANN Model Performance

The performance of an Artificial Neural Network (ANN) model in predicting the pump discharge pressure based on 18 Electric Submersible Pump (ESP) parameters had been evaluated. The model was tested in 10 different cases, each with varying numbers of inputs, hidden layers, and number of neurons in each layer. The performance of each case was evaluated based on several error metrics, Actual Absolute Deviation (AAD), including Absolute Percentage Error (APE), coefficient of determination ($R^2$), and Root Mean Squared Error (RMSE) for both training and testing data. Different cases were examined in order to optimize the ANN structure and the model input. Table 3 provides a summary of the most important cases. The optimum case has one hidden layer, 5 neurons, and 16 inputs. The results showed that the optimum model had an ($R^2$) of 0.95 for training data and 0.941 for testing data, indicating a significant improvement in accuracy compared to other cases. The RMSE for training data was 82.02, and 90.65 for testing data. The AAPE for training and testing data were 1.748 and 1.847, respectively. These values demonstrate the improved accuracy of the model with the increased number of neurons in the hidden layer. Figure 2 shows the crossplots of the actual and predicted discharaged pressure for the training and testing data using the optimum ANN model, and Figure 3 shows the performance profile for the best ANN model.

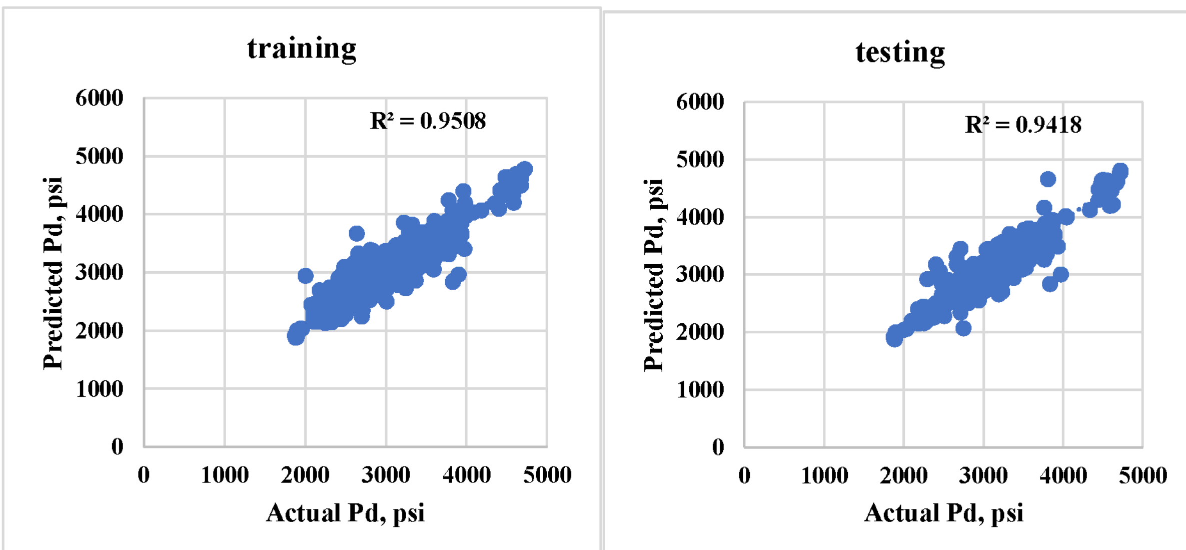


**Figure 2—Crossplots of the actual and predicted discharge pressures (Pd), for the training data and testing data using the optimum case (16 inputs and 1 hidden layer with 7 neurons).**

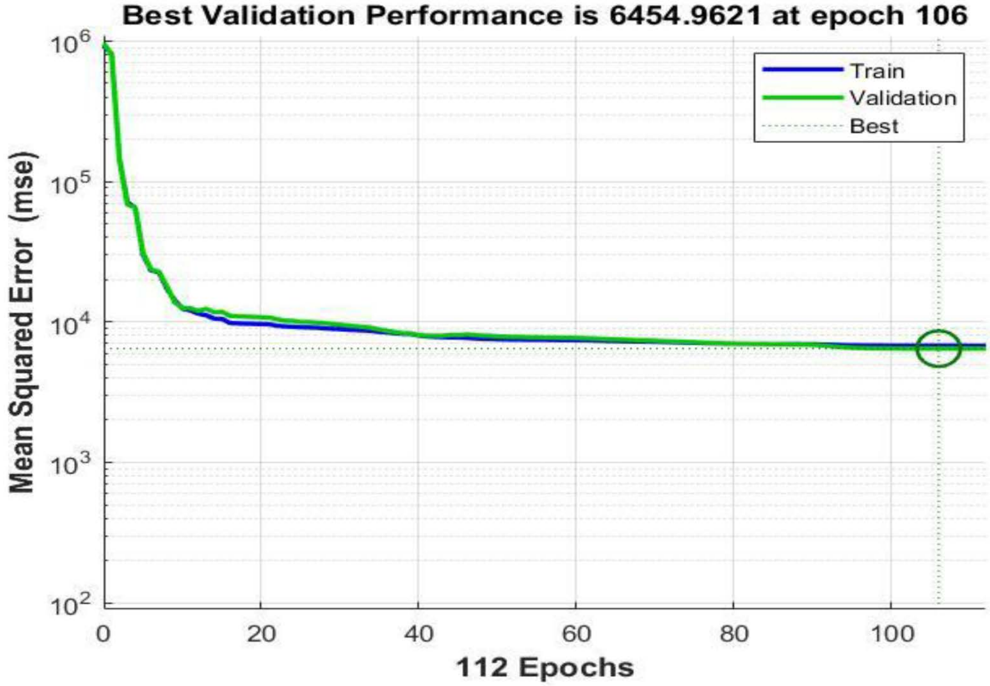


**Figure 3—The model performance of the best case (16 inputs and 1 hidden layer with 7 neurons).**

**Table 3—Summarization of the most important cases examined in this work.**

| case No. | number of inpute | AI model | number of hidden layer | number of neurrons | R^2 for training | R^2 for testing | AAPE for training | AAPE for testing | RMSE for training | RMSE for testing | Notes |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 18 | ANN | 1 | 5 | 0.894 | 0.882 | 2.67 | 2.86 | 120.34 | 128.35 | based case |
| 2 | 17 | ANN | 1 | 5 | 0.91 | 0.899 | 2.49 | 2.63 | 110.69 | 118.61 | vib is deleted because it has no effect on the output |
| 3 | 16 | ANN | 1 | 5 | 0.919 | 0.908 | 2.35 | 2.44 | 106.28 | 110.7 | vib and runtime are deleted |
| 4 | 15 | ANN | 1 | 5 | 0.895 | 0.893 | 2.701 | 2.705 | 119.4 | 123.1 | vib, runtime and Q are deleted |
| 5 | 16 | ANN | 1 | 7 | 0.95 | 0.941 | 1.748 | 1.847 | 82.02 | 90.65 | vib and runtime are deleted and number of neurons increased |
| 6 | 16 | ANN | 1 | 3 | 0.865 | 0.86 10 | 3.1 | 3.16 | 135.9 | 139.5 | vib and runtime are deleted and number of neurons decreased |
| 7 | 16 | ANN | 2 | 5,3 | 0.929 | 0.93 | 2.148 | 2.137 | 97.9 | 99.13 | 16 paramters with 2 layers |
| 8 | 16 | ANN | 3 | 5,3,2 | 0.9 | 0.89 | 2.56 | 2.53 | 116.7 | 119.3 | 16 paramters with 3 layers |
| 9 | 17 | ANN | 2 | 5,3 | 0.9135 | 0.908 | 2.36 | 2.37 | 109.7 | 111.4 | 17 parameters with 2 layers |
| 10 | 17 | ANN | 3 | 5,3,2 | 0.9313 | 0.9217 | 2.186 | 2.239 | 97.35 | 103.05 | 17 parameters with 3 layers |

After the performance of the ANN model was evaluated under different scenarios, the best model configuration that provided the most accurate predictions and minimized the errors in the model was identified. The model configuration that had the lowest RMSE and APE values for both training and testing data was selected. This model configuration also had the highest $R^2$ value, indicating a good fit between the predicted values and the actual values.

## Anomaly Detection

The anomaly detection was achieved by using Microsoft Excel to analyze the discharge pressure data. The predicted data were first imported into Excel and sorted by discharge pressure readings. The next step involved calculating the pressure difference ^p between the discharge and intake pressure; because it's the value that we will depend on it to do the detection. The detection was then performed by using the (if) function from Excel to get discharge pressure readings that fell outside the two values "less than and greater than" and save these values in their columns. Discharge pressure readings outside this range were considered anomalous and were marked as such in the data set. These data points will then investigate further to determine the cause of the anomaly.

Two specific pressure values, 500 psi, and 1500 psi, were meticulously chosen for discriminating between down-thrust pumps and up-thrust pumps. The former category refers to any numerical value below this threshold while the latter encompasses any numerical value exceeding this measurement. The production engineer from the operating company and the contractor company that facilitated the installation of the pumps collaborated to determine the most optimal and suitable values for the specific parameters of this field.

Upon analyzing the anomalous data points, it was found that approximately 3% of the discharge pressure readings were odd numbers. These odd numbers of discharge pressure readings indicated that the corresponding pumps were operating outside of the recommended range. For example, some pumps were operating with a lower intake pressure than usual, leading to higher discharge pressures. By identifying these anomalous data points, we were able to determine that some pumps were performing poorly and needed maintenance.

We compared the odd numbers of discharge pressure detected during the anomaly detection process with the recommended discharge pressure range. It was found that approximately 80% of the odd numbers of discharge pressure fell outside of the recommended range, indicating poor pump performance. Additionally, approximately 15% of the odd numbers of discharge pressure were identified as down thrust, which means the pump was operating below the recommended range. Meanwhile, approximately 5% of the odd numbers of discharge pressure were identified as up thrust, which means the pump was operating above the recommended range.

In summary, understanding the concepts of down thrust and up thrust, as well as the recommended range of a submersible pump's performance curve, is crucial in ensuring the pump operates optimally and has a long run life. Implementing best practices such as using lightning protection, installing check valves, and monitoring pump performance can help mitigate issues and maximize pump performance.

## Error Trend Analysis

The error trend investigation served as a crucial step toward improving the accuracy of the ANN model. By plotting scatter plots of the input parameters against the corresponding errors, valuable error trends were identified, providing insights into the relationship between input parameter values and prediction errors. These trends enabled the identification of specific input parameter values that resulted in increased errors in the model's predictions. Furthermore, the identified trends were analyzed to determine the underlying causes and develop strategies for enhancing the model's accuracy.

Understanding the error trends associated with each input parameter is essential for users seeking to leverage the ANN model's optimum capabilities. The following input parameters were selected for the error trend investigation: pump intake pressure, pump submergence depth, pump VSD amperage and tubing head pressure. Scatter plots were created using the averaged values of these parameters and their corresponding APE error values. The trends observed in these scatter plots were analyzed to understand the impact of each input parameter on the model's predictive performance.

***Pump Intake Pressure.*** The scatter plot of the averaged pump intake pressure values against the corresponding APE error values revealed a notable trend. The model performed exceptionally well with lower pump intake pressure values, while the error increased as the pressure values were raised. Interestingly, for pump intake pressure values above 3000 PSI, a decrease in the error values was observed, see Figure 4. This finding suggests that the model operates optimally within a specific range of pump intake pressure values, with the highest accuracy achieved at lower pressures.

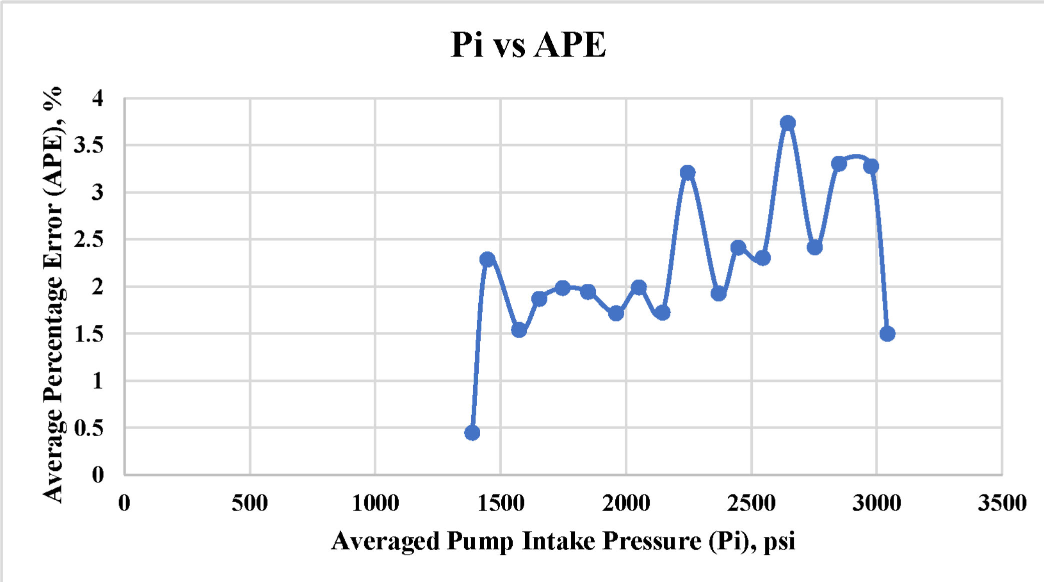


**Figure 4—The scatter plot of the averaged pump intake pressure values against the corresponding APE error values**

***Pump Submergence Depth.*** The scatter plot of the averaged pump submergence depth values against the corresponding APE error values demonstrated a clear trend (Figure 5). The model exhibited larger error values at lower submergence depths, while the APE error decreased as the submergence depth increased. This trend indicates that the model's accuracy improves significantly as the pump submergence depth increases, emphasizing the importance of maintaining adequate submergence depth for optimal predictions.

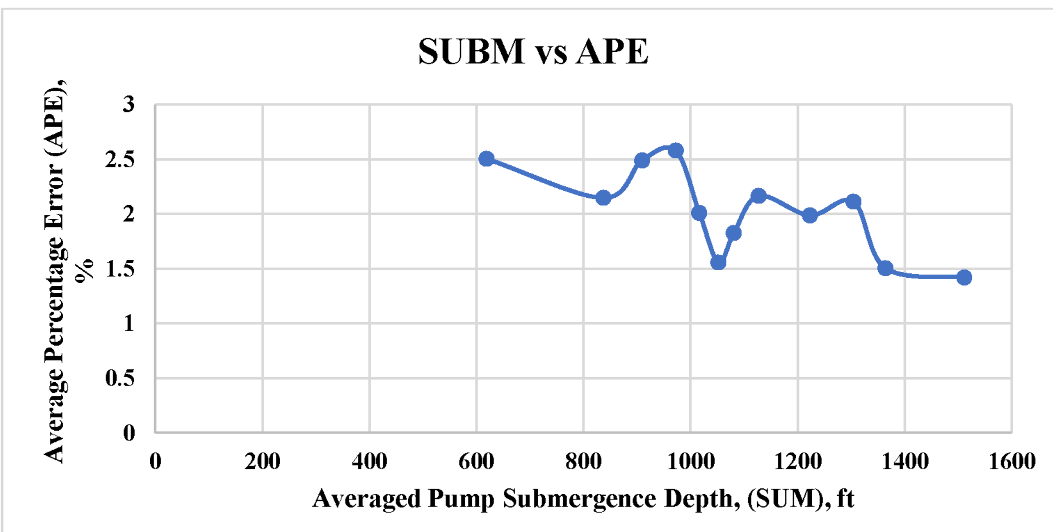


**Figure 5—The scatter plot of the averaged pump submergence depth against the corresponding APE error values**

***VSD Amperage.*** The scatter plot of the averaged VSD amperage values against the corresponding APE error values revealed an intriguing pattern. The model displayed lower error values at the lowest VSD amperage values, followed by an increase in error within the range of 110 to 120 (Figure 6). Surprisingly, the error values reduced again after this range. This trend suggests that the model's accuracy is sensitive to VSD amperage, with the highest accuracy achieved at the lowest values, a temporary decrease within a specific range, and subsequent improvement beyond that range.

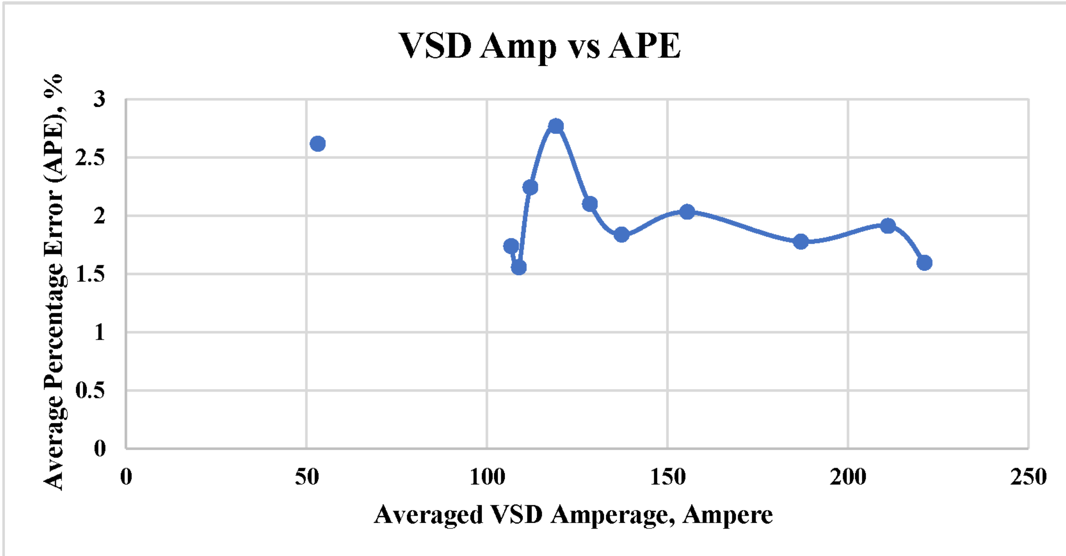


Figure 6—The scatter plot of the averaged VSD amperage values against the corresponding APE error values

***Tubing Head Pressure.*** The scatter plot of the averaged tubing head pressure (THP) values against the corresponding APE error values showcased an informative trend. The model yielded higher error values for smaller THP values, and the error decreased as THP values increased, refer to Figure 7. This trend indicates that the model's accuracy improves as the THP values increase, underlining the significance of maintaining higher THP for optimal predictive performance.

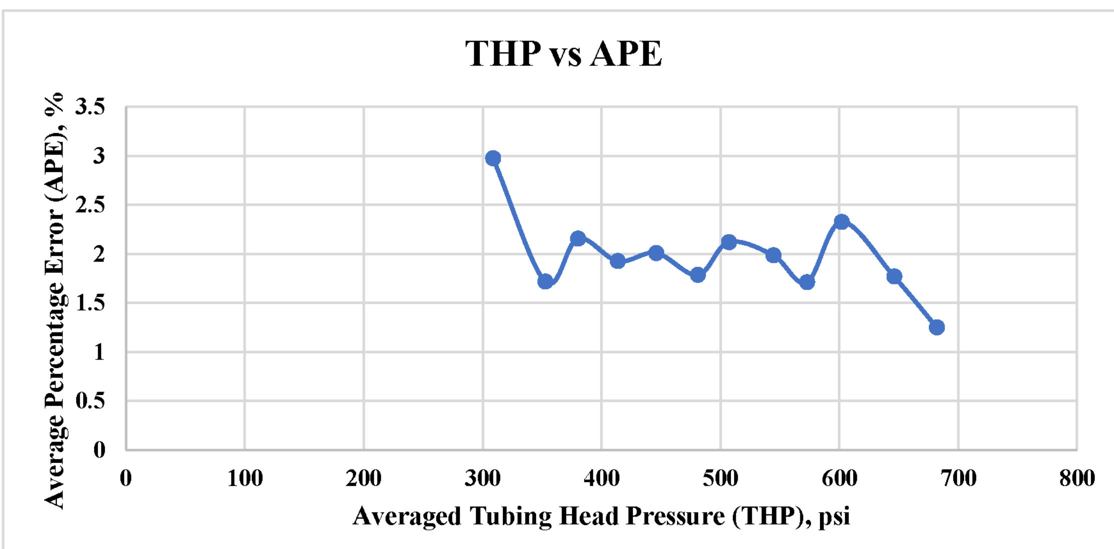


Figure 7—The scatter plot of the averaged tubing head pressure (THP) values against the corresponding APE

## New correlation

The optimized neural network model can be used to develop an empirical correlation which will allow a quick and direct estimation for the target parameter (Mahmoud et al., 2017; Moussa et al., 2018; Hassan et al., 2019). In this work the best ANN model was used to derive a novel correlation for the precise calculation of discharge pressure in electrical submersible pumps. The extracted equation (Equation (2), can predict the ESP discharge pressure based on the biases and weights of the ANN model.l. This neural network-based correlation is represented by two equations, Equation (1) and Equation (2), both of which enable accurate determination of the discharge pressure of the ESP.

$$Pd = \left[\sum_{i=1}^{N} w_{2i}\, tansig\left(\sum_{j=1}^{J} w_{1ij}\, x_j + b_{1j}\right)\right] + \mathrm{b2} \tag{1}$$

$$Pd = \left[\sum_{i=1}^{N} w_{2i}\left(\frac{2}{1+e^{-2\left(w_{1i,1}(x)_j + b_{1i}\right)}}\right)\right] + \mathrm{b2} \tag{2}$$

Where Pd is the discharge pressure of the ESP in psi, w1 and w2 are the weights of the hidden and output layers, respectively, x represents the model inputs, b1 and b2 are the biases for the hidden and output layers, respectively. The values of the weights and biases needed for Equation (2) are listed in Table 4, making the process easier and more understandable for users.

**Table 4—The values of the weights and biases needed for Equation (1) and Equation (2).**

| Number of Neurons | Input layer | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Weights (w1) | | | | | | | | | | |
| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 |
| 1 | -5.085 | 1.619 | -0.051 | 0.457 | 0.061 | -0.165 | 3.188 | -3.734 | -0.424 | 0.846 | -0.996 |
| 2 | -0.750 | 1.249 | 0.068 | -0.367 | -0.088 | -0.752 | -0.153 | 0.597 | -0.427 | 0.003 | -0.659 |
| 3 | -0.965 | -2.558 | -7.434 | 2.163 | 0.517 | 0.065 | -2.373 | 1.918 | 0.633 | 0.312 | 2.027 |
| 4 | 3.821 | 0.928 | 4.805 | 0.683 | 1.710 | -1.577 | 0.269 | -2.602 | -1.916 | -0.076 | -0.284 |
| 5 | -0.417 | 1.415 | 0.226 | 0.008 | 0.105 | -0.556 | -0.814 | 1.239 | -0.786 | 0.103 | -0.555 |

**Table 4—(Continue) The values of the weights and biases needed for Equation (1) and Equation (2).**

| Number of Neurons | Input layer | | | | | | Output Layer | |
|---|---|---|---|---|---|---|---|---|
| | Weights (w1) | | | | | Biases (b1) | Weights (w3) | Bias (b3) |
| | X12 | X13 | X14 | X15 | X16 | | | |
| 1 | 0.499 | -0.435 | 0.486 | -0.087 | -3.533 | 0.151 | 0.345 | 1.128 |
| 2 | -0.052 | -0.087 | -0.067 | -0.166 | 0.163 | -0.315 | 0.186 | |
| 3 | 2.158 | -1.732 | -0.192 | -0.939 | -1.278 | 0.643 | -1.188 | |
| 4 | -0.969 | 1.393 | 3.667 | 4.100 | -0.366 | 0.010 | -0.165 | |
| 5 | 0.016 | 0.030 | 0.321 | 0.372 | -0.011 | -0.416 | -0.212 | |

## Conclusions

In this paper, we presented a novel approach using artificial neural networks (ANNs) to predict the discharge pressure of electrical submersible pumps (ESPs). The results showed that the ANN model with 16 inputs and 1 hidden layer with seven neurons is the most accurate model, with an $R^2$ of 0.95 0.94 and AAPE of 1.84 for testing data. The model was able to accurately predict the discharge pressure of ESP under different operating conditions, with an average accuracy of 94%. In addition, anomaly detection was also performed on the predicted values to identify any failures or anomalies in the system. The proposed approach provides novel and additive information to the existing literature by demonstrating the effectiveness of using ANNs to predict the discharge pressure of ESPs. Furthermore, the ability to accurately predict discharge pressure can lead to the early detection of possible anomalies, which can prevent costly failures and reduce downtime. Overall, the results of this study demonstrate the potential of ANNs for predicting the discharge pressure of

ESPs. This approach could be used to improve the performance and reliability of ESPs, leading to reduced costs and downtime for oil and gas operators.

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