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Prediction of Run Life of Electrical Submersible Pumps by Machine Learning in the Egyptian Western Desert

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Abstract

Electrical Submersible Pump (ESP) is one of the most common artificial-lift methods in oil fields worldwide, due to its large volume capacity and wide range of sizes. Despite the high cost of an ESP system and its maintenance, ensuring its reliability is considered a vital goal. Simply, the longer the ESP system run life, the more reliable and profitable it is. In this paper, we will build a model that predicts the run life of ESP systems in the Egyptian Western Desert by Machine Learning (ML). ML has been used to build statistical models for complex systems. We will discuss various ML algorithms, which are widely used by data scientists.The data used to build this model were collected from several ESPs installed in Egyptian Western Deserts oil fields. The data cover every aspect of the system to describe the ESPs and operating conditions precisely. This paper clarifies that the ESP system complexity involves complex modeling algorithms to achieve the required results. The model succeeded in predicting ESP systems' run life. The main reasons beyond these systems' failure are electrical ones. Several ML algorithms have been used to evaluate the collected data to select the most informative data to build the model. The developed model succeeded in predicting the run life with high accuracy. It could be also used to evaluate designs, equipment choice, and operating parameters. It is an economic choice to enhance overall ESP operations.

Keywords: *Electrical submersible pump; Machine learning; Failure prediction; Run life; Neural network; Random forest.*

1. Introduction

Electrical Submersible Pump (ESP) is an artificial-lift method used in oil fields worldwide for its large production volumes, as it is responsible for 60% of oil global production [1]. This contribution granted ESP its significance in the oil industry. ESP system contains downhole and surface components that are all connected together. Some of them are electrical components such as electrical motors, cables, switchboards, and transformers. Others are mechanical such as multi-stage centrifugal pumps, and gas separators [2].

These different types of components and their interactions are the reasons beyond the ESP system complexity. This complexity makes it harder for us to examine and predict its performance. Thus, ESP failures appear random and unpredictable [1].

The ESP failure can be simply described as losing its ability to lift fluid to the surface [1]. The failure can be either mechanical or electrical depending on the failed component of the system. The most common type of failure is found to be electrical [2]. Figure 1 illustrates several failures related to various ESP components. In Figure 2, the percentage of each failure type in one field is listed, showing that 48% of the failures are electrical.

One of the main drawbacks of the ESP system is the high cost of intervention. When the system fails, it requires a workover rig regardless of the failure cause. During the workover time, the oil production loss is significant. Annually, the production loss due to intervention is about \$3 million, while the workover operation costs around \$1 million [3].

It is noteworthy that these costs are lower in the Egyptian Western Desert. The intervention cost is about $300 thousand, while production loss is estimated to be around $320 thousand. These numbers are calculated and collected from drilling reports, service tickets, and workover rates in the fields subject to the study.

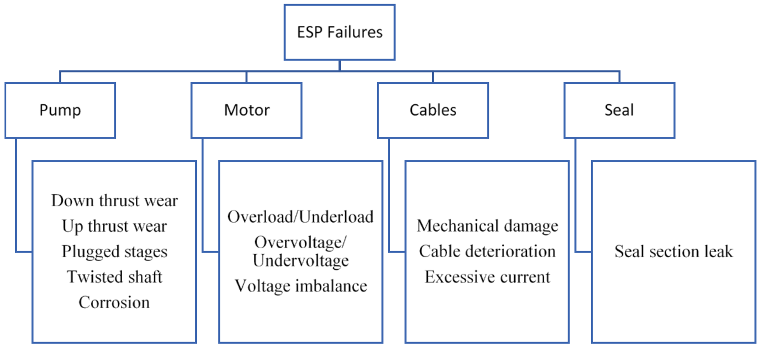

Figure 1. ESP components related failures [2]

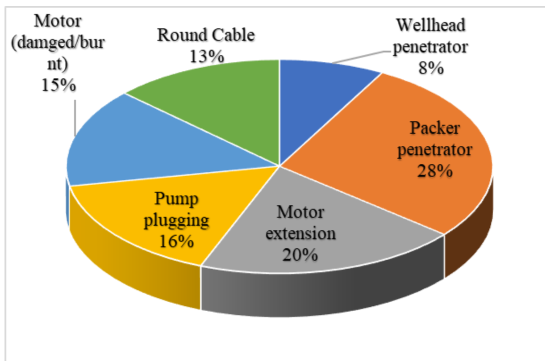

Figure 2. ESP failures in one field [1]

Due to these high costs, oil operators seek the most reliable ESP system. The reliability of the ESP system can be evaluated by defining two parameters:

- Mean time to failure (MTTF): The period of time that the system operates before failing.
- Mean time to repair (MTTR): The average period of time needed to repair the system and put it back in service.

Thus, the reliability of the system is defined as in equation 1 [4]:

$$Reliability = \frac{MTTF}{MTTF+MTTR} \quad (1)$$

Therefore, increasing the run life of the system increases its reliability. Consequently, prediction of ESP run life is significant to justify the economic costs and plan maintenance operations. It also helps in enhancing ESP design and operating conditions to ensure higher reliability [4].

To predict ESP run life, it is necessary to build a model that describes the system and its components relying on the available data. Different types of models could be used. The physical models contain mathematical equations that describe the system's behavior. However, the complexity of ESP systems makes it extremely difficult to build such models.

Another type is data-driven models. These models utilize historical data to predict the future through statistical algorithms. This model is the most suitable choice, since it gets enhanced as a result of collecting more data, and it can handle different types of information. The Data-driven model adheres to the term machine learning (ML) and both describe the same concept [1].

ML can be simply defined as a method of solving a specific problem by collecting a data set that contains the information necessary to build a statistical model. This model yields certain output or helps somehow with solving the problem in hand [5].

ML can be classified into two main types:

- **Supervised learning**: It is used to predict a certain outcome from the input data. The data set in this type takes the form of pairs (input/outcome), where the outcome is already known. The algorithms find a way to produce the outcome from the input data, then use the result to predict the outcome for new data that algorithms have never seen before. Supervised learning can handle regression and classification problems. In regression, the outcome is a continuous number, whereas in classification the outcomes are pre-defined groups or a list of possibilities.
- **Unsupervised learning**: This differs from the other type in that the outcome is unknown. It is used in transforming data set to another form easier for humans, or other ML algorithms to deal with. It is also used to classify the data set into groups with similar items. This process is called clustering [6].

As this paper's goal is to predict the run life of an ESP system, supervised learning algorithms have been used to build the model.

2. Literature review

The applications of ML in real life are numerous. Some examples are: identifying people from their pictures at airports and surveillance systems, determining whether a tumor is benign from medical images, and identifying online posts related to certain topics [6]. In the oil industry, ML has been used in several applications recently. Here, we will represent a few examples of these applications:

- The use of text mining algorithms to extract essential data from drilling reports. These reports usually come in an unstructured format, text mining works on these reports and extracts qualitative and quantitative data, and transforms them into a structured format that can be used by others and make it easier to find useful data and information [7].
- ML was used to predict the failure of rod pump systems using supervised learning algorithms. The problem was formulated as a classification problem. The results showed promising results in failure prediction [8].
- In the reservoir characterization field, ML was used to predict the permeability and porosity of the reservoir. This technique achieved a success rate of 98% and 81% in permeability and porosity prediction respectively [9].
- ML supervised learning algorithms were used to obtain the bottom hole pressure in ESP wells in real-time. The study used a Neural Network algorithm to tune the model. The model showed promising results and could replace expensive downhole gauges in the future [10].

In this paper, a model is built to predict ESP system run life using several algorithms of regression supervised learning. Then, each algorithm will be evaluated to select the most accurate one.

3. Methodology

Building a successful ML model involves several steps to ensure that the model represents the faced problem and predicts future never-seen data with an acceptable range of accuracy.

The Steps of building a model is summarized in Figure 3 as follows:

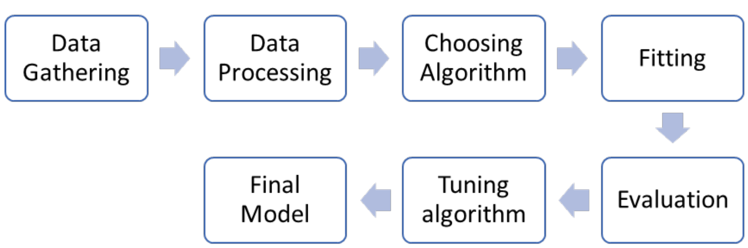

Figure 3. ML model building steps

3.1. Data gathering

The First step is collecting data that describe the problem. Due to the complexity of the ESP system, as stated before, all available data are collected to cover each aspect of the system. The data are divided into three groups: design data, fluid characteristics data, and electrical data.

The ESP systems were installed in Qarun, East Baharia, and Karama fields in the Egyptian Western Desert. The data were obtained from drilling reports, well tests, and ESP designs. Table 1 shows the types of data collected for each system.

Table 1. Data collected for ESP systems

Data type	Definition
Pump depth	The setting depth of the ESP pump; Unit: ft
Phase to phase resistance	The resistance measurement of the electrical cable between each two conductors; Unit: Ω
Phase to Ground resistance	The resistance measurement of the electrical cable between each conductor and the ground (earth); Unit: MΩ
Motor horsepower	The power of the electrical motor;Unit: hp
Motor Load	The running current in AMP is divided by the nameplate current in AMP Unit: percentage
Intake Pressure (PI)	Intake pressure of the pump calculated from the fluid level above the pump; Unit: psi
Discharge Pressure (PD)	The discharge pressure of the pump calculated from pump depth and wellhead pressure; Unit: psi
Motor number	The number of motors installed; Unit: integer number
Motor grade	The classification of the motor. A class for new motor B class for re-run motor
Seal number	The number of motor seals installed; Unit: integer number
Seal grade	The classification of the motor seal. A class for new seal B class for re-run seal
Separator number	The number of gas separators installed; Unit: integer number
Separator grade	The classification of the gas separator. A class for new separator B class for re-run separator
Pump number	The number of pump sections installed; Unit: integer number
Pump grade	The classification of the pump sections; A class for new separator B class for re-run separator
Stages number	Total number of stages in the pump sections Unit: integer number
Relative rate	The actual fluid rate related to the pump curve as following: Relative rate = $\frac{Actual\ rate - Min\ rate\ of\ the\ pump}{Max\ rate\ of\ the\ pump - Min\ rate\ of\ the\ pump}$ Unit: positive or negative number Negative means down thrust Positive and >1 means upthrust Positive and <1 means within the operating range
Pump OD	The Pump outer diameter; Unit: inch
Tubing ID	Tubing inner diameter; Unit: inch
Flat cable grade	The classification of the flat cable; A class for new flat cable B class for re-run flat cable
Round cable grade	The classification of the round cable; A class for new round cable B class for re-run round cable
GOR	The gas-Oil ratio from PVT analysis; Unit: SCF/STB.
Salinity	The Salinity of produced water; Unit: ppm
API	API gravity of the oil produced
Power source	The power source used in running the well; Either generator or OHTL

363 ESP systems data were collected. Each system has 31 data points, from now on each data point will be called a *feature*. Features in ML have the notation of “X”, and the target, in

this case, run life, has the notation of "y". So, for the first ESP system, the run life is denoted "y_1" and has the features: X_1, X_2, …., X_{31}. Our data is represented as a matrix with a dimension of 363*32. Representing data sets as matrices is the common practice in ML [5].

Table 2 shows a summary of the collected data; maximum, minimum, and average value for each feature.

Table 2. Summary of collected data

Feature	Min value	Max. value	Average	Unit
Run life	62	2034	671	day
Pump depth	3663	10288	5895	ft
PH-PH IR	2.2	10.6	5	Ω
PH-GR IR	50	2000	468	MΩ
Motor HP	43	469	125	hp
Motor load	0.3647	1	1	-
PI	18	3656	662	Psi
PD	1747	4730	2860	Psi
Motor number	1	2	1	-
Motor Grade	B	A	-	-
Seal number	1	2	1	-
Seal grade	B	A	-	-
Separator number	0	2	0	-
Separator grade	B	A	-	-
Pump section number	1	4	2	-
Pump grade	B	A	-	-
Pump stages number	134	861	308	-
Relative rate	-0.8952	2.6206	1	-
Pump OD	4	5.7	5	in.
Tubing ID	2.19	2.991	2	in.
Flat cable grade	B	A	-	-
Round cable grade	B	A	-	-
GOR	10	450	76	SCF/STB
Salinity	2385	157300	32435	ppm
API	20	43	32	°API
Power source	Generator	OHTL	-	-

3.2. Tools and platform

Several programming languages offer their platforms or tools to apply ML algorithms, process raw data, and evaluate different models. However, the Python language has become one of the most favorable languages for data scientists and ML practitioners. It is a free open source, a general-purpose language with the advantages of ease of use and having hundreds of libraries for data processing, visualization, statistics, and many more.

Scikit-Learn is an open-source project that contains different ML algorithms, data processing tools, visualization tools, and evaluation matrices. It is the most used ML python library among the ML community. It contains also other necessary libraries for mathematical and matrices operations for ML projects.

Keras is another ML Python library specialized in neural networks and deep learning. It is the most common tool used in building different types of neural networks. It can be also used with Scikit-Learn to make use of its evaluation and processing tools.
This paper will rely on these libraries to process the data, build a model and evaluate it.

3.3. Data processing

The process of transforming the raw data into a form that can be used by ML algorithms is called "*Feature Engineering*". It is an important step as it affects the outcome of the model significantly. It also requires a lot of effort and domain knowledge to be done probably [5].

Most algorithms work only with numerical values. Thus, all categorical data must be transformed into a binary representation. For example, the pump motor is either new "Condition-A" or used "Condition-B". The representation for these data will be:
Condition-A = [1,0]
Condition-B = [0,1]

All these transformations were done manually to ensure the proper representation of data. However, Scikit-Learn offers valuable tools that can be used for these transformations.

There are different features and each feature has a different range. In ML, the best practice suggests that all features should have the same range. To transform all features to the same range, "*Standardization*" is used. It is the process in which features are rescaled to have a mean of 0 and a standard deviation of 1 as in equation 2 [5]:

$$X_{Stand} = \frac{X - mean(X)}{Standard\ Deviation\ (X)} \qquad (2)$$

3.4. Features selection

One can assume that adding more features means more information provided to the algorithm and a better model obtained. Nonetheless, this is not the case in ML practice. In some cases, some features may have the same information, which are considered repetitive. A large number of features create a complex model and cause overfitting. Therefore, it is considered good practice to reduce the number of features to the most important ones [6].

Scikit-Learn offers several methods to choose the best features. This paper depended on three approaches:

- Recursively Eliminating Features (REF)
- Feature selection based on model (linear models)
- Removing irrelevant features using the "Kbest algorithm" [11].

After running these three methods and comparing the selected features by each method, the most frequent features are selected to be used in the model.

The chosen features are Phase to ground resistance, motor load, PI, separator number, pump grade, relative rate, GOR, salinity, and API.

3.5. Splitting the dataset

The dataset is now ready to be used in regression algorithms. First, the data set is split into two sets: a training set and a test set. The training set is a portion of the dataset used to build our model. The test set is a much smaller portion used to evaluate the model [5]. ML practice usually suggests using another set called validation set that is used to tune the model hyperparameters before evaluating it one last time on the test set. However, ML datasets usually have thousands or even millions of data points, which are not the case neither in this problem nor in most other oil industry problems. Therefore, only two sets; training and test sets, are used. The same approach was used by Devon Energey in several models built for failure prediction [12]. The test set was chosen to be 20% of the whole data set.

3.6. Regression algorithms

Now, the data set will be run through different regression algorithms to evaluate their performance, starting with the simplest algorithms until reaching the more complex neural network algorithm. The used algorithms are the most common methods used in regression in Scikit-Learn library. Some are chosen to represent simple methods as linear regression; others are chosen for their high accuracy in complex problems such as Neural Network and Random Forests. The paper focuses on some methods, whereas some other methods could be used in other studies.

Linear Regression:

It is a commonly used type of ML that uses a linear function of the input features as shown in equation 3 [5]:

$$y' = w[0] * x[0] + w[1] * x[1] + \cdots \ldots + w[p] * x[p] + b \qquad (3)$$

where x [0] to x[p] are the features. The algorithm solves for the weight w[p] for each feature and b. In the case of one feature, the model is in one dimension. For more features, the model becomes a hyper plane rather than a line.

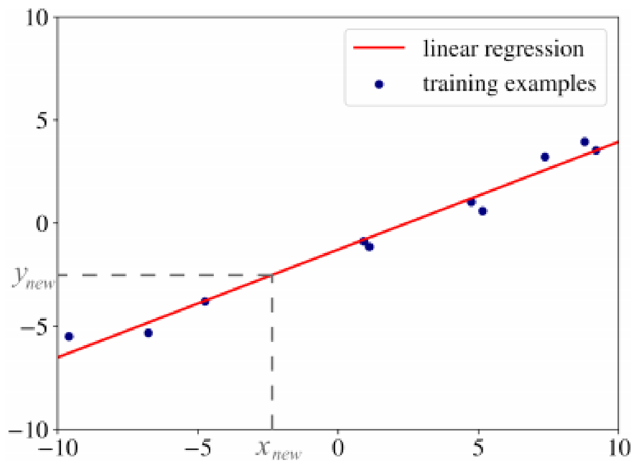

Figure 4. Linear regression in one dimension [5]

There are several algorithms for linear regression. The *Lasso* method is used where the weight of each feature is near or equal to zero to avoid overfitting and achieve regularization.
The simple linear regression model is shown in Figure 4.

Decision tree:

It is a widely used method for both classification and regression problems. It consists of an acyclic graph, in each node a specific feature is examined, and depending on certain rules; the left or the right path is taken. A sample decision tree is shown in Figure 5:

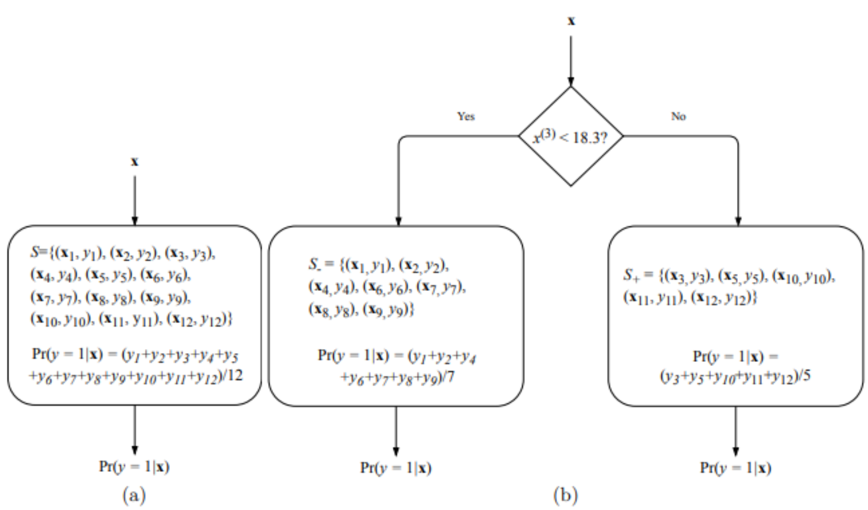

Figure 5. Sample decision tree [5]

Random Forest:

It is a collection of decision trees, where each tree is slightly different from the others. Random forest (RF) is used to avoid the overfitting of a single decision tree. However, due to its complexity, it cannot be visualized and is harder to interpret the decisions and rules, unlike the single decision tree [6].

Neural Network:

A neural network (NN) is a form of ML called *deep learning*. In NN, the input data are not transformed directly to the output. However, input data are transformed through several successive layers called *hidden layers*. The number of hidden layers represents the *depth* of the model. Each layer transforms the data through weights for each input. The output of one layer is the input of the next one [13]. Figure 6 shows the idea behind NN:

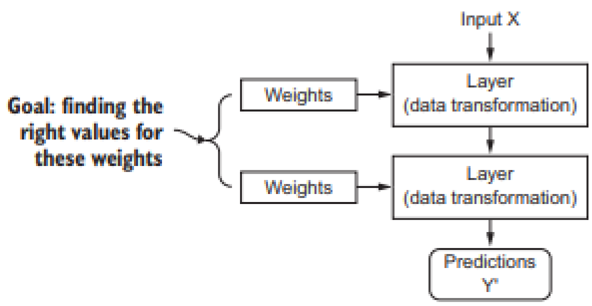

Figure 6. Representation of neural network [13]

The data were run through each of the above algorithms and tune their hyperparameters to get the best result from each one. Finally, each model is evaluated to be compared with others.

3.7. Model evaluation

There are several evaluation matrices used in ML depending on the type of the problem, classification or regression, and the objective of the model.

Since the model is a regression model that predicts the ESP run life in days, which is a positive integer number, three evaluation matrices have been chosen: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2). MAE is calculated by equation 4 as following [11]:

$$MAE = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} \left|(y_i - y'_i)\right| \qquad (4)$$

where: n is the number of samples; y_i is the true value and y'_i is the predicted value.

MAPE is calculated by equation 5 as following [11]:

$$MAPE = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} \frac{|(y_i - y'_i)|}{\max(|y_i|)} \qquad (5)$$

where: n is the number of samples; y_i is the true value and y'_i is the predicted value.

R^2 is calculated by equation 6 as following [11]:

$$R^2 = \left(\frac{n(\sum y_i y'_i) - (\sum y_i)(\sum y'_i)}{\sqrt{[n \sum y_i^2 - (\sum y_i)^2]\,[n \sum {y'_i}^2 - (\sum y'_i)^2]}} \right)^2 \qquad (6)$$

where: n is the number of samples; y_i is the true value; y'_i is the predicted value and $\bar{y}$ is the mean of all true values.

4. Results and discussion

At first, a closer look at our dataset will be beneficial. Table 3 shows some information about training and test sets.

Table 3. Summary of the dataset

Set	Data points	Max. run life	Min. run life	Average run life
Dataset	363	2034 days	62 days	670 days
Training set	290	2034 days	62 days	676 days
Test set	73	1683 days	95 days	618 days

The dataset is split into training and test sets randomly. In addition, the split ensures that each set has representative data of the whole dataset. This is necessary to make sure that the model predicts all ranges of run life accurately, not only high or low values. The ESPs' run life in the study ranges from 2034 to 62 days. This will help the model to predict the run life accurately for all ranges. Therefore, the test set was chosen to have all ranges to test the accuracy of the model in all ranges.

4.1. Study limitation

In the Egyptian Western Desert fields in our study, we surveyed to find the reason behind ESP failure. It was found that 63% of failures were due to electrical causes. This shows the significance of electrical failure in these fields. Therefore, all ESP systems in this study have failed due to a short circuit in either the motor or the cable.

4.2. Lasso model results

Lasso model results are shown in Figures 7 and 8. Lasso model performs slightly better on training set than test set. However, its performance is considered poor on both sets.

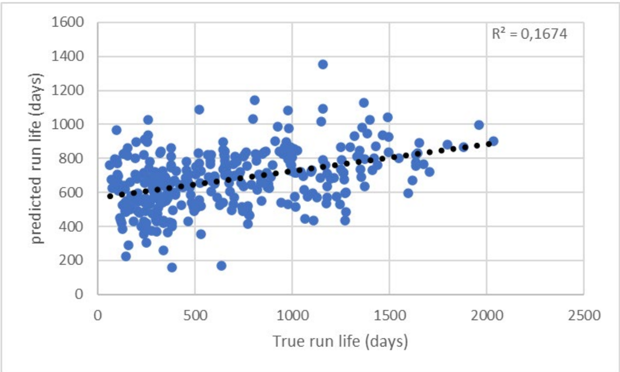

Figure 7. Lasso model prediction results on training data

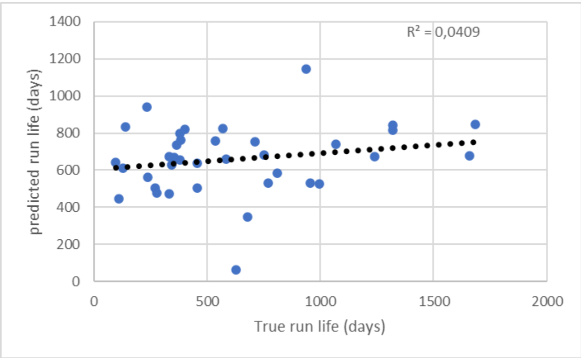

Figure 8. Lasso model prediction results on test data

4.3. Decision tree model results

Decision tree model results are illustrated in Figures 9 and 10. The decision tree model performs very well on the training data. However, the model performance on test data is significantly poor. In this case, the model performance is described as overfitting, which is the main disadvantage of decision tree models.

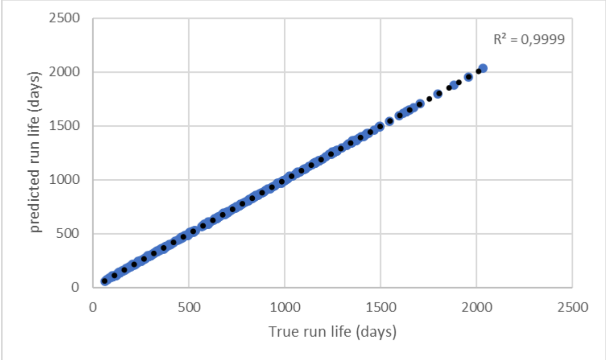

Figure 9. Decision tree prediction results on training data

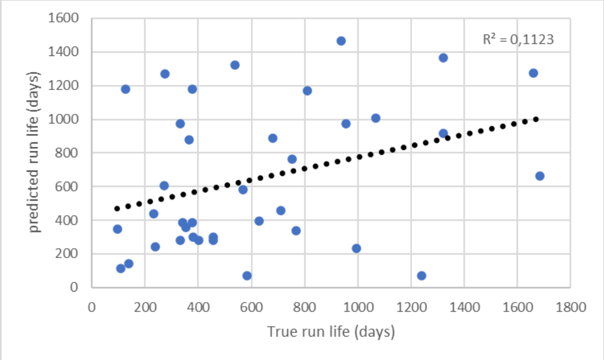

Figure 10. Decision tree model prediction on test data

4.4. RF model results

RF model results are clarified in Figures 11 and 12. The model has good performance over both training and test sets. It overcomes the disadvantage of a single decision tree by avoiding overfitting. The RF model used 1500 trees with maximum depth of 15 splits. The minimum samples to be split was 2 and the leaf node has one sample.

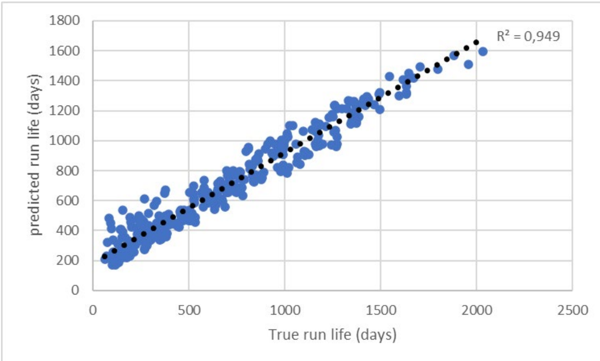

Figure 11. Random Forest model prediction on training data

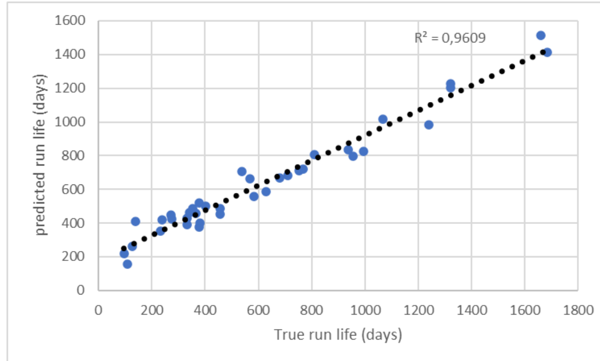

Figure 12. Random Forest model prediction on test data

4.5. Neural Network model results

NN model results are shown in Figures 13 and 14.

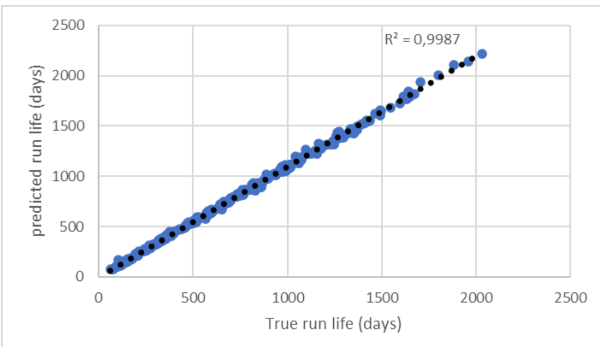

Figure 13. Neural Network prediction results on training data

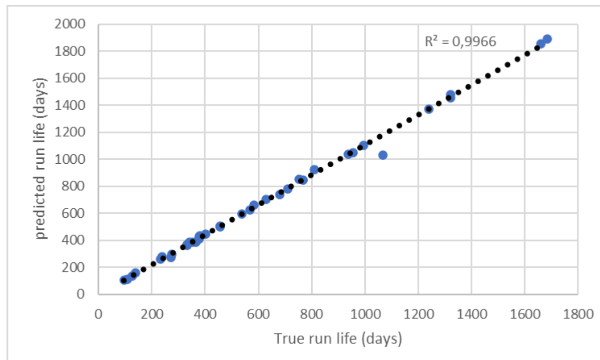

Figure 14. Neural Network prediction results on test data

NN model performs very well on both training and test sets. The NN architecture was 7 hidden layers with 30 hidden units. The number of epochs was 1000 and the batch size was set to be 10 samples. After calculations of all evaluation matrices for each model on training and test sets. The results can be summarized for each model in Table 4.

Table 4. Evaluation summary of each model

Model	Training data			Test data		
	R^2	MAE	MAPE	R^2	MAE	MAPE
Lasso	16.74	331	97%	4.09	366	100.06%
Decision Tree	99.99	2	0.52%	11.23	342	85.9%
Random Forest	94.9	107	31.54	96.09	104	30.55%
Neural Network	99.87	63	9.16%	99.87	66	10.55%

Table 4 reveals the following results:

- Lasso model has a very low accuracy score in every evaluation matrix. On average, it predicts the run life with an error of ± 331 days on the training set. Where the average true run life is 676, this margin of error is very high and not acceptable.
- As stated before, Decision Tree has very good performance over the training set and very poor performance on the test set. The good model is described as the model that can predict new data correctly [5], which is not the case with a Decision Tree. Therefore, this model is not acceptable.
- RF has very close performance on both training and test sets. The model predicts the run life within ±107 of the true value of the training set. This is an error of nearly 1/3 of the average true value, which is also considered inaccurate enough.

- In NN, the model predicts the run life within ±63 days of the true value in the test set. This is about a 10% error. Considering that the average run life is 676 days, this margin is considered accurate.
- It is also important to compare RF and NN scores. Despite they both have close R^2 scores, NN has 3 times better MAPE score and 1.5 times better MAE score. This is the reason beyond pre-determining the evaluation matrices depending on a deep understanding of the problem. It is also favorable to have several evaluation matrices to have a better view of the model's performance.

Table 5 shows the results of applying the NN model on current ESP systems running in the same fields, where the data were collected to predict their failure date.

Table 5. Expected run life for current ESP wells

Wells	Date of installation	Expected run life	Expected failure date
Well-1	10-Jun-20	507	29-Oct-21
Well-2	01-Oct-18	1298	20-Apr-22
Well-3	28-Dec-20	1481	16-Jan-25
Well-4	02-Jun-19	1098	03-Jun-22
Well-5	16-May-19	801	24-Jul-21
Well-6	25-Jan-21	583	30-Aug-22
Well-7	25-Nov-18	1335	21-Jul-22
Well-8	30-Aug-17	1446	15-Aug-21
Well-9	18-Apr-18	1865	27-May-23
Well-10	20-Sep-19	680	30-Jul-21
Well-11	05-Mar-21	242	02-Nov-21
Well-12	04-Sep-20	379	17-Sep-21
Well-13	09-Feb-21	236	03-Oct-21
Well-14	21-Jun-21	316	03-May-22
Well-15	29-May-21	1193	02-Sep-24
Well-16	12-Feb-21	465	23-May-22
Well-17	08-Sep-20	464	15-Dec-21
Well-18	24-May-21	703	27-Apr-23
Well-19	13-May-21	749	31-May-23
Well-20	07-May-21	172	25-Oct-21
Well-21	15-Sep-20	307	18-Jul-21
Well-22	26-Nov-17	1769	30-Sep-22
Well-23	20-Feb-20	782	12-Apr-22
Well-24	12-Dec-19	1170	23-Feb-23
Well-25	08-Feb-19	991	26-Oct-21
Well-26	13-Dec-17	1515	05-Feb-22

These results give the operator a chance to plan the workover rigs schedule and mobilization plans. The installation date was obtained from drilling reports. The run life in days is the result of the NN model used in this paper. The failure date was calculated by adding the number of run life in days to the installation date.

To clarify the results of the model, Well-1 in Table 6 is taken as an example to show the real data, which are fed to the model and from which the result is obtained. Table 5 shows the collected data for this ESP. The well is expected to run for 507 days. These calculations were done before the ESP failure. This well has failed on 30-Aug-21. This makes the prediction accuracy as high as expected in the model evaluation. The real run life is 447 days. The MAE for this prediction is 60 days, which is close to the MAE of the test set, 66 days. Thus, the developed model could be used with current ESP installation to help in failure prediction.

Table 6. Well-1 data

Expected run life (days)	507
Phase to Ground resistance (MΩ)	1300
Motor load	0.590909
PI (psi)	2556
Separator number	1
Pump grade	A & B
Relative rate	0.64431
GOR (SCF/STB)	50
Salinity (ppm)	107800
API	35

5. Conclusions

In this paper, an ML model was built to predict an ESP run life with acceptable accuracy. Based on the results; we can conclude the following:

- ML solutions are applicable in the Oil industry. ML algorithms and tools are either free to use or very cheap compared to other industry software. Also, the ML developers' community provides beneficial and continuous support to users.
- The most significant obstacle in applying ML in the Oil industry is the lack of a sufficient quantity of representative data. ML algorithms sometimes require thousands of data points.
- ML has great potentials in the Oil industry, especially in failure prediction.
- Failure prediction helps with choosing suitable equipment, proper designs, and operating parameters.
- It will help with planning workover operations before failure occurs. This will save time and reduce production loss.
- The complexity of ESP systems requires complex algorithms such as NN and RF.
- The complex models are harder to optimize and interpret.

6. Recommendations

For better implementation of ML in the Oil industry; these are our recommendations:

- It will be a great asset for all companies operating in the Egyptian Western Desert to build a database for their ESP systems designs, operating parameters, and failure analysis. These data are the core for building and tuning ML models. It will also help with enhancing field practice for each company.
- Applying the developed model to other ESP systems in different Western Desert fields to enhance the results and achieve more generalization.
- Encouraging petroleum engineers to work with data scientists and ML practitioners to integrate their knowledge into building and improving failure prediction models.
- Regarding ESP operations, ML could help with optimizing operating parameters such as flowing rate, discharge pressure, and running ampere.

Nomenclature

y_i	*True run life, days*
y'_i	*Predicted run life, days*
n	*Number of samples*

Abbreviations

ESP	*Electrical Submersible Pump*
MAE	*Mean Absolute Error*
MAPE	*Mean Absolute Percentage Error*
ML	*Machine Learning*

MTTF	*Mean Time to Failure*
MTTR	*Mean Time to Repair*
NN	*Neural Network*
RF	*Random Forest*
OHTL	*Overhead Transmission Line*
PI	*Intake pressure*
PD	*Discharge pressure*

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