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Benchmarking ESP Run Life Accounting for Application Differences

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Abstract

When benchmarking ESP Run Life performance between operations, application differences (e.g., bottomhole temperature, water cut, presence of solids, etc.) must be taken into account, in order for it to be an appropriate comparison.

This paper presents the results of a preliminary attempt to build a statistical model to achieve appropriate benchmarking. The model, based on a large, worldwide database of ESP installations, takes into account the most severe failure mechanisms (i.e., those that result in the higher percentage of failures), and the most influential factors (i.e., application characteristics) affecting the failure rates for these mechanisms.

The approach taken to build the model and the difficulties encountered are described in the paper. Plots of "actual" versus "expected" average run-life are also presented, to illustrate how a fair run life comparison may be made between different applications, based on the predictions of the statistical model.

The results show that an application with a relatively low run-life (i.e., lower than the overall "industry" average) may be doing better than what should be expected under the particular circumstances, while another application with a relatively high run-life (i.e., higher than the overall average) may be doing worse than expected under its own particular circumstances.

Introduction

Since 1999, several operators have been sharing ESP Run Life and failure data, as well as other pertinent information, through a Joint Industry Project (JIP) entitled ESP-RIFTS (ESP Reliability Information and Failure Tracking System). Through this JIP, operators are cooperating with the goal of gaining a better understanding of the factors affecting ESP Run Life in a broad range of applications. In the initial phases, the focus was on establishing consistent practices for collecting, tracking and sharing ESP Run Life data and failure information. The preliminary results of this effort were reported in a paper presented at the 2001 ESP Workshop[1]. More recent work in the JIP has focused on establishing proper procedures to ensure the quality of the data that is being shared, and on developing different analysis techniques to facilitate extracting valuable information from such data.

One of the analysis techniques that have been investigated consists of a statistical model to determine the expected average ESP Run Life (or average failure rate) for given a set of operational conditions. The model is based on the available dataset, which covers ESP operations worldwide (Figure 1). This model serves three main purposes: (1) to estimate ESP Run-Life for new applications, so that proper economic evaluations can be performed as part of initial artificial lift assessments, and overall field development feasibility studies; (2) to estimate a likely change in historical ESP Run-Life for an on-going operation, so that the benefits of a possible change in the operational practices (e.g., re-run of used equipment, use of gas separators, introduction of higher horsepower systems, etc.) can be properly evaluated; and (3) to benchmark average ESP Run-Life between operations taking into account individual application differences.

The following sections describe the approach used to build the model and the difficulties encountered. Results are also presented illustrating a benchmarking exercise recently conducted with the data currently available in the JIP database. The technique is not unique, and has been used in many other scientific fields, such as to predict life expectations for cancer patients, given a set of their characteristics (age, gender, time since diagnosis, etc.)[2].

Model Description

ESP Run Life models have been built in the past by other authors[3,4]. However, they are usually restricted to one specific operation. Patterson[3] used failure data gathered over eight years on 34 Permian Basin ESP wells to develop a model to estimate ESP Run Life for that application. Sawaryn and Ziegel[4], on the other hand, used ESP failure data from wells in two pads in the Kuparuk field in Alaska to predict the number of failures, and associated workover rig requirements, in the upcoming year for one of the pads.

One common approach in building these models is that the data follows an Exponential lifetime distribution, i.e., the reliability of an ESP system can be described by the following equation:

$$S(t) = e^{-\lambda t} \tag{1}$$

This is a single parameter (λ) model, in which *S(t)* represents the percentage of ESP systems that should survive until time t, and λ represents the average failure rate. The implicit assumption behind this model is that the instantaneous risk of failure does not change with time in operation. While this may sound like a very strong assumption, actual data does in fact support this approximation, as demonstrated by Patterson[3]. Other lifetime distribution models are also possible, such as the Weibull model, and have been used by other authors[5].

The objective here, however, was to build a model that would account for differences in operating conditions of several operations. To accomplish this, we followed an approach similar to that used by Upchurch[6] to analyze ESP failures in the East Wilmington Field in California. Upchurch analyzed different failure mechanisms separately and broke up the data into different classes or categories, according to key parameters that might affect the overall failure rate.

The exponential lifetime distribution model given by Eq. 1 was also used. However, it was recognized that the overall failure rate is composed of the sum of the rates of failure by each different physical mechanism (e.g., a pump plugs with sand, a motor burns, etc.):

$$\lambda_{Total} = \sum_j \lambda_j \tag{2}$$

where λ_j is the failure rate of each mechanism. Second, it was also recognized that different factors may affect the failure rate of each mechanism:

$$\lambda_j = \lambda_j(x_1, x_2, ..., x_n) \tag{3}$$

where x_1 , x_2 , ..., x_n are the values of the contributing factors (such as bottomhole temperature, water cut, pump vendor, etc.).

The function used to represent the relationship above was again the exponential function:

$$\lambda_j = e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n} \tag{4}$$

or

$$\log(\lambda_j) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n \tag{5}$$

One advantage of this function is that it guarantees that the estimated value for each failure rate λ_j is always positive, as it should be. A second advantage is that, given Eq. 5, its coefficients (β) can be determined by applying relatively simple regression techniques.

Determining the Model Parameters and Coefficients

The model parameters and coefficients were determined by regression techniques, using the large dataset of worldwide ESP installations that was made available in the JIP database.

It is not practical to consider every possible failure mechanism, and all parameters that may affect the failure rate of each mechanism. For this preliminary attempt to build the model, only the four predominant mechanisms found in the data, which account for the majority of the observed failures were considered. These were:

- plugged and stuck pumps
- contaminated seals
- burn and shorted motors
- burn and shorted cables.

In addition, only the two most influential parameters for each mechanism were used to construct the preliminary model.

Problems Encountered

Censored Data. One problem with fitting field data to such a model is that the dataset is censored, i.e., it contains ESP systems that did not fail or are still running. For these systems, the actual time to failure is unknown; all that it is known is that these systems survived up to a certain point in time. Note that when the failure mechanism was, for instance, a motor burn, the pump may have survived up to that point. Therefore, when considering one failure mechanism, systems that failed by other mechanisms are in fact “survivors”, according to the failure mechanism being considered. Caution must be taken such that each failure is counted only once for the analysis (i.e., so that the total failure rate is the sum of the failure rates of the different mechanisms).

The censored dataset introduces complications, with the main consequence being that simple linear regression techniques cannot be applied. Again, this is not different than what happens in other scientific fields (in the medical field, for instance, the available datasets also include survivors). Techniques exist to deal with these situations[2]; however, they are more complex than simple linear regression analysis.

Incomplete Records. Another problem in fitting field data to such a model is that the dataset is often incomplete, i.e., the values of certain parameters may be unknown for a number of records.

There are two ways to deal with this problem: (1) one can simply neglect the incomplete records, and fit the model to the complete records only; or (2) one can compute an average failure rate for the incomplete records, and “correct” the predictions of the model proportionally. This second approach tends to bias the predicted failure rate to the average failure rate of the whole dataset, reducing somehow the predictive capability of the model.

As one might expect, no matter the approach taken, if the values of the key parameters are unknown, the best prediction that can be made for the expected failure rate is the average failure rate of the population.

In this preliminary work, only those parameters for which a high percentage of records had information for were considered in constructing the model.

Choice of Parameters. There are a relatively large number of parameters that may affect the failure rates of different mechanisms. As a result, there are an even larger number of combinations of parameters that must be tested when constructing the model (the larger the number of parameters used in Eqs. 4 and 5, the larger the number of combinations possible).

In addition, while some combinations of parameters may indeed provide a better fit than others, there are still a number of possible combinations of parameters that may fit the model quite well. As a result, the final choice of parameters is not straightforward.

In this preliminary work, the choice of the two top parameters for each mechanism was made based on several considerations: (1) degree of fit of the dataset to the respective model; (2) degree of completeness of the information about the parameters in the whole dataset; and (3) engineering considerations.

Benchmarking Exercise

A benchmark exercise was conducted with the data currently available in the JIP database, using the model constructed as explained above. For each ESP operation covered in the dataset, "actual" average failure rates and average values for the key parameters were calculated. Then, "predicted" failure rates were computed using with the model and the average values previously calculated for the key parameters.

Uncertainty in the predictions. The "predicted" failure rate represents the "most likely" ESP Run-Life for each operation, based on the model, and given the average values for the key parameters in that particular operation. However, since the model is a statistical model, one must recognize that there is an inheriting uncertainty in this prediction. The same regression techniques that can be used to determine the values of the model coefficients (β) can also be used to determine the uncertainty in these predictions.

The "actual" failure rate is also uncertain since, as explained above, the dataset is censored (i.e., for a number of installations the actual time to failure is unknown). Again, all that that can be determined, based on the dataset, is the "most likely" actual failure rate for each operation. Sawaryn and Ziegel[4] presented ways to evaluate the uncertainty in the "actual" failure rate estimates.

Results. Figure 2 shows a plot of "actual" versus "predicted" MTTF values for each operation covered in the dataset (MTTF was simply calculated as the inverse of the average failure rate; i.e., the total number of failures divided by the total time in operation).

The results show that an application with a relatively low run-life (i.e., lower than the overall "industry" average) may be doing better than "expected" under the particular circumstances (e.g., point A), while another application with a relatively high run-life (i.e., higher than the overall average) may be doing worse than "expected" under its own particular circumstances (e.g., point B).

Caution must be taken, however, when interpreting these results, given the uncertainty in the predictions (both in the "predicted" MTTF and in the "actual" MTTF) as explained above.

Further Benefits from the Model Development

The three main purposes served by the model were listed in the Introduction. The benchmarking exercise described above illustrates how the model can be used to compare Run Life between operations accounting for the differences in their key application characteristics.

There are other benefits that result from the development of the model. Identifying the most influential parameters in the total failure rate, and the extent of their influence (through determination of the values for the coefficients β) is an integral part of the model construction. Therefore, the development of a proper model is a key step in gaining a better understanding of the factors affecting ESP Run Life.

Outliers, i.e. operations that have actual failure rates much higher or much lower than those predicted by the model, are natural targets for further investigations. Hopefully, this will lead to improved practices among operators and improved overall ESP Run Life.

Conclusions

1. When benchmarking ESP Run Life performance between operations, application differences must be taken into account in order for the benchmark to be appropriate.
2. ESP Run Life Models have been built in the past by other authors; however, most were restricted to only one or a few specific operations.
3. A new statistical model was built to predict ESP Run Life, which takes into account specific operating conditions.
4. A large dataset, covering a broad range of operational conditions worldwide was used to determine the parameters and coefficients of this statistical model.

5. A benchmarking exercise was conducted to illustrate how the statistical model can be used to conduct appropriate ESP Run Life benchmark comparisons.

Nomenclature

$S(t)$ = survival function
t = time, days
β = regression coefficient
λ = failure rate, days^{-1}

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References

1. Alhanati, F.J.S., Solanki, S.C. and Zahacy, T.A.: "ESP Failures: Can We Talk the Same Language?", paper presented at the 2001 Gulf Coast Section ESP Workshop held in Houston, TX, April 25-27, 2001.
2. Lawless, J.F.: "Statistical Models and Methods for Lifetime Data", Wiley, ISBN 0-471-08544-8.
3. Patterson, M.M.: A Model for Estimating the Life of Electrical Submersible Pumps, SPE Production and Facilities, November 1993, 247.
4. Sawaryn, S.J. and Ziegel, E.: "Statistical Assessment and Management of Uncertainty in the Number of ESP Failures in a Field", paper SPE 71551, presented at the 2001 SPE ATCE held in New Orleans, LA, 30 September – 03 October 2001.
5. Oliveira, L.F., et al.: "Analysis of ESP Failure Data from the Northeast Pole of Campos Basin", paper presented at the 1997 Gulf Coast Section ESP Workshop, held in Houston TX, April 30 – May 02, 1997.
6. Upchurch, E.R.: "Analyzing ESP Failures in the East Wilmington Field of California", paper SPE 20675, presented at the 1990 SPE ATCE held in New Orleans, LA, September 23-26, 1990.

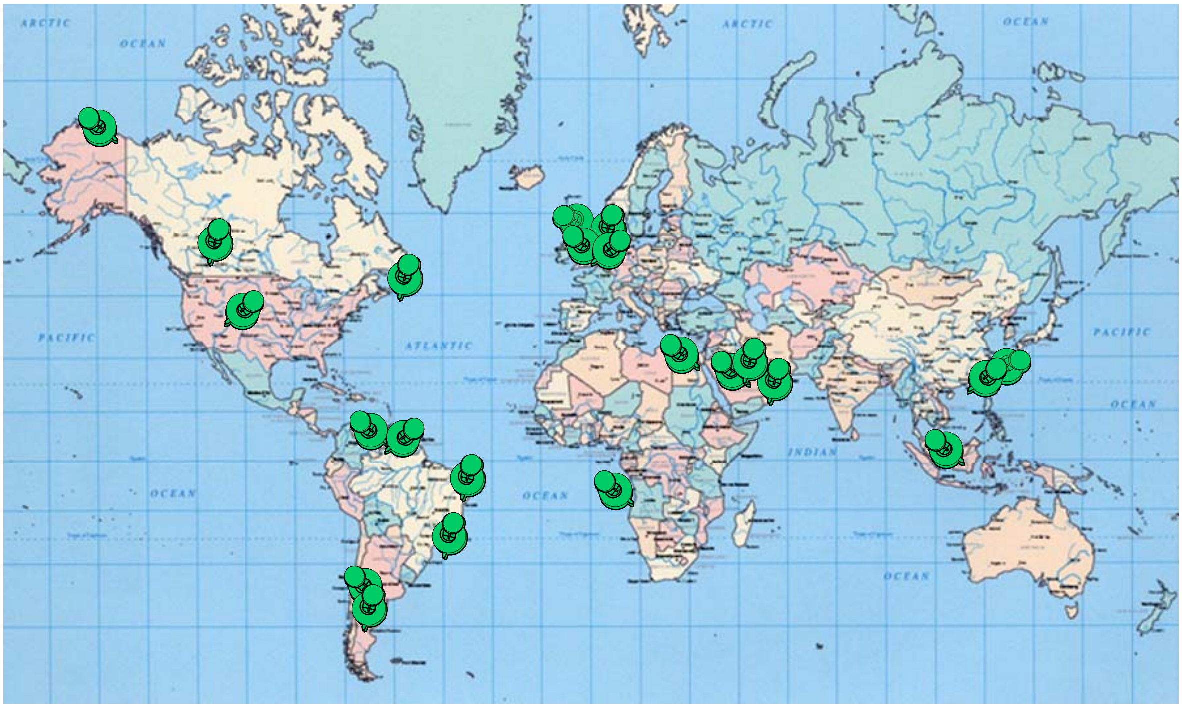

Figure 1 - World Map of Operations in the ESP-RIFTS System

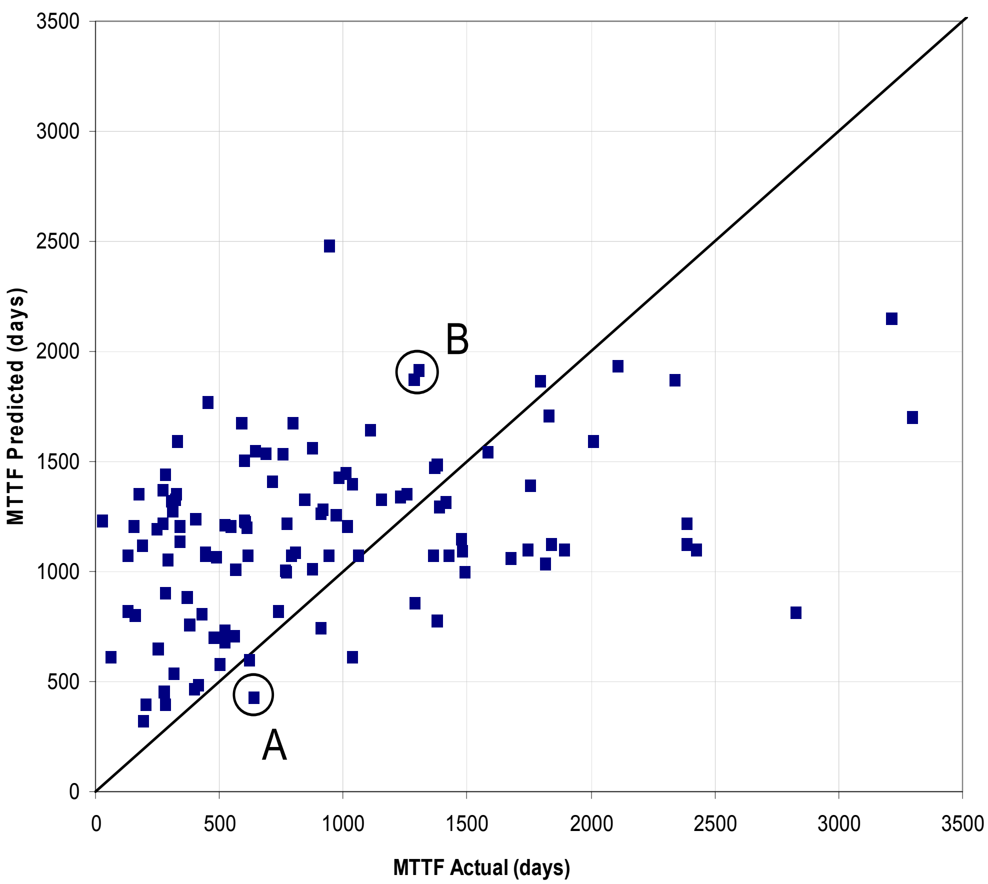

Figure 2 - Actual MTTF vs. Predicted MTTF for Operations in the ESP-RIFTS System