SPE 56663

The Analysis and Prediction of Electric-Submersible-Pump Failures in the Milne Point Field, Alaska

S.J. Sawaryn, SPE, BP-Amoco, K.S. Norrell, SPE, Centrilift Baker-Hughes, O.P. Whelehan, BP-Amoco

This paper was prepared for presentation at the 1999 SPE Annual Technical Conference and Exhibition held in Houston, Texas, 3–6 October 1999.

Abstract

Electric Submersible Pumps (ESPs) are the predominant lift method used in the Milne Point Field (MPU), Alaska. Each year some 50 ESP failures occur, adversely effecting lifting costs, rig utility and production. Statistical methods based on the Weibull distribution and the Bathtub reliability model have been used to analyse ESP reliability data collected over a thirteen year period. The analysis differs from earlier works by treating a portion of the infant failures (the early part of the Bathtub model) as a series of Bernoulli trials. Analysis shows the three main factors effecting ESP reliability in MPU are reservoir, sand control and if the ESP is newly installed or a replacement. Further, the ESP failure rate is shown to be dynamic, influenced by the delivery of new wells and the time lag between failure and replacement. The results have been incorporated in to a computer based failure simulator which uses Monte-Carlo techniques to simulate the failure rates. Numerical values for the statistical parameters are included together with details of the simulator.

The simulator is currently used within the MPU asset as a planning tool to establish changes in rig utility, production loss and ESP replacement strategies in a cash constrained environment. It is also used to assess improvements in ESP performance and to secure commercial terms for ESP lease and purchase options. In the future it is recommended that the simulator be used, with suitable analogue data, to predict the economic impacts of ESP failures on development programs prior to sanction.

Introduction

There are over 112 operating ESPs producing fluids from four distinct reservoirs in MPU. As the field has matured and reservoir fluid composition has changed, completion practices have been improved to help increase the productivity of the wells and the longevity of the ESPs. Over time, the number of production wells has increased and additional ESPs have been brought on line. Upchurch[1] has demonstrated that the variations inherent in such dynamic conditions are reflected in the ESP run times.

Analysis reveals the run lives of the MPU ESPs vary considerably. The current mean time to failure is 330 days with the age of the longest surviving pump being in excess of 10 years. 46 ESP failures were recorded in 1997 and a total of 67 failures in 1998. A rig workover, costing in a range of $300,000 is required to replace a failed ESP. The burden on the asset's operational cost is large, exceeding $20 Million per annum. The ESP failures also result in lost production estimated at 1.7 MM bbl per year.

Earlier methods used in the asset to predict the number of ESP failures for a given year were not successful. The number of failures predicted for 1997 and 1998 were underestimated by 50% and 40% respectively. This underestimation resulted in a shortfall in the asset's production, over runs in the operating budget and disruption to the rig schedules. It was for these reasons that a more formal analysis[1,2,3,4] was attempted.

Well Categorisation and ESP Data

Detailed information was gathered on 318 ESP's installed in MPU production wells. Well conditions and completion types were recorded along with the number and types of ESPs installed throughout the history of the well. The data was used to categorise each well in to a class type and calculate runtimes of each ESP.

Reservoir Type - The reservoir / formation from which the well is producing; Prince Creek, Schrader Bluff, Kuparuk and Sag River. Each formation has distinct reservoir characteristics which contribute significantly to the completion design and operation of the individual ESP's. The temperature of the main reservoirs, the Schrader Bluff and Kuparuk are 75F and 170 F respectively.

Sand Control - Identifies the type of sand control based on completion. Kuparuk wells have either full or no sand control, Schrader Bluff wells have all three. All Water Source wells have full sand control and all Sag River wells have no sand control. Full sand control; all production zones are fully screened, frac packed or gravel packed. Partial sand control; either resin coated proppant has been used to control proppant back production and sand production, or at least one, but not all zones have been screened. No sand control; the well has been cased and perforated and that nothing has been put into place to prevent sand or proppant from being produced.

Well Type - Distinguishes between a new completion versus a second or subsequent ESP installed in a well. It is known that the run life of the first ESP is typically shorter that the run life of the second or subsequent ESP.

Equipment Type - Identifies the type of ESP installed. This enables ESP performance to be tracked under different reservoir and completion conditions.

Stimulation - Specifies if a well as been fractured. In the Kuparuk and Sag River reservoirs, approximately 75% of the producers have been stimulated with propped fractures. In the Schrader Bluff, virtually all conventional producers have been fractured with a minority simply gravel packed or left in a natural state.

Inhibition - If a Scale Inhibition Job was performed. With an increased water cut scale has become a significant contributing factor of ESP failures. An aggressive scale inhibition program has been established to combat this effect.

Reason for ESP Failure - Root Cause Code reason for ESP failure. Each ESP failure has been coded to identify the component that failed and the assessed reason for the failure.

Production Sand - Identifies the open producing zones. Currently the N sands in the Schrader Bluff exhibit the highest sanding tendencies and create the most operational problems.

Manufacturer - Over 95% of the ESPs installed in MPU have been provided by the same vendor . No further analysis of this classification has been made.

The runtime of a unit is defined to be the difference between the POP and Failure dates. The POP date represents the day a first start attempt was made, the failure date stipulates the day that it was determined that further attempts to restart the ESP would be futile. Any well downtime between these dates was not taken into account due to the difficulty of obtaining the information and quantifying the hours of downtime. Only the day of POP and failure are recorded, not the hour.

Censoring

Data was available for 212 failed ESPs and on another 108 ESPs that were still running. It should also be noted that the number of ESPs that are still running comprise a significant proportion of the data. This set of right censored data contains many of the longer running ESPs. Oliveira *et al*[4] emphasised the importance of including this data (which they termed suspensions) in their analysis. Without these data, the parameters derived for the distributions will be unduly pessimistic. This is demonstrated by the 30% reduction in the number of failures predicted using parameters determined by the more rigorous method of maximum likelihood[5] pp50, compared to those determined by the simple graphical method used in the screening process.

Model Development

In the screening process, histograms of run life versus number of failures were prepared for both failed and running ESPs. The histogram for failed ESPs shows a steady decrease in the failure rate with time (**Fig. 1**).

A simple graphical method[5], was used to fit a Weibull curve to all the failed ESP data. The resulting correlation between cumulative probability of failure versus days run time to failure (**Fig. 2**) is good. The encircled area A on the graph highlights a discrepancy created by ESPs which had failed within the first day of operation, called "non-starts" in this study. This divergence led to the adoption of the bathtub reliability model with the these failures being included as a separate term.

Bathtub Reliability Model.

The "bathtub" reliability model applied to ESP's is described by Brookbank[2]. The "bathtub" concept consists of 3 phases, each characterising a stage in an ESP's life. The first phase A, consists of ESPs that fail to start, the second phase B, represents the in-service failures, where the failure rate is nearly constant, and the final phase C, is characterized by an increased failure rate due to natural wear. A more detailed mathematical representation of this type of failure model is given in **Ref. 6**.

In this study, in order to distinguish between the expected life of an ESP operating in ideal conditions, versus the accelerated failure rate attributed to non-ideal conditions such as abrasion and temperature, only phase A and B are included. The natural wear component, phase C, is ignored since few ESP's reach this point. Phase A represents the non-start failures and phase B represents the in-service failures. In this study, the probability of failure p(0) at start-up is assumed to be the same for all ESPs. The cumulative reliability function $F_0(t)$ for the composite distribution is:

$$F_0(t) = p(0) + (1 - p(0)) \int_0^t f(t) \quad dt \text{ ....(1)}$$

Non-Starts In-Service Failures

Non-Start Failures

Historically non-starts comprise approximately 9% of all recorded failures, or 6% of all installations. In practice, these failures may have occurred several hours after the ESP was first placed on line, but since the ESP did not run for over 24 hours it is recorded as having zero days runtime. Measured in this way, the non-starts represent a short time period compared with the overall time-scale in which failures are measured. In the model, the non-starts are assumed to be time-independent, therefore the probability of a ESP failing to start p(0) can be represented as a single Bernoulli[6] trial.

In-Service Failures

Patterson[3] used the exponential distribution to model ESP failures. One of the assumptions implicit in this is the probability that a single ESP will fail within a short time depends only on that period, not on the total elapsed run time. This same model was used by both Brookbank[2] and Upchurch[1]. Upchurch presented a series of log-linear plots of run life versus the number of remaining ESPs for three producing zones with the ESPs classified according to production rate. He observed that most of the distribution curves could be approximated by a single straight line, though a few curves appeared to possess two linear sections. Further inspection of the data reveals that they could have equally be interpreted as smooth curves. This non-linearity suggests an exponential model may not be the only fit and that other distributions should be investigated.

In 1997, Oliveira *et al*[4]. demonstrated that a two parameter Weibull distribution provided a better model to their ESP failure data. They further demonstrated that their ESPs exhibited a decreasing failure rate over their run life. The two parameter Weibull probability density function f(t) and cumulative probability distribution F(t) are:

$$f(t) = m\lambda t^{m-1} e^{-\lambda t^m} \text{ ....(2)}$$

$$F(t) = 1 - e^{-\lambda t^m} \text{ ....(3)}$$

Note that the Weibull distribution collapses to an exponential distribution with a failure rate λ when the shape factor m equals 1.

Composite Failure Model

The cumulative failure distribution for the composite failure model is obtained by combining equations 1 and 2 to give:

$$F_0(t) = p(0) + (1 - p(0)) \int_0^t m\lambda t^{m-1} e^{-\lambda t^m} dt \text{ ....(4)}$$

A separate distribution is needed for each of the ESP classes identified in the data analysis as explained below. The parameters p(0), m and λ must be determined for each class.

Parameter Estimation

Over the period of investigation, 19 non-starts were recorded out of a total of 320 installations resulting in an estimate[6] for p(0) of 19/320 or 0.06.

A commercial statistical data package was used to determine the significance of the various independent variables and estimate the parameters m and λ for the Weibull distributions. The package looks only at first order effects. For example, it assesses the overall effect of sand control, not the effect of sand control for new versus workover wells. To investigate second order effects, the data must be split manually prior to the analysis. This process can result in data sets that are too sparse.

Initial investigation showed reservoir type, sand control and new well versus workover were statistically significant and that stimulation and equipment type were not. To further investigate the effects of sand control and new well versus workover, the data was split into the four reservoir types. This results in the Prince Creek and Sag River data sets being quite small. Splitting the data in this way showed:

- Schrader Bluff wells are particularly sensitive to the sand control employed.
- The failure rate associated with sand control is highest for no sand control and lowest for full sand control. The rate for partial sand control is in between. The difference between full and partial sand control is much larger than that between partial and no sand control.
- New wells fail more quickly than workover wells for all four reservoirs.

With four reservoirs, three sand control categories and two well types, this categorisation results in 24 ESP classes (4 x 3 x 2 = 24), ten of which have no ESPs installed. This leaves 14 classes needed to classify the MPU data **(Table 1)**.

The significance of a variable is determined from it's parameter estimate and it's standard error. If the absolute value of the ratio of the parameter to it's standard error is approximately greater than 2 then the variable is statistically significant at the 5% level. The greater the ratio of the parameter to it's standard error, the greater the statistical significance and the higher confidence there is in the model.

Inspection of **Table 2** shows two of the ratios are less than 2 (italicised). However, the consistent trend of the effects of the two variables sand control and well type gives confidence in the model overall.

Adjusted Mean

The distribution mean includes all run lives ranging from zero to infinity. In practice, the mean calculated for a set of ESPs will differ from the distribution mean for two reasons. Firstly, an infinite run life is not attainable because the ESPs will wear. This failure mode has not been included in the model. Secondly, the sample population is not infinitely large, so the distribution is not fully populated. Even with a vigorous drilling program, the maximum possible run life after 10 years development is 10 years. In both cases it is the longer run lives that will be absent from the sample and the mean run life of the actual ESP population will always lag the mean life calculated for the distribution.

It is possible to obtain a rough estimate of this effect by assuming the sample population is complete up to the age of the longest surviving ESP t_{max} in each class and integrating the distribution to this value. The adjusted mean $\bar{t}$ can be expressed in terms of the incomplete gamma integral[7] as in Eq. 5.

$$\bar{t} = \left(\frac{1}{\lambda}\right)^{\frac{1}{m}} \Gamma\left(1+\frac{1}{m}\right) G\left(\left(\lambda t_{max}^{m}\right),\left(1+\tfrac{1}{m}\right)\right) \quad \ldots\ldots\ldots (5)$$

Qualitatively, comparison of the distribution mean[4] and adjusted mean in **Table 1** reveals the distribution mean is heavily influenced by the longer surviving members. For the larger sample sizes, the adjusted mean is closer to the actual mean. This calculation explains why running means are not, of themselves a good measure of ESP performance. Even if the underlying reliability of the ESP remains unchanged, the running mean should always increase with time because the population naturally gains a greater proportion of longer surviving members.

ESP Replacement Cycle

From this we conclude that the failure rate depends on the reliability of the ESP, characterised by the Weibull parameters m and λ, the proportion of run life that has already been expended and the number of ESPs that are running. By implication, any activities which either increase or decrease the number of ESPs, such as drilling and suspension will also effect the failure rate. Thus, the life, failure and replacement of an ESP is a dynamic process, influenced by economic and operational factors in addition to it's mechanical integrity. The life cycle is summarised in **Fig. 3**.

Once an ESP fails, an economic analysis is conducted to determine if it will be replaced. This analysis considers factors such as run life, oil price, production rate, water cut, gas-liquid ratio, completion type and workover cost. Until recently, 96% of ESPs that failed in MPU would have been replaced. With the drop in oil price and onset of water and gas production, the proportion of failed wells able to pass the economic threshold has fallen to 75%.

If the well meets the economic hurdle it is pooled with the new well completions from the drilling program and placed on the rig workover schedule. Once the new ESP is installed, it will either be put back on line, or if it fails to start, it will once again be queued back with the new and work over wells and the cycle starts again.

ESP Failure Simulator

It is not possible to obtain the solution to the ESP replacement cycle analytically. The complex feedback loops, time delay introduced by the workover, and transition from one ESP class to another results in coupled integral equations. Some form of numerical solution is therefore necessary. A computer based simulator was constructed to simplify the calculation process.

The simulator was designed to conduct the following tasks:

- Assess the reliability of multiple ESP classes
- Assess the effect of the workover time delay from the date of failure to reinstatement (POP)
- Represent the proportion of ESPs that fail to start, the "Non-Starts"
- Test the economic viability of the workover
- Simulate the number of failures and production loss, both historically and looking forward
- Commence the simulation at an arbitrary starting time
- Account for the survival times of the ESPs to the commencement date of the simulation
- Determine the confidence in both the predicted number of failures and production loss
- Generally, model each of the stages in the ESP replacement cycle

Because of the need to assign an arbitrary starting time, a critical component of the simulator is the ability to determine the status of the ESPs at that date. At any time, each ESP can be placed in one of four categories (**Table 3**) governed by one of three distinct simulation sequences. The sequence is determined by the first activity (whether or not the ESP is running at the start of the simulation), and whether the ESP is a new completion or the result of a workover. To maintain flexibility in manipulating the data, a commercial PC based relational database management system with a powerful query builder was chosen as the prototype development tool. The more specialised numerical algorithms needed for the statistical calculations are well documented in the public domain[7,8,9] and were readily incorporated using the programming language associated with the database.

Solution Methods

Two types of numerical solution are employed. The first is a forward calculating finite difference solution. This determines the fraction of ESPs that survive to a chosen time directly from the conditional probability of failure and survival time to that point. The second method is a Monte-Carlo scheme similar to that used by Brookbank[2] which generates random failure times for each ESP in turn and repeats the process many times to determine the expected failure rates. The logic for the Monte-Carlo component is represented in **Fig. 4**. The mathematical keys to the simulator are the evaluation of the conditional probability of failure and the generation of Weibull distributed failure times.

The Monte-Carlo scheme is preferred. It avoids the mathematical difficulties that would otherwise be encountered with the integrals that average quantities, such as a production loss associated with the failure. However, both methods were built into the simulator, principally to check the correctness of the Monte-Carlo algorithm. There is also a difference in execution speed between the two methods. Over a simulation period of 24 months the finite difference scheme is rapid, calculating the number of failures in around 60 seconds. For the same analysis, the Monte-Carlo scheme takes 20 minutes to reach a workable precision, obtained after approximately 1000 trials. The time taken for the finite difference scheme increases with the square of the step size, where as the Monte-Carlo scheme increases linearly.

When testing the Monte-Carlo scheme it was found that the proportion of non-starts was higher than that calculated by the finite difference scheme. After investigation, this aberration in the Monte-Carlo results was attributed to the relatively short time over which the simulations were conducted. During periods of rapid development, many new wells are put on line. If the expected ESP life is longer than the simulation period, there will be a higher proportion of wells being placed on line and the distribution of failures will be biased towards the non-starts.

Conditional Probability

An exponential distribution has a unique property that the expected life of a component that has already survived to some time t* is the same as it was at time zero. This is not the case for a Weibull distribution and an allowance must be made for the proportion of the ESP's life that has already been expended. The conditional probability of an ESP failing between times t_1 and t_2 having survived to a time t* (see appendix) is:

$$= \left[\frac{e^{-\lambda t_1^m} - e^{-\lambda t_2^m}}{e^{-\lambda t^{*m}}}\right] \qquad (6)$$

Weibull Distributed Random Variable

If X is a randomly generated number such that $0<=X<1$ then it can be shown (see appendix) that τ represents a Weibull distributed time of failure given that the ESP has survived to a time t*.

$$\tau = \left[t^{*m} - \frac{1}{\lambda}\log_e(1-X)\right]^{\frac{1}{m}} \qquad (7)$$

Time Step Size

As ESP lives are rounded to the nearest day, a day is a convenient step size for both calculation methods. A further requirement is the inclusion of the workover delay. As a guide[10] a "reasonably safe" time step should be at least an order of magnitude smaller than the workover delay. This places a non-zero lower limit of 10 days on the delay. With this step size, simulations covering a period of 10 years have been successfully conducted with the Monte-Carlo scheme.

Production Loss

A loss of production is associated with each ESP failure. With the exception of the Sag wells (**Table 1**), all of the ESP classes exhibit a decreasing failure rate ($m<1$). The chance of an ESP failing is higher earlier in it's life, decreasing as it ages. Generally, production rate also declines with time and therefore production losses are biased towards failures occurring early in the ESP's life. With the Monte-Carlo simulation the calculation of the production loss is simplified as it can be associated directly with a specific ESP failure.

A simple exponential decline curve was employed to estimate these losses. The production loss between the time of failure and reinstatement comprises the loss from the point of failure and the additional loss resulting from any failed reinstatement (non-start).

Production recommences when the ESP is back on line. As the simulation is conducted over a finite time interval, the time of reinstatement may be beyond the end of the period over which the simulation is conducted. Also by definition, if the well has been deemed uneconomic to workover, it will remain off-line throughout the rest of the simulation. This loss is also accounted for.

Production was also attributed to the water source wells. For these wells, the decline rate was assumed to be zero and the loss of oil production was assumed to be a fixed proportion of the water production. The losses calculated in this way match closely that calculated in the asset's production model.

Results

Simulations were run for each of the years from 1995 to 1998 using 10,000 trials with the Monte-Carlo simulator. New wells were accounted for using their actual POP dates. To match earlier practice within the asset, an economic limit of 50 bbl/day and a workover delay of 30 days was assumed. For each case, at the end of the 12 month period, the modeled number of failures fall within one standard deviation of the actual number of failures recorded (**Figs. 5-8**).

Inspection of the graphs shows an abnormally low failure rate during the first quarter each year (the encircled areas marked A). The failure rate then increases sharply during May (the encircled areas marked B).

The effect was particularly pronounced in 1997. No failures were recorded during a two month period from 15th February to 12th April. With 88 ESPs running, the probability of this happening was 0.0012. Similarly, in 1999 between 24th January and 16th March, no failures were recorded with 113 ESPs running. The probability of this event was 0.0002 (see appendix). These events are statistically significant and merit further investigation.

At MPU, this period in May corresponds to "break-up" when the temperature rises sharply and the ice thaws. At this time operational and maintenance activities increase, diverting attention from the ESPs. The investigation of this observation is ongoing. However, large potential savings could be gained by maintaining the low ESP failure rates and avoiding the sharp increase seen in May each year.

Confidence Limits

The confidence around the predicted number of failures is a function of the failure distributions, distribution of non-starts and errors in the distribution parameters themselves. From the Central Limit Theorem[6] pp182, it is known that for a sufficiently large number of trials the resulting distribution around the mean is approximately normally distributed regardless of the distributions of the components.

Therefore, the variance of the number of failures or production loss can be calculated using the Monte-Carlo simulator. Using this value for the variance, standard tables for the Normal Distribution can then be used to define the confidence limit for the prediction. Note that the distribution is not normal at the start of the time period over which the prediction is being made.

1999 Failure Prediction

At the end of 1998 MPU finalised it's response to the low oil price. The constraints placed on operating expenditure meant that not all of the ESPs that would fail in 1999 would be replaced. This model was used to help determine (1) the feasibility of running the workover rig a 2 week on / 2 week off rotation and (2) the additional loss of production that would result from increasing the economic threshold below which a well would not be worked over. It was estimated that the proposed change to the workover rig schedule would increase the fail to POP time from 30 to 45 days. No new wells (which are less reliable than ESPs installed in workovers) were planned to come on line until Q4 1999. All three of these actions will reduce the number of failures as compared to 1998. Intuitively, the failure rate should also decrease throughout the year as the number of running ESPs declines. This is what the ESP Failure Simulator predicted (**Fig. 9**).

The simulator demonstrated that if all wells were worked over 57 failures could be expected (compared to the 67 failures recorded in 1998). By setting the economic limit below which wells would not be put back on line, at 200 bbl/day, the number of failures would be reduced to 52 +/- 7(1σ) (**Fig. 10**). At the same time, the corresponding number of workovers would be reduced to 40. Finally, as can be seen, the results suggested that the changes could be made with only a moderate loss of production in 1999.

This 22% reduction in the expected number of failures compared to 1998 illustrates the importance of considering the influence of development activity, workover programs and economics on ESP failures. The difference is approximately twice the standard deviation. **Fig. 9** shows the 1999 failures recorded to date. Note the low failure rate in Q1 similar to that seen in 1997 **Fig. 7**.

Further Applications

The effect on mean time to failure, or other performance measures can be assessed using the simulator. By simulating the planned addition or removal of wells, the variation in the performance measures can be calculated and new, more meaningful benchmarks can be established. In this way, the effects of an aging or rejuvenating population can be accounted for.

From an operator's perspective, by weighting production with the probability density functions, commercial measures such as the rate of return (ROR) can be assessed for prospective wells. From a vendor's perspective, the probability density functions and predicted failure rates can be used to assess cash flow and pay back of ESP rentals. In this way the potentially injurious economic effects of infant mortality can be avoided.

Finally, by extending the simulation to cover the entire life of a prospective field, the effects of ESP reliability on the field's growth, operation and decline can be assessed. The workover and intervention requirements can be determined directly from the predicted failure rates.

Conclusions

1. A Weibull probability density function combined with the bath-tub reliability model provides a good fit to the ESP failure data.

2. The number of failures modeled over a four year period is a reasonable match to the actual number of failures recorded.

3. Statistically, the main factors effecting ESP reliability in MPU are reservoir, sand control and new well versus work over well. Currently 14 ESP classes are required to categorise the MPU data.

4. The failure rate is dynamic and is influenced by the increased well count, the time lag between ESP failure and replacement and the economics of the replacement itself. These factors must be considered if a reliable estimate of the number of failures is to be made.

5. When incorporated in a Monte-Carlo simulator the model can be used to predict the probable number of failures and identify which ESPs are the most likely to fail.

6. The simulator permits the commercial value of a workover to be tested and the lost production associated with the failures to be estimated.

7. The statistics show an abnormally low failure rate during the first quarter of the year and a subsequent rapid increase during May in each of the years from 1995 through 1998. The same abnormally low trend is being observed in the first quarter of 1999.

8. Assuming analogue data is available, it is expected that the simulator can be used to better assess the economics of different ESP strategies of a project development prior to sanction.

Nomenclature

$f(t)$ = Probability density function
$F(t)$ = Distribution function
$F_0(t)$ = Distribution function with non-starts
G = Incomplete gamma integral
m = Weibull shape parameter
$p(0)$ = Probability of an ESP not starting on installation
t = Arbitrary time variable, t, days
t^* = Time to which an ESP has already survived, t, days
t_{max} = Age of the longest surviving ESP, t, days
X = Random number
Γ = Gamma function
λ = Weibull scale parameter, t^{-m}, days^{-m}
Ψ = Dummy variable
τ = Weibull distributed time of failure, t, days

Acknowledgments

We thank BP-Amoco, Centrilift Baker-Hughes and Oxy USA Inc. for permission to publish this paper; Bill Hill for his valuable support of this project; the Colorado School of Mines 1999 EPICS teams for reviewing some of the failure data and Eric Ziegel for his helpful comments and suggestions.

References

1. Upchurch, E.R.: "Analyzing Electric Submersible Pump Failures in the East Wilmington Field of California", paper SPE 20675
2. Brookbank, B.: "How Do You Measure Run Life?", presented at the ESP Workshop May 1st - 3rd 1996 North Side Branch of Gulf Coast Chapter, SPE
3. Patterson, M.M.: "A Model for Estimating the Life of Electrical Submersible Pumps", *SPE Production & Facilities*, November 1993, 247
4. Oliveira, L.F., Bardy, M.B. *et al.*:, "Analysis of ESP Failure Data from the NorthEastern Pole of the Campos Oil Basin", presented at the ESP Workshop April 30th - May 2nd 1997 Houston Texas, SPE
5. Crowder, M.J., Kimber, A.C., Smith, R.L. and Sweeting T.J.: *Statistical Analysis of Reliability Data*, Chapman & Hall, London (1994) ISBN: 0-412-59480-3
6. Hines, W.W., Montgomery, D.C.: *Probability and Statistics in Engineering and Management Science*, Wiley (1980) ISBN: 0-471-04759-7
7. Lau, Chi-Leung. (1980) Algorithm 147, A Simple Series for the Incomplete Gamma Integral, *Applied Statistics*, **29**, 113-4
8. Abramowitz and Stegun: *Handbook of Mathematical Functions*, Dover, New York (1972) ISBN: 0-486-61272-4
9. Pike, M.C., Hill, I.D. (1966) Algorithm 291. Logarithm of the Gamma Function, *Comm. ACM*, **9**, 684
10. Dutton, K., Thomson, S., Barraclough, W.: *The Art of Control Engineering*, Addison-Wesley, Harlow (1997) 472 ISBN: 0-201-17545-2

Appendix

Adjusted Mean

In the adjusted mean, the top limit of the integration becomes t_{max} rather than infinity.

$$\bar{t} = \int_0^{t_{max}} t.m\lambda t^{m-1} e^{-\lambda t^m} dt \quad \text{.........................(A-1)}$$

Substitute $s = \lambda t^m$

$$= \left(\frac{1}{\lambda}\right)^{\frac{1}{m}} \int_0^{\lambda t_{max}^m} s^{\left(1+\frac{1}{m}\right)-1} e^{-s} \quad ds \quad \text{.................(A-2)}$$

Using the nomenclature used in **Ref. 7** the expression A-2 becomes

$$= \left(\frac{1}{\lambda}\right)^{\frac{1}{m}} \Gamma\left(1+\frac{1}{m}\right) G\left(\left(\lambda t_{max}^m\right), \left(1+\tfrac{1}{m}\right)\right) \text{.......(A-3)}$$

Conditional Probability

Let P(A) be the probability that an ESP fails between times t_1 and t_2, P(B) be the probability that an ESP has already survived to a time t^* and P(A|B) be the probability that an ESP fails between times t_1 and t_2 given the ESP has already survived to a time t^*. Assuming A and B are statistically independent events:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad \text{.........................(A-4)}$$

$$= \frac{\int_{t_1}^{t_2^-} f(t)dt}{\int_{t^*}^{\infty} f(t)dt} \text{ ....(A-5)}$$

$$= \frac{F(t_2) - F(t_1)}{1 - F(t^*)} \text{ ....(A-6)}$$

$$= \left[\frac{e^{-\lambda t_1^m} - e^{-\lambda t_2^m}}{e^{-\lambda t^{*m}}} \right] \text{ ....(A-7)}$$

Weibull Distributed Random Variable

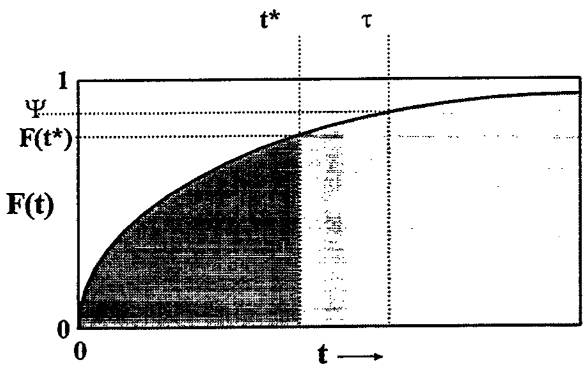

Fig. 11

If the ESP has already survived to a time t*

$$F(t^*) = 1 - e^{-\lambda t^{*m}} \text{ ....(A-8)}$$

If X is a randomly generated number such that 0<=X<1 then Ψ is a random number such that F(t*)<=Ψ<1.

$$\psi = (1 - F(t^*)).X + F(t^*) \text{ ....(A-9)}$$

Substituting F(t*) from A-8 in to A-9 gives

$$\psi = 1 - e^{-\lambda t^{*m}}(1 - X) \text{ ....(A-10)}$$

From **Fig. 11** Ψ can also be written

$$\psi = 1 - e^{-\lambda \tau^m} \text{ ....(A-11)}$$

Equating the two expressions, A-10 and A-11 for Ψ and rearranging gives:

$$\tau = \left[t^{*m} - \frac{1}{\lambda} \log_e (1 - X) \right]^{\frac{1}{m}} \text{ ....(A-12)}$$

Probability of Zero Failures

Assuming the failure of each of the n ESPs are statistically independent, the probability that there are no failures between times t_1 and t_2 given the ESP has already survived to a time t_1 is the product of the conditional probabilities of each of them not failing. Using the expression for the conditional probability of failure from A-7:

$$= \prod_{i=1}^{n} \left[1 - \left(\frac{e^{-\lambda t_1^m} - e^{-\lambda t_2^m}}{e^{-\lambda t_1^m}} \right) \right] \text{ ....(A-13)}$$

$$= \prod_{i=1}^{n} e^{-\lambda (t_2^m - t_1^m)} \text{ ....(A-14)}$$

$$= e^{\sum_{i=1}^{n} \lambda (t_1^m - t_2^m)} \text{ ....(A-15)}$$

Note: for clarity, the subscript i has been omitted from the scale and shape factors m and λ in equations A-13 through A-15.

Class	Reservoir	Sand Control	New Workover	No. Pumps (Dec 98)	Weibull m	Weibull λ	Actual MTBF (Days)	Weibull MTBF (Days)	Max. Life (Days)	Adjusted MTBF (Days)
1	Kuparuk	No	New	78	0.828	0.0057	337	568	1425	334
2	Kuparuk	No	Workover	103	0.828	0.0036	299	989	1772	457
3	Kuparuk	Yes	New	10	0.828	0.0041	480	845	1324	341
4	Kuparuk	Yes	Workover	24	0.828	0.0026	422	1465	1072	233
5	Prince Creek	Yes	New	9	0.541	0.0710	93	232	309	56
6	Prince Creek	Yes	Workover	27	0.541	0.0292	496	1199	3921	612
7	Sag River	No	New	4	1.139	0.0029	164	161	283	93
8	Sag River	No	Workover	7	1.139	0.0014	254	306	630	204
9	Schrader Bluff	No	New	14	0.728	0.0301	40	150	114	9
10	Schrader Bluff	No	Workover	5	0.728	0.0121	13	525	26	1
11	Schrader Bluff	Partial	New	21	0.728	0.0168	324	335	2229	305
12	Schrader Bluff	Partial	Workover	26	0.728	0.0068	535	1159	2183	497
13	Schrader Bluff	Yes	New	12	0.728	0.0029	1064	3736	2748	198
14	Schrader Bluff	Yes	Workover	8	0.728	0.0012	352	12557	660	34

Table 1: MPU ESP classes

Ratio Estimate / Standard Error	Kuparuk	Prince Creek	Sag River	Schrader Bluff
Intercept (Determines λ)	21.6	14.5	16.0	13.4
No	*1.2*			4.2
Partial				3.8
Yes				
New	2.4	2.0	*1.1*	2.7
Workover				
Scale (Determines m)	12.6	6.1	3.6	8.4

Table 2: Statistical significance of parameter estimates

No.	Category	Description	Simulation Sequence
1	Running Pumps	Pumps that were running at the beginning of the period of interest and failed.	1. Fail (New or WO) 2. Start 3. Fail (WO)
2	New Pumps Workovers	Pumps that fail during the period of interest and are replaced following a workover.	1. Start 2. Fail (WO) 3. Start 4. Fail (WO)
3	New Pumps Drilling Program	Pumps that are placed online during the period of interest as a result of the development drilling program.	1. Start 2. Fail (New) 3. Start 4. Fail (WO)
4	New Pumps Carry-Over	Pumps that have failed prior to the period of interest. If economically attractive they are worked over and replaced.	1. Start 2. Fail (WO) 3. Start 4. Fail (WO)

Table 3: ESP simulation categories and associated simulation sequence

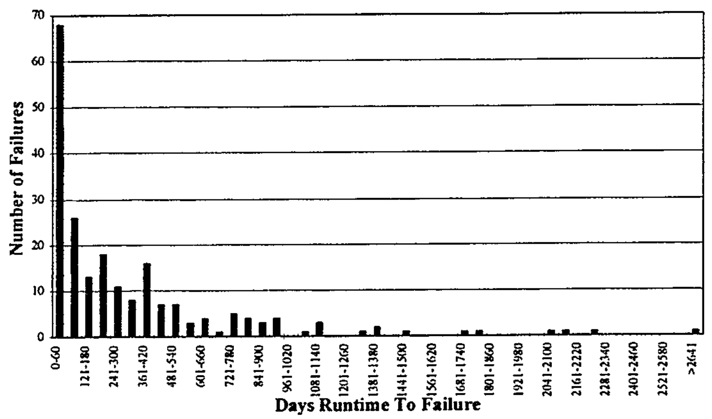

Fig. 1 MPU ESP's Days Runtime to Failure July 31st, 1998

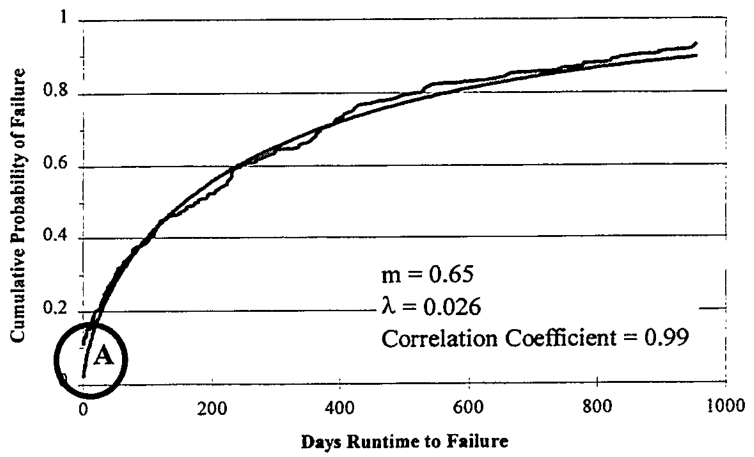

Fig. 2 MPU All ESP's Cumulative Probability to Failure

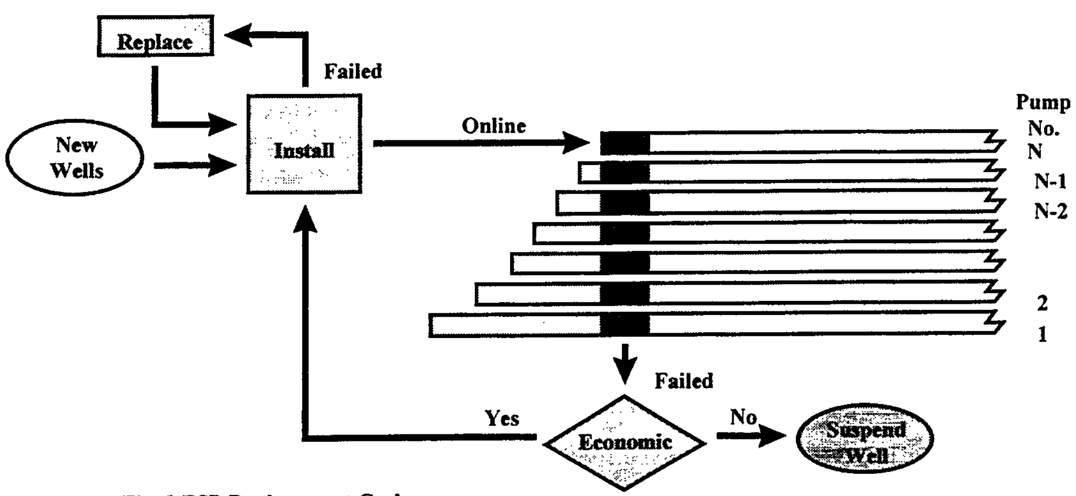

Fig. 3 ESP Replacement Cycle

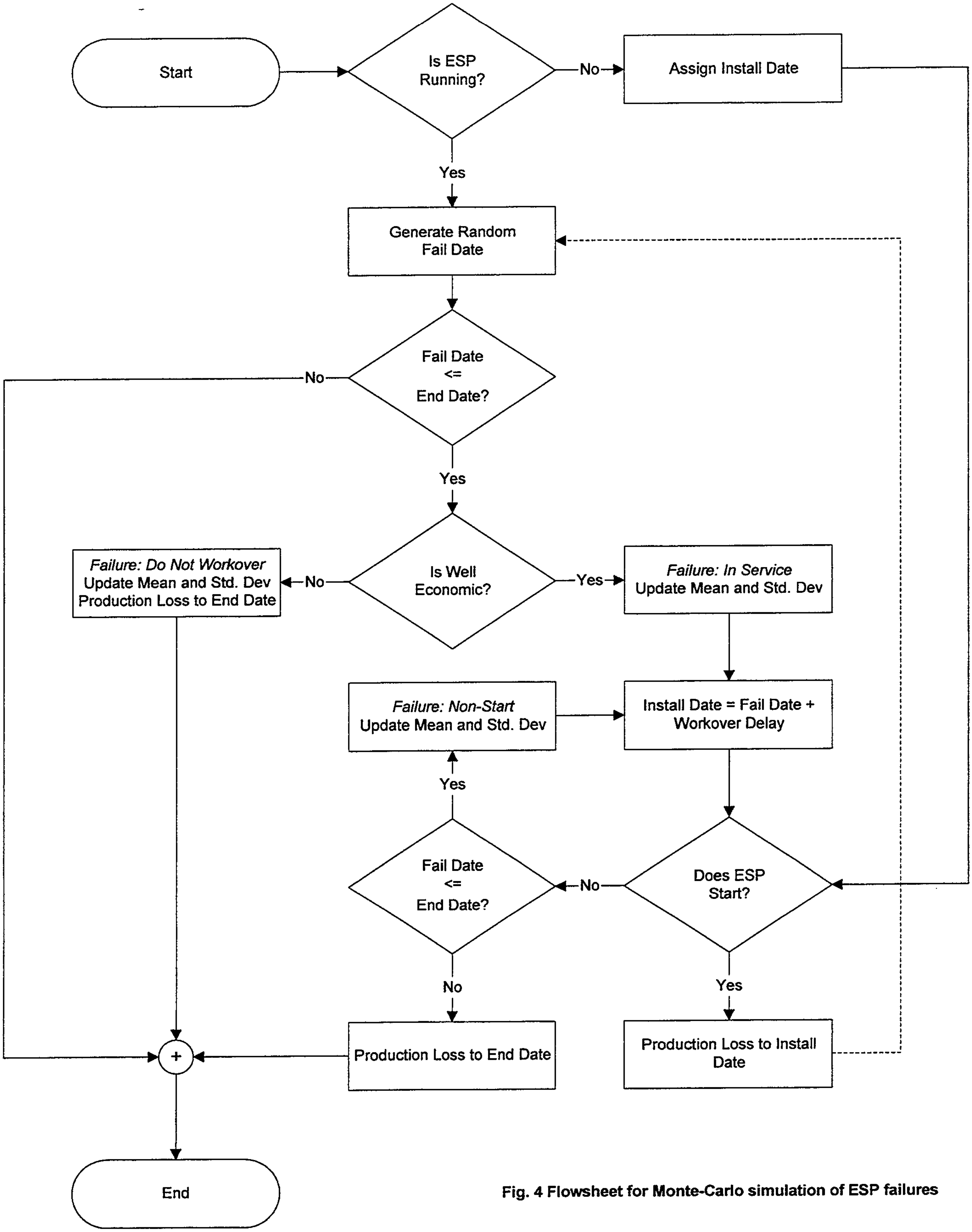

Fig. 4 Flowsheet for Monte-Carlo simulation of ESP failures

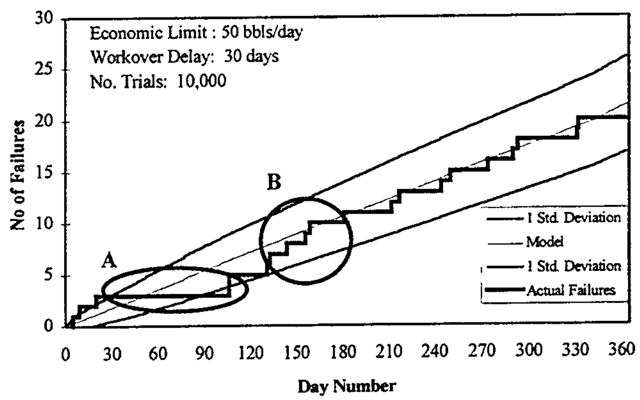

Fig. 5 ESP Failures - 1995 History Match

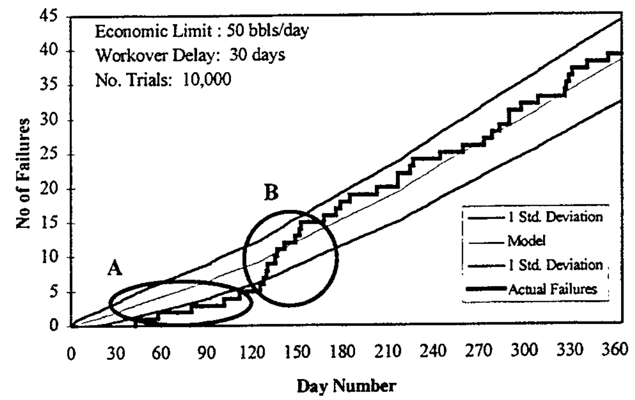

Fig. 6 ESP Failures - 1996 History Match

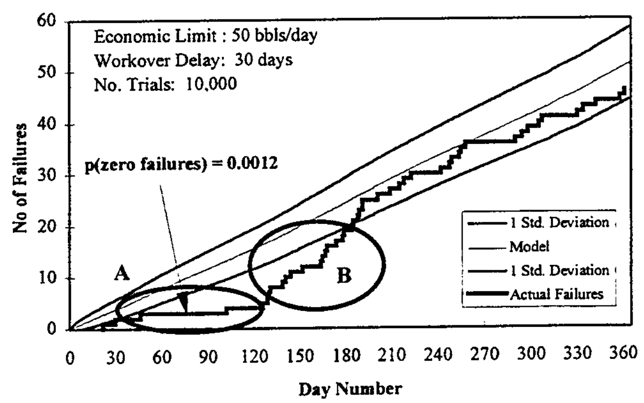

Fig. 7 ESP Failures - 1997 History Match

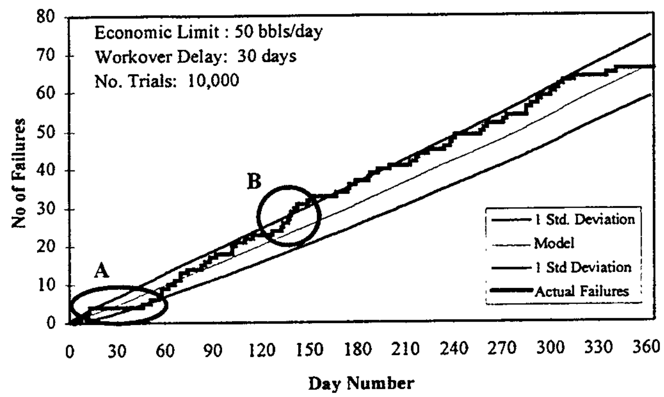

Fig. 8 ESP Failures - 1998 History Match

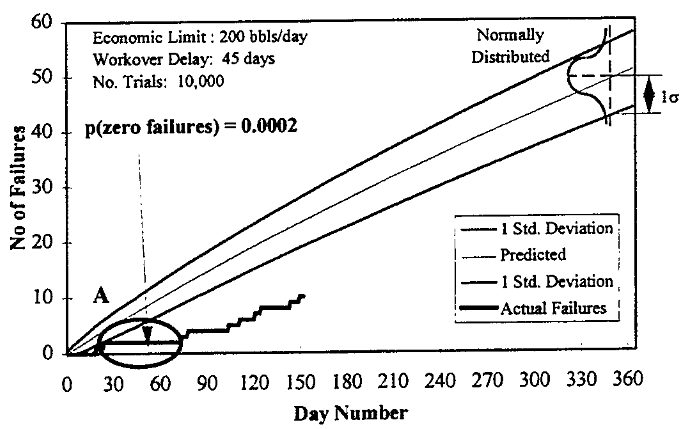

Fig. 9 ESP Failures - 1999 Predicted

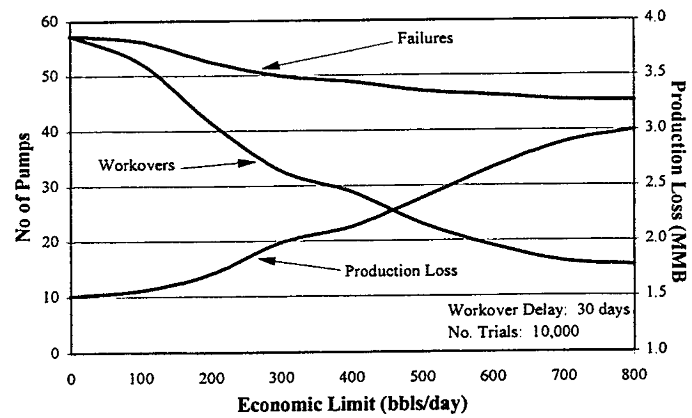

Fig. 10 Predicted Production Loss Versus Economic Limit 1999