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On Distribution Asset Management: Development of Replacement Strategies

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I. INTRODUCTION

The components of electricity networks are ageing. It is expected that within a horizon of 15 years, the performance will deteriorate significantly, while the costs for operating the networks will increase enormously. The main problem is that a significant part of the population of the assets is installed in the same period, resulting in a highly concentrated number of failures in a short time. The currently applied replacement strategy has to be revisited, in order to accommodate the effects of ageing assets: higher maintenance costs, high failure rates, and a steep increase of capital expenditure (CAPEX).

Methods like long-term simulation, multi-criteria decision-making under uncertainty, critical asset identification, condition assessment, and advanced statistics for the extrapolation of condition assessments of representative samples of assets should be applied. By using these methodologies in a smart and integrated way, costs and performance can be kept at an acceptable level.

The problem of resource management has long been recognized as one of the burning issues in electric utilities. Knowing how much to invest in creating a reliable and successfully performing resource pool (i.e. distribution cable network), when to repair or replace, and what human and financial resources are needed from year to year in order for such a network to operate successfully, the answers to those questions may represent substantial savings for the utility. Among the most acute problems that utilities are facing is the problem of accurate logging of system past performance and failure rate. As far as cables go, very little or no information is available to support such an activity.

Prior work by one of cable reliability researchers (Bill Forrest, [8]) is used here as a basis to extract the parameters of the Weibull distribution, which is assumed to describe the failure rate performance of the entire cable population. We have expanded and modified that approach to include multiple parameters identification and nonlinear models, and tested it using field data which was obtained from an actual cable population.

In addition, the have expanded the methodology to include Monte Carlo simulations of the failure rates in order to produce the estimates of distributions of failures rather than the most likely estimates. By doing so, we have developed a capability to associate confidence ranges with estimates of failure and replacement rates that are forecasted in the short time horizon of one to three years into the future. By doing so, planning can be associated with the desired level of confidence, which provides better quality information for a cost-conscious utility planner. It should be noted that the accuracy of the proposed methodology strongly depends on the quality and quantity of the input data, and it is envisioned that it could be enhanced in the future by combining chronological failure rate information with some form of condition monitoring, which can be coupled with the failure model that may sharpen the accuracy of the failure forecasts needed for a precise planning.

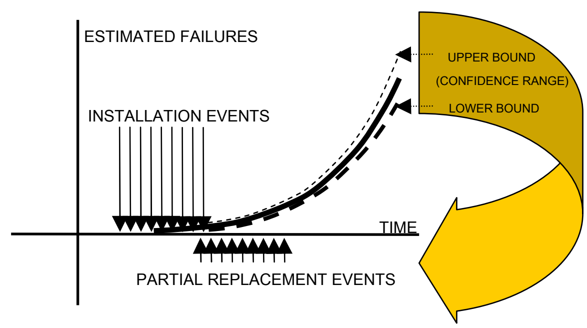

Fig. 1. Illustration of replacement scheduling events based on desired failure performance [9].

II. IMPROVING THE PREDICTIONS

There are two types of information which can be obtained and combined with the historical failure data. They are: (1) updated and complete historical failure data and (2) condition monitoring (if it can be associated with failure model and utilized to produce more accurate forecasts) The first item is simple to understand. If a statistical distribution of a random variable (a component's time to failure) is as shown in Figure 3 (original PDF), then by knowing a component has survived up until time t_1, the estimate becomes more accurate as more time is passing and we acquire the additional information that the failure did not occur until a given time instant. The change in distribution of failure estimate, which is treated here as Bayesian probability model, is shown in Figure 3 (updated PDF).

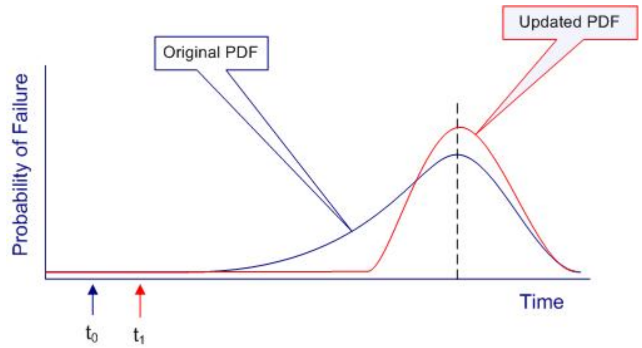

Fig. 2. Updated PDF of the next failure considering component survives to t = t_1.

As the time passes, the shape of the distribution will be modified. As the component approaches its expected time to failure, the distribution of time to failure becomes narrower and so do the confidence intervals (on either side of the maximum likelihood value). It must be kept in mind that the component can still fail at anytime; however, it is most likely to fail at the expected value of the PDF.

Suppose now data is available that is obtained through condition monitoring of some device parameter such as temperature, current, etc. The question is how to integrate this data into the failure prediction algorithm. This can be done using Bayes' Theorem. This theorem shows how additional information made be combined with an assumed PDF to yield a more accurate PDF. This can be stated in equation form

$$g(\theta \mid x) = \frac{f(x \mid \theta) g(\theta)}{\int f(x \mid \theta) g(\theta) d\theta}$$

where

x - a random variable whose value depends on event θ

θ - a variable

$g(\theta)$ - Prior distribution (i.e. the assumed initial PDF, in this case a Weibull PDF)

$f(x|\theta)$ - Conditional distribution relating x to θ

$g(\theta|x)$ - Posterior distribution (i.e. updated PDF)

The difficult aspect of this approach is how to relate the condition monitoring to a failure distribution since it is necessary to know precisely what the measurements mean to the life expectancy of the component. In some cases this information is known and in others it is not.

The greatest difficulty in utilizing condition monitoring data is defining how that data affects the lifetime of the component in question. For a given component there may be numerous parameters which may be monitored and understanding how all of them affect the device could be virtually impossible. Fortunately, it may only be necessary to understand the one or two most influential or critical of these parameters as the others may only produce very slight changes in the posterior.

It is clear that, in any failure forecasting procedure, a single number failure prediction (x number of failures in future year y) is virtually meaningless as there is no confidence attached to it. Therefore, stochastic simulation techniques have been employed to extract some level of confidence. By performing thousands of simulations, the algorithm yields a distribution for each of the parameters of interest and from these; the confidence intervals may be extracted. The confidence intervals then indicate how likely the forecasted parameter is to fall within a certain range.

This algorithm may be extended to include data obtained through condition monitoring to increase the accuracy of results. It may also be modified to take advantage of more complete historical data, thereby eliminating one of the necessary assumptions. A final modification would be to dispose of the assumed Weibull distribution and use non-parametric methods to generate the predictions.

III. METHODOLOGY

Suppose that $p(t)$ is the probability density function (PDF) of the time to failure t of a single component. The probability of that component failing before time t is given by

$$P(t) = \int_0^t p(u) du. \tag{1}$$

If we have a system of N such components connected in series, the probability that the system will fail is

$$P_0(t) = 1 - (1 - P(t))^N \tag{2}$$

where $P_0(t)$ is cumulative distribution function (CDF) of the time to failure, and the corresponding PDF is

$$p_0(t) = N(1 - P(t))^{N-1} p(t). \tag{3}$$

If the times to failure T are distributed as Weibull $Wei(\alpha,\beta)$, with parameters α - scale parameter and β - shape parameter, the PDF of time to failure of the overall system is

$$p_0(t) = N \beta \alpha^{-\beta} t^{\beta-1} e^{-(t/\alpha)^\beta N}, \quad t \ge 0. \tag{4}$$

Depending on the values of its parameters, the Weibull distribution can model a range of different reliability behaviors. For example, the value of the shape parameter β dictates the behavior of failure rate function. If β>1 (β<1), the failure rate is increasing (decreasing) with time, while for β=1 the Weibull distribution coincides with the exponential distribution and, as it is well known, the failure rate is constant in time in such a case.

It is interesting to observe that $p_0(t)$ can be rewritten as

$$p_0(t) = \beta \alpha_m^{-\beta} t^{\beta-1} e^{-(t/\alpha_m)^\beta}, \quad t \ge 0 \tag{5}$$

where

$$\alpha_m = \frac{\alpha}{N^{1/\beta}} \tag{6}$$

which means that $p_0(t)$ is also a Weibull density. The expected value of T (the time to failure of a single component) is

$$E(T) = \alpha\Gamma\left(\frac{1}{\beta}+1\right) \tag{7}$$

and the expected value of the time to failure of a system consisting of N identical units is

$$E(T_0) = \frac{\alpha}{N^{1/\beta}}\Gamma\left(\frac{1}{\beta}+1\right). \tag{8}$$

We therefore begin with the assumption that the expected number of failures that occur in a population of X components of the same type at time t years after the installation is given by

$$N_f(t) = X \cdot a \cdot (t-g)^b, \quad t > g. \tag{9}$$

where a is a scaling constant, b is a constant which is related to time dependency, and g is a quiet period (without failures) following the initial deployment of the component. If a component is installed in year i following the first installation and consists of X_i units, then the expected number of failures at t years after the *initial* population installation will be:

$$N_f(t) = X \cdot a \cdot (t-g-i)^b \text{ for } t > g+i. \tag{10}$$

Under the assumptions used in the above derivation (Weibull distribution), the failure rate possesses a linear relationship with the number of components. Finally, if we combine component populations installed in years *1, 2,…,i, i+1, …, n*, the cumulative estimated (in some sense, most likely) number of failures of such a population will be [8]

$$F(a,b,t,g) = \sum_{i=1}^{n} N_{f_i}(t) = \sum_{i=1}^{n} X_i \cdot a \cdot (t-g-i)^b$$
$$\text{for } t > g+i \tag{11}$$

That is a four-parameter function of time. Our earlier work [9] shows how to identify the three unknown parameters (*a,b,g*) from the knowledge of the observed number of failures over a finite (often quite short) period of time, by extracting the needed parameters from the observations by fitting the model to the observations in the least squares sense.

As we know the elements of X up to the time when all installations and replacements are known, the solution of the equations yields the parameter set $\{a,b\}$. With knowledge of the parameters, a set of equations can be solved for any desired time horizon $\{n+1, \ldots, n+k\}$ in order to determine: **i)** the estimated number of failures when a replacement schedule is planned for and known in that period; or **ii)** the estimated necessary replacement schedule, which should maintain the estimated number of failures at the desired (planned) rate within the time horizon of interest. In practical terms, the time horizon should be as short as reasonably possible in order to avoid the accumulation of uncertainty that would invalidate the results. Figures 3-5 show the confidence ranges for failure estimates calculated from chronological failure performance records up to the moment of estimation (we call it evolving time window). The results were obtained using stochastic simulations. Each estimate is the result of repetitive simulations, which is producing the estmate of the *PDF* of estimated failures in any given year.

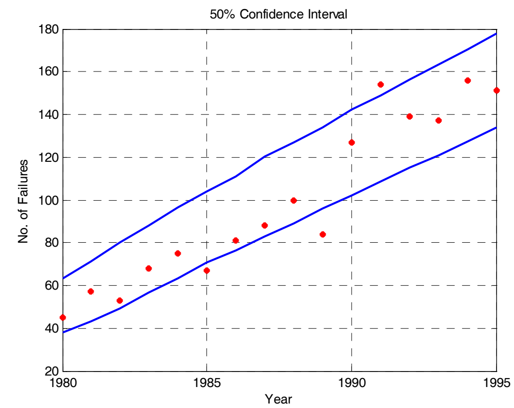

Fig. 3. Failure estimates for 50% confidence interval from evolving window simulation.

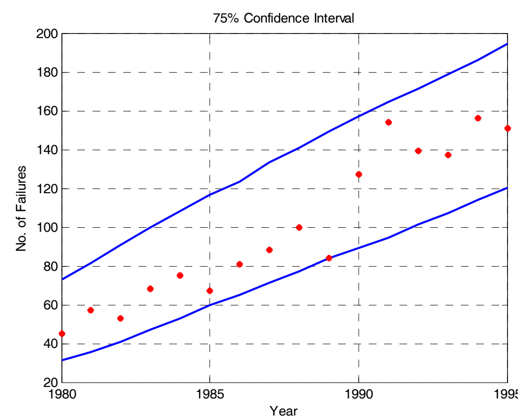

Fig. 4. Failure estimates for 75% confidence interval from evolving window simulation.

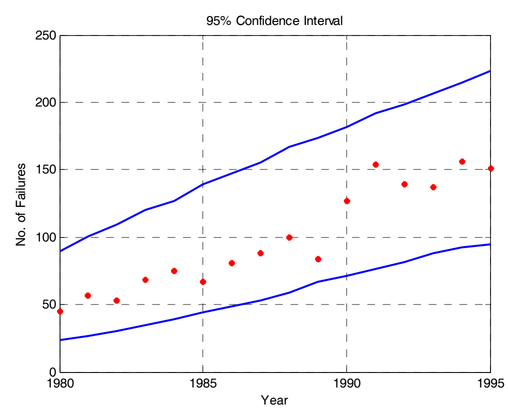

Fig. 5. Failure estimates for 95% confidence interval from evolving window simulation.

Naturally, as the confidence grows (larger fraction of simulation outcomes are contained in the confidence range), the range grows ever wider. In some cases, when insufficient information is available, confidence ranges can grow impractically wide (yield completely uncertain estimates).

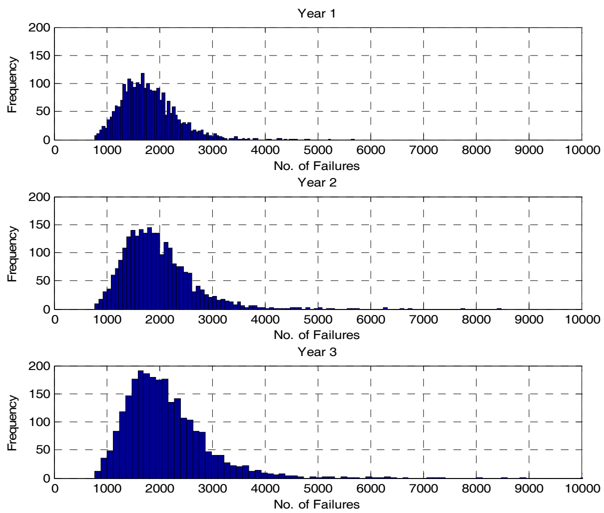

Fig. 6. Three year failure projection histograms for 2500 Monte Carlo simulations.

Similar effect can be observed as simulations are applied to estimate failure distributions in a growing time horizon. Replacements are calculated based on failure forecasts and objective to keep the future failure rates constant. The distributions appear to spread as we attempt to forecast failures farther into the future. The reason for that effect is the accumulation of uncertainty from years 1 through k in estimation of failure rate for the year k+1.

IV. COST OF DIAGNOSTICS

When forecasted number of failures exceeds the capacity of the O&M budgets, it is reasonable to consider deployment of certain diagnostic procedures in order to reduce the cost of replacement by avoiding the cost of replacement on failures and targeting the most vulnerable parts of the system. Depending on several factors, such as the percentage of bad components in the tested population, cost and accuracy of the diagnostic tests, as well as time between the tests on the same components, it is possible to estimate how effective the diagnostic tests would be. *In the following example, the numbers used are selected to illustrate various effects (primarily the dependence of annual maintenance budgets on diagnostic accuracy and the rate of failures inherent to the system).*

In order to introduce the subject through a simple example, let us assume that we have a diagnostic area consisting of 100 miles of distribution cables of the same type and different ages. The population consists of segments which are 500 ft long at median, but are distributed approximately as Weibull distribution with minimum length of 400 ft, and scale and shape parameters of 120 and 2.0 respectively, making 95-th percentile length of segment equal to 608 ft.. Let us also make a reasonable assumption that such an area is possible to be completely tested using certain diagnostic procedure which costs $6,000 per tested mile, and that the diagnostic cycle is 6 years long (which requires a diagnostic budget of $100,000 pa when spread over the diagnostic cycle).

Based on the chronological failure data (presented in the previous section) the forecasted failures are estimated as Weibull distribution with location, scale and shape parameters of 8.96, 24.0 and 2.37, respectively, which corresponds to 5-th, 50-th and 95-th percentile failure rates of 15.82, 29.53 and 47.08 failures/100 miles/year (median failure rate of ~30 failures/100 miles/year).

We also assume that the initial cost of replacement on failure is uniformly distributed between $5,000-$10,000/failure, and that the per unit length cost of the cable replacement is uniformly distributed ±10 percent around $30/ft. In addition, the accuracy with which a prescribed diagnostic is able to identify both a good and a bad section is arbitrarily selected to be uniformly distributed between 80% and 100%.

Under such circumstances, we choose to perform the stochastic simulation, by running a Monte Carlo test with 10^5 simulations consistent with the above assumptions.

With the use of diagnostics, the total cost (which amounts to the cumulative cost of diagnostic tests, diagnostic directed replacements and the cost of non-diagnosed bad segments due to diagnostic inaccuracy amounts to the distribution shown in Figure 7, which has a mean of $493.8K/yr, with 10-th and 90-th percentiles at $238.4K/yr and $750.0K/yr, respectively.

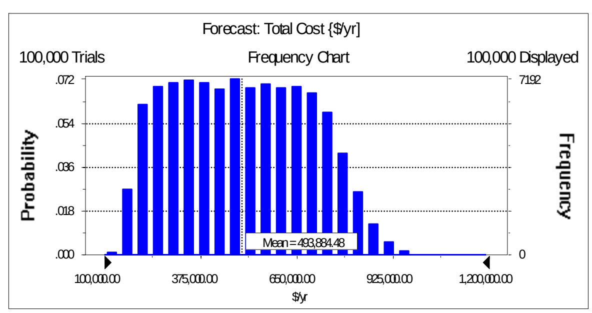

Fig.7. Distribution of the total cost of failures (in $/yr) if diagnostic tests are used, as per example in the text.

It is interesting to look into the cost of imperfect diagnostic testing (assumed here to have accuracy uniformly distributed between 80 an 100 percent). With a diagnostic accuracy of 100% every "bad" circuit diagnosed will in fact be bad. However we know that there will be some "diagnosed as bad" circuits that, if they were left alone would not fail in the diagnostic cycle; thus they would be viewed as “good” it is this discrepancy between diagnosed condition and actual condition that drives the cost of accuracies below 100%. The cost of the “in perfect accuracy is spread between $0 and $189.2K/yr, with mean value of $68.5K/yr and 10-th, 50-th and 90-th percentiles at $12.3K/yr, $61.0K/yr and $134.9K/yr, respectively.

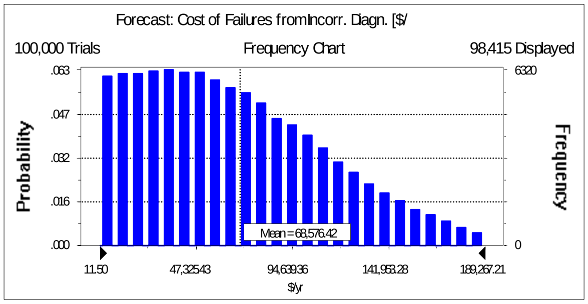

Fig. 8. Total cost of failures occurring from incorrect diagnostic testing (assumed 90% accurate on average).

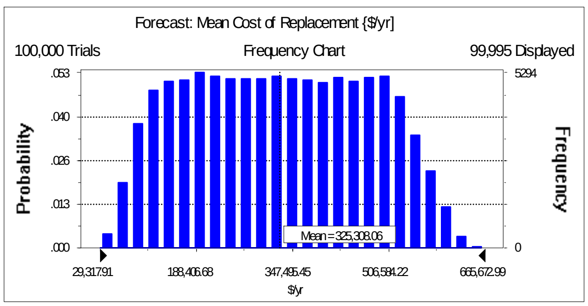

Fig. 9. Total cost of replacements based on recommendation after diagnostic testing (assumed uniformly likely to be accurate between 80% and 100%).

Total cost of replacements done upon diagnostic test recommendation is distributed as shown in Figure 9. It is almost uniformly spread between $30k/yr and $650K/yr, having a mean of $325.3K/yr and median of $324.0K/yr.

When the cost of running diagnostic tests is added to the costs of replacements and costs incurred from undiagnosed failures (Figures 8 and 9), the total cost (shown in Figure 7) is obtained. As the numbers presented in this example are used just as an example, it is of interest to evaluate their dependency on changing some of the important parameters of the experiment, primarily the failure rate in the system under testing and diagnostic accuracy.

For example, if diagnostic test accuracy is increased to a uniform distribution [90%,100%], the resultant total cost of diagnostics and replacement (both due to diagnostic recommendations and undiagnosed failures) would be as in Figure 10. The mean cost is reduced to $335K/yr (a reduction of 32 percent compared to the previous scenario) with 10-th and 90-th percentiles at $204.4K/yr and $467.3K/yr, respectively.

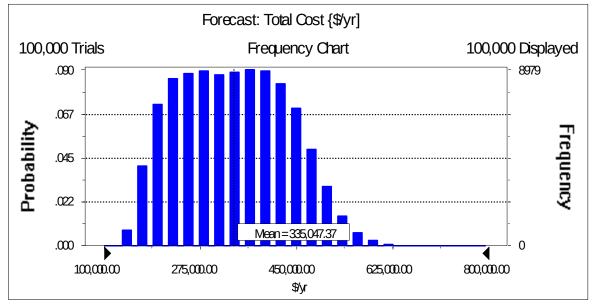

Fig. 10. Distribution of the total cost of diagnostics and replacement (in $/yr). Diagnostic accuracy is assumed to be uniformly distributed between 90 and 100 percent.

As seen in Figure 11, the situation can be quite different if the diagnostic accuracy is increased to an average of 97.5% (uniformly spread between 95 and 100 percent). In that case, the total cost would be $255.96K/yr (10-th, 50-th and 90-th percentiles are -%184.0K/yr, $254.0K/yr and $330.3K/yr, which represents another significant reduction of the cost.

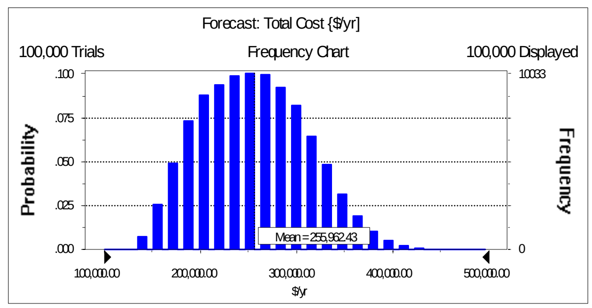

Fig. 11. Distribution of the total cost of diagnostics and replacement. Diagnostic accuracy is assumed to be uniformly distributed between 95 and 100 percent.

Finally, when the diagnostic accuracy is assumed to be perfect (100%), the total cost reaches a minimum distribution, shown in Figure 12. Mean yearly expenditures are $176.6K/yr, and 10-th and 90-th percentiles are $145.0K/yr and $211.6K/yr, respectively.

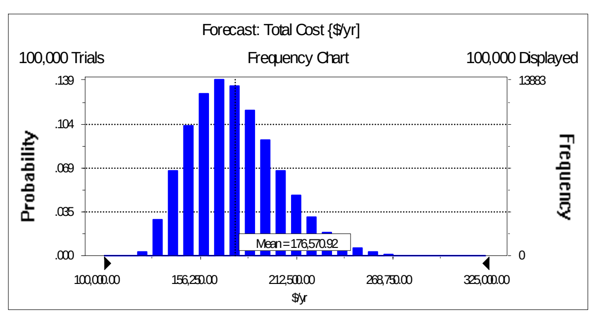

Fig. 12. Distribution of the total cost of diagnostics and replacement. Diagnostic accuracy is assumed to be perfect.

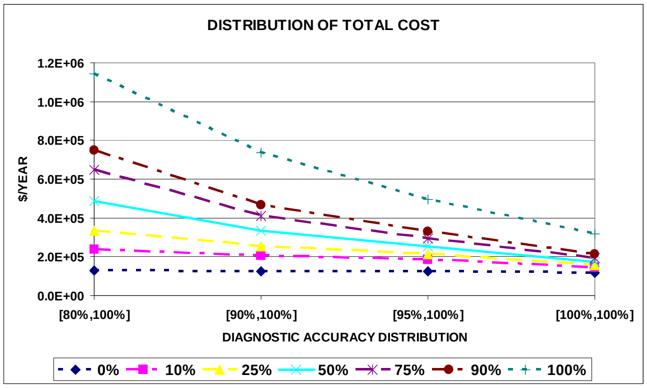

Fig. 13. Percentile distribution of the total cost (seven percentiles shown from 0-100%) of diagnostics and replacement (in $/yr) for various values of diagnostic accuracy and assumed failure rate of 30 failures/100 miles/year.

Figure 13 shows the distribution of costs (through representative percentiles) for various levels of diagnostic accuracy. The benefits of diagnostic accuracy are significant (worst case expenditures reduction from almost $1.2M/yr to $320K/yr.)

As system failure rate is one of the dominant factors in the calculation of the diagnostic benefit, it would be interesting to calculate the diagnostic benefits in a system whose estimated failure rates are lower than those assumed so far. Figure 14 shows the diagnostic benefit distribution in the system where the average failure rates are Weibull-distributed with mean number of failures of 20 failures/100 miles/yr. The mean total cost is $449.6K/yr, and 10-th, 50-th and 90-th percentiles are $210.0K/yr, $447.3K/yr and $687.4K/yr, respectively.

If the calculations of total cost were repeated on such a system, but with an assumed use of the procedure with various diagnostic accuracies (as in the previous examples) the total cost distribution becomes even more obviously attractive, as shown in Figure 15.

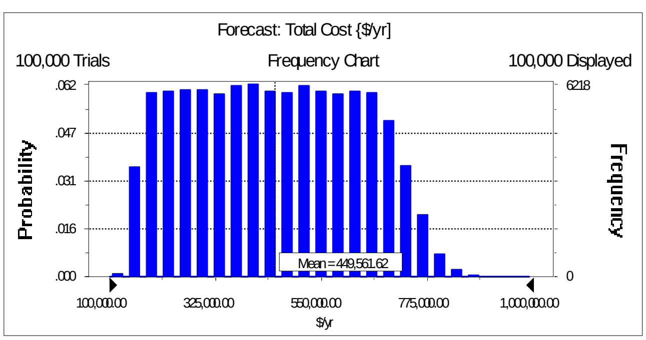

Fig. 14. Total distribution of cost with the use of diagnostic testing in the example when mean failure rates are 20 failures/100 miles/year. Diagnostic accuracy is assumed to be uniformly distributed between 80 and 100 percent.

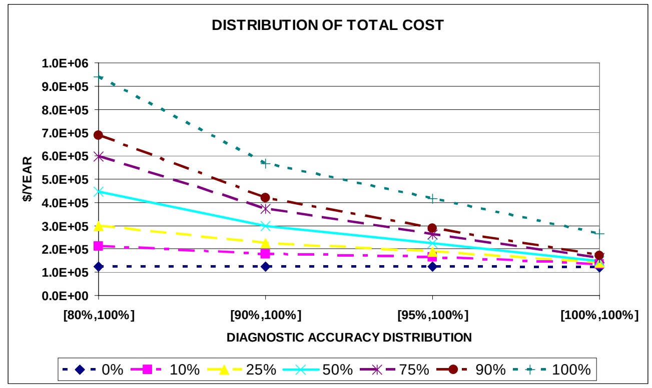

Fig. 15. Total cost distribution (seven percentiles shown from 0-100%) in the example when mean failure rates are 20 failures/100 miles/year. Diagnostic accuracy is assumed to be uniformly distributed from [80,100] % to 100%.

V. CONCLUSIONS

The failure forecasting procedure relies solely on basic historical data to forecast the number of failures. As a consequence of the available data, assumptions are made to make the analysis possible:

- The components have a lifetime consistent with a three-parameter Weibull distribution.
- The actual component that failed is unknown so it is assumed that the oldest components are always replaced first.

In addition, the algorithm allows for repeated calculation of failures assuming the component population has been altered. This allows for the calculation of replacement components needed to achieve desired changes in the failure curve. In effect, the algorithm can predict how actions in the present will impact the overall failure trend.

On the other hand, a single prediction is virtually meaningless as there is no confidence level attached to it. Monte Carlo simulation techniques have been employed to extract the information on the level of uncertainty. By performing multiple simulations, the algorithm yields a distribution for each of the parameters of interest and from these confidence intervals may be extracted. These tell how likely the forecasted parameter is to fall within a certain range.

The accuracy in forecasting failures, as well as the accuracy of diagnostic testing play a major role in evaluation of the total cost of replacement when diagnostic testing is used. The results depend very strongly on system conditions (forecasted failure rate, diagnostic accuracy, average length of the segments, etc.) The examples shown in the text demonstrate how the capabilities of the diagnostic tests can reduce the total system replacement costs.

ACKNOWLEDGMENT

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