Integrity Maintenance of Petroleum Pipelines

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Summary
In this paper, a data-driven model is applied to derive optimum maintenance strategy for a petroleum pipeline. The model incorporates structured expert judgment (classical model) to calculate the frequency of failure, considering various failure mechanisms. Optimization models are applied to derive optimum maintenance intervals for petroleum pipelines on the basis of the frequency of failure estimated. Two separate maintenance-optimization models are proposed. The first is a use-based optimization model that minimizes the expected total cost from a petroleum pipeline. The second is a benefit/cost (B/C) -ratio model that seeks to maximize the benefit derived from the pipeline, while minimizing operation and failure costs. The B/C-ratio model is less data intensive, and it has been used to optimize failure data obtained in the classical model. In this approach, the maintenance optimization is a further attempt at reducing the influence of subjectivity in maintenance decisions.

Introduction
According to Gabbar and Kishawy (2011), integrity of pipelines is the cornerstone of many engineering systems, which explains why pipeline maintenance is taken very seriously by major service companies, especially those involved in the transmission of oil and gas. The huge impact of pipeline failure on operational costs has necessitated the development of more-effective risk-management strategies to help mitigate potential risks. Ideally, most pipeline operators ensure that during the design stage, safety provisions are created to comply with a theoretical minimum failure frequency for the pipeline. Quantitative risk assessment (QRA) has been a valuable tool to operators in minimizing risk and complying with the minimum safety requirements for engineering structures.

QRA of pipeline networks is complex and can sometimes be laborious because of the differences in the system networks. According to Li (2007), one approach to simplify the QRA process is the use of the hierarchical approach. Hierarchical approaches, such as fault-tree analysis, event-tree analysis, and failure-mode event analysis, have found applications in risk assessment for complex structures, as explained in Dhillon and Singh (1981). However, such methodologies are data intensive. The rupture of pipelines occurs rarely in most countries, and as such, the data of failures are often insufficient to carry out a thorough hierarchical approach. Also, when failure data are gathered, the classifications may not cover all the known failure mechanisms and attributes.

A systematic approach to integrity maintenance of pipelines has been proposed in this paper using the classical model proposed by Cooke (1991). The model is a structured expert-judgment-based approach and is able to provide rational probability assessments. According to Cooke and Goossens (2008), the classical model has been applied successfully to more than 45 expert elicitation case studies, covering both academic and industrial areas. One of the benefits of the approach is that the level of subjectivity in expert judgment is reduced reasonably. This is because of the performance-based calibration of the experts used in the model. In other words, the inputs from the experts are used on the basis of the consistency of the experts during the elicitation process.

In this paper, the frequency of failure because of rupture for an existing petroleum-pipeline system is determined. The pipeline system is divided into three different segments on the basis of the uniqueness of physical and process parameters, and the probability of failure for each segment is determined. Five failure mechanisms are considered: external interference, corrosion, structural defects, operational errors, and minor failures. On the basis of the frequency of failure obtained using structured expert judgment, the expected cost of failure and maintenance cost for each of the pipeline segments can be determined. Furthermore, maintenance-optimization models are presented and applied to derive optimum maintenance intervals for the pipeline segments. The frequency of failure obtained in the classical model serves as an input to the optimization model.

The approach presented in this paper can be used both under limited data and when failure data are available. The findings of this research are very beneficial both academically and in the industry. The expert-judgment study, for example, is capable of reducing the level of subjectivity inherent in expert-judgment-based decision making. In addition, the maintenance-optimization study will be very beneficial in maintenance planning, both to the pipeline operator and the society at large. Moreover, the maintenance framework can be applied to existing pipelines and can provide an adequate benchmark for new pipeline installations. It is also hoped that the study can be extended to other production facilities.

Study Data
The case study is a petroleum pipeline that was commissioned in 1989, supplying petroleum products nationally. Some figures in the failure data of the pipeline have been modified slightly for confidentiality reasons. The pipeline has a diameter of 24 in., a total length of 340 km, with a design pressure and an operating temperature of 100 bar and 26.8°C, respectively. The material of the pipeline is fabricated from API5LX42 carbon steel, with a concrete-type coating. The pipeline is basically located onshore, but connects to a compressor station located offshore.

In the analysis, the entire pipeline is classified into three segments (X1, X2, and X3), in line with its natural stretch. The classical model is used to assess the frequency of failure for each pipeline segment. The failure parameters also can be used to arrange the segments of pipeline into a hierarchical ranking of risk. The aim of the analysis is to obtain the frequency of failure for the pipeline, which could serve as input to integrity-maintenance initiatives. The analysis takes into consideration various failure mechanisms that may occur in any segment of a typical, onshore petroleum pipeline.

To begin the classical model, six pipeline experts from the company were invited and trained on the application of the model. A failure-data sheet for each pipeline segment was made available to

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TABLE 1—RESULTING SOLUTION FOR THE DM

Item	5%	50%	95%	Failure Mechanism
		Segment X1		
1-X	0.00025	0.00132	0.00479	External interference
2-X	9.29E–5	0.00045	0.00402	Corrosion
3-X	3.97E–5	0.00022	0.00064	Structural defects
4-X	5.37E–5	0.00016	0.00080	Operational error
5-X	2.37E–5	0.00013	0.00041	Other failures
	4.6E–4	2.28E–3	10.66E–3	Total failure
		Segment X2		
1-Y	1.02E–4	0.00114	0.00332	External interference
2-Y	3.20E–5	0.00022	0.00317	Corrosion
3-Y	1.64E–5	0.00016	0.00054	Structural defects
4-Y	2.14E–5	0.00012	0.00059	Operational error
5-Y	1.02E–5	0.00011	0.00033	Other failures
	1.82E–4	1.75E–3	7.95E–3	Total failure
		Segment X3		
1-Z	8.20E–5	0.00122	0.00244	External interference
2-Z	2.67E–5	0.00021	0.00241	Corrosion
3-Z	1.36E–5	0.00012	0.00040	Structural defects
4-Z	1.76E–5	0.00020	0.00048	Operational Error
5-Z	6.97E–6	0.00008	0.00024	Other failures
	1.47E–4	1.73E–3	5.97E–3	Total failure

the experts. The failure-data sheet contains information related to pipeline repair history, design parameters, inspection records, and current operating conditions. All the experts are familiar with the pipeline and pipeline segments under study. They all participated in the structured expert judgment to obtain frequency of failure for the pipeline segments.

Estimation of Failure Frequency Using the Classical Model

In the classical model, the failure mechanisms of the pipeline can be seen as target variables. In total, 28 variables were obtained, considering five target variables for each segment of the pipeline and 10 seed variables that are used to calibrate the experts. The seed variables are obtained using generic equipment-failure rates from literature and textbooks to calibrate the experts. Initially, the experts were elicited on the values of the seed variables. Thereafter, each of the experts was required to provide 5, 50, and 95% quantiles for the uncertainty distributions for the frequency of failure (in km/a) by rupture because of the failure mechanisms for Segments X1, X2, and X3 of the pipeline.

Expert Calibration and Robustness Analysis. The experts' responses were processed using EXCALIBUR software (Cooke and Goossens 2008). The optimal decision maker (ODM) was also computed. The ODM was obtained as the normalized weighted linear combination of the experts' distributions. In EXCALIBUR, the experts' distributions can be combined using either global weight, item weight, or equal weight. However, in this approach, global weight was used because it possesses the best calibration and unnormalized weight, which is the combined score of the experts. In addition, a robustness analysis is performed on the seed variables and the experts. In the robustness analysis, the variables of interest are removed one at a time and the analysis is repeated until all variables have been covered. The robustness analyses performed on the experts indicated that the calibration score for the experts ranged from 0.474 to 0.55. These scores are much greater than the calibration scores of 0.29 and 0.114 obtained for the item-weight decision maker (Item DM) and equal-weight decision maker (Equal DM), respectively, in the software.

Resulting Solution. The resulting solution is the combined decision-maker (DM) distribution of values assessed by experts that contribute to the ODM. The DM optimization is achieved at a significance level of 0.0358, giving a 96.4% acceptable level. The acceptance level is sufficient, and the outcome of the structured expert judgment on the frequency of failure of the pipeline because of the identified failure mechanisms for the segments of the pipeline (X1, X2, and X3) is satisfactory. Detailed results of the calculation of failure frequencies are given in **Table 1.** The 50% uncertainty frequencies of failure for Segments X1, X2, and X3 are 2.28E–3, 1.75E–3, and 1.73E–3 km/a, respectively.

The overall failure frequencies compare favorably with results reported in the literature. For example, Little (1999) reported a value of 0.42E–3 km/a for frequency of failure in western European petroleum pipelines, 0.3E–3 km/a for cross-country oil pipelines in the United Kingdom, and 0.53E–3 km/a for total failure of the US Department of Transportation liquid pipelines. The difference between these values and the frequency of failure obtained for the case study could be because of factors such as difference in location and physical and process properties of the pipelines. These factors have been shown to have significant influence on the frequency of failure of pipelines, according to Restrepo et al. (2009).

From Table 1, using a 50% quantile estimate, it appears X1 is the most vulnerable among the three pipeline segments, having the highest frequency of failure, followed by X2 and then X3. However, it is interesting to note that X3 has the highest frequency of failure because of operational error. This can be explained partially by the presence of more control valves that involve manual operations in X3 compared with X1 and X2.

Maintenance Optimization

A life-cycle maintenance model can be derived for the failure attributes on the basis of the failure parameters developed in Table

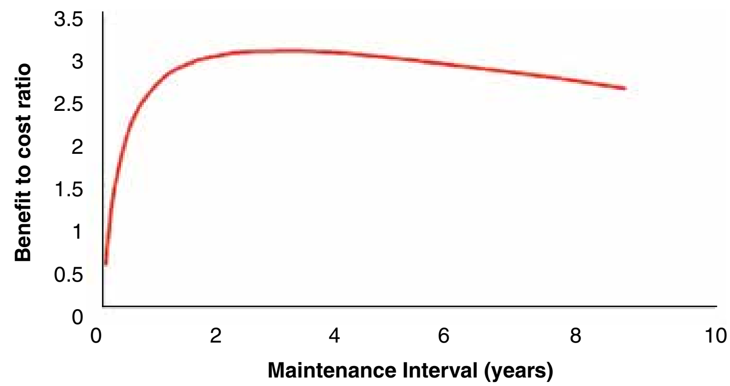

Fig. 1—Maintenance optimization of pipeline under external interference.

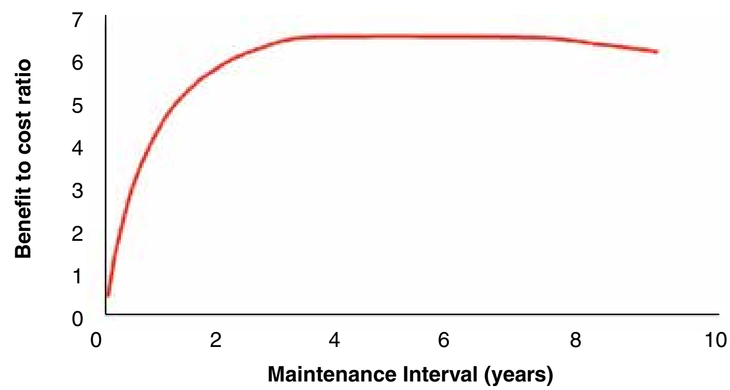

Fig. 2—Maintenance optimization of pipeline under corrosion.

1. There are many techniques that can be defined to solve a maintenance-optimization problem. These techniques include functions such as the optimization of reliability and minimizing downtime, production loss, quality loss, and expected total costs per unit time. The functions are defined on the basis of a number of variables, including the type of production systems, the production philosophy, and the level of demand of the product (Chareonsuk et al. 1997).

The maintenance-optimization technique proposed in this paper involves the combination of two approaches:

1. Minimizing the expected-total-cost function.
2. Maximizing the B/C ratio.

The total-cost function $E[C \mid \tau]$ is applied to achieve a robust maintenance optimization. A major benefit of this approach is that it measures failure cost spread over time. Other benefits of the approach, such as its reliability and robustness, have been demonstrated in Restrepo et al. (2009). The determination of the total-cost function can be challenging, especially because of the difficulty in measuring potential safety loss in monetary terms. This is very controversial and somewhat political. In addition, the total-cost function is data intensive, as it will be demonstrated. Another shortcoming of the expected total-cost-function $E[C \mid \tau]$ model is that statistical parameters of failure β and θ have to be available before maintenance optimization can be carried out. As might be expected, it is generally difficult to obtain these parameters when adequate failure data are not available.

The B/C ratio measures the amount of benefit derived from conducting maintenance activity relative to the cost expended in carrying out the maintenance. The limitations in the total-cost-function model generally make it impractical to apply the model to achieve maintenance optimization in which failure parameters have been estimated in a classical model. Therefore, the B/C ratio serves as a buffer in the case that $E[C \mid \tau]$ cannot be applied or if its application fails to achieve a global optimum.

In analyzing an operating facility for maintenance optimization, there are indeed instances in which minimizing the expected total cost would not necessarily lead to optimality (Dawotola et al. 2012, *in press*). In such cases, maintenance optimization can be extended to include maximization of the benefit derived from risk reduction (Jiang et al. 2006; Natti 2008). An additional benefit of the model is that it is less data intensive and can be applied to both qualitative and quantitative risk models. The B/C model is thereby presented to allow the application of maintenance optimization in the classical model.

Expected-Total-Cost-Function Model. The expected-total-cost-function $E[C \mid \tau]$ model optimizes the maintenance interval and searches for a balance between preventive and corrective maintenance costs on the basis of the time-based failure behavior of the pipeline. For a single maintenance cycle τ, it is computed mathematically as

$$E[C \mid \tau] = C_r \times P\{t \mid \tau\} + C_p \times [1 - P\{t \mid \tau\}], \quad (1)$$

where C_r and C_p are corrective maintenance and preventive maintenance costs, respectively. The corrective maintenance cost consists of replacement cost, downtime cost, and consequences of failure (damage cost). The preventive cost, on the other hand, is obtained from inspection cost and downtime cost. It is expected that the downtime cost resulting from the preventive-maintenance cost will be less than or, at most, equal to the downtime cost because of the corrective-maintenance cost.

The term $P\{t \mid \tau\}$ is the conditional probability that the system survives failure at time *t*, given that it did not fail until τ. The reliability function is described by $R(t) = 1 - P\{t \mid \tau\}$. The mean time before failure can be obtained from $R(t)$ or vice versa by solving

$$MTBF = \int_0^{\infty} R(t)\,\mathrm{d}t. \quad (2)$$

Similarly, the expected length of the maintenance cycle $E(\tau)$ is given as

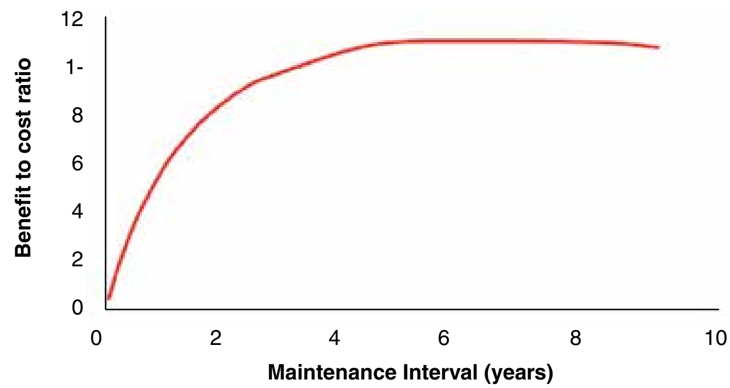

Fig. 3—Maintenance optimization of pipeline under structural defect.

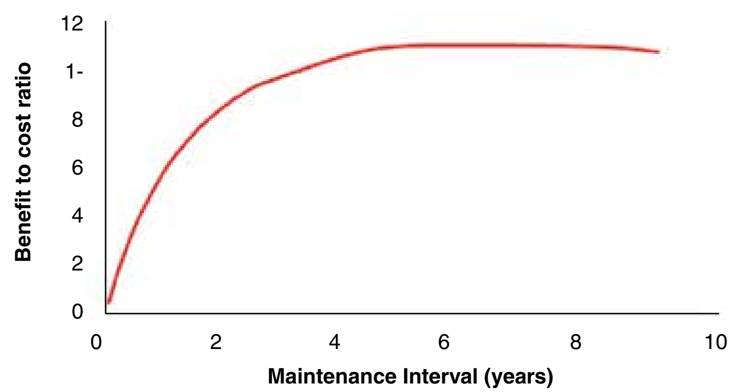

Fig. 4—Maintenance optimization of pipeline under operational error.

$$E(\tau)=\int_0^{\tau}R(t)\mathrm{d}t. \quad (3)$$

The cost per unit time (Q), otherwise known as the asymptotic cost rate, is the ratio of the expected cost over a renewal cycle to the expected length of the renewal cycle. It is given by van der Weide et al. (2010) as

$$Q=\frac{E\left[C|\tau\right]}{E(\tau)}=\frac{C_r\times P\{t\mid\tau\}+C_p\times\left[1-P\{t\mid\tau\}\right]}{\int_0^{\tau}R(t)\mathrm{d}t}. \quad (4)$$

$P\{t \mid \tau\}$, which is the conditional probability described earlier, can be further expressed as

$$P\{t\mid\tau\}=\frac{P(t+\tau)}{P(\tau)}. \quad (5)$$

Using $T=t+\tau$ for the interval from t to T, Eq. 1 becomes

$$E[C\mid\tau]=C_r\left[\frac{P(T)}{P(\tau)}\right]+C_p\left[1-\frac{P(T)}{P(\tau)}\right]. \quad (6)$$

Eq. 6 is the equation for maintenance cost of the pipeline during the interval t to T. Assuming that the service life of the pipeline is $\overline{T}$ then the preceding expression for the expected total cost can be generalized into

$$E[C\mid\tau]=\frac{\overline{T}}{\tau}\left\{C_rP(T)+C_p\left[1-P(T)\right]\right\}. \quad (7)$$

Substituting for $R(T)$, the equation becomes

$$E[C\mid\tau]=\frac{\overline{T}}{\tau}\left[C_rP(T)+C_pR(T)\right]. \quad (8)$$

The failure frequency of any failures that can be described by a homogeneous Poisson process has a constant value (λ). In addition, its failure-distribution function and reliability function are given as $P(T)=1-e^{-\lambda t}$ and $R(T)=e^{-\lambda t}$, respectively. The expressions for $P(T)$ and $R(T)$ can be substituted into Eq. 8 to obtain $E[C \mid \tau]$ for the homogeneous-Poisson-process case.

Similarly, for the power-law model, the failure-distribution function at any given time t is given by

$$P(T)=\lambda(t)=\frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1},\ t>0, \quad (9)$$

where the parameters of β and θ are the shape and scale parameters of the failure-intensity function, respectively. The intensity function decreases if $\beta<1$ and increases if $\beta>1$. If $\beta=1$, then the power-law model reduces to a homogeneous Poisson process with intensity function $\lambda(t)=1/\theta$. If $\lambda(t)$, then the system is improving.

The maximum-likelihood estimates of β and θ, for time-truncated data having N number of failures, is given as

$$\hat{\beta}=\frac{N}{\sum_{i=1}^{N}\log\left(t/t_i\right)} \quad (10)$$

and

$$\hat{\theta}=\frac{t}{N^{1/\hat{\beta}}}, \quad (11)$$

where N equals the number of failures recorded before failure was truncated at time t.

Similarly, the reliability function for the power-law model is given as

$$R(T)=\exp\left[-\left(\frac{t}{\theta}\right)^{\beta}\right]. \quad (12)$$

TABLE 2—MAINTENANCE OPTIMIZATION OF PIPELINE SEGMENT X1				
Failure Mechanism	External Interference	Corrosion	Structural Defect	Operational Error
Frequency of failure (per km•year)	1.32E–3	4.50E–4	2.20E–4	1.60E–4
Expected maintenance cost ($m)	0.86	0.45	0.25	0.20
Maintenance interval (years)	2.5	3.3	5.0	5.5
B/C ratio	3.07	6.64	9.13	9.69

Eqs. 9 and 12 are substituted into Eq. 8 to obtain the final expression for $E[C \mid \tau]$ under the power-law model. The optimum maintenance interval τ is the time that minimizes Eq. 8. It is obtained by solving for τ that satisfies Eq. 8.

B/C-Ratio Model. The B/C ratio for a repairable system can be defined by considering the cost of failure and the benefit derived from preventing the occurrence of failure. The benefit derived from periodic preventive maintenance, $B(\tau)$, can be defined as the product of the average difference in the reliability of the equipment with and without maintenance and the incidence cost, C_{inc} (Lapa et al. 2006). The cost of failure can be estimated from the expression for expected cost of failure $E[C \mid \tau]$ in Eq. 8.

This expression for determining $B(\tau)$ is stated as (Ghosh and Roy 2009):

$$B(\tau) = C_{\text{inc}} \left[\frac{1}{\lambda \bar{T}} \left(\frac{e^{-\lambda \bar{T}} - 1}{1 - e^{\lambda \tau}} + \frac{e^{-\lambda \bar{T}} - 1}{1 - e^{-\lambda \tau}} \right) + \frac{1 - e^{-\lambda \tau}}{\lambda \tau} \right], \quad (13)$$

where C_{inc} is the incidence cost, which is the cost resulting from lost production and financial losses because of equipment failure, and λ is the equipment-failure frequency.

The B/C ratio caused by maintenance activity is defined as

$$\text{B/C ratio} = \frac{B(\tau)}{E[C|\tau]}. \quad (14)$$

Eq. 8 can be maximized to achieve optimum maintenance in the case of constant failure frequency.

Application of the Maintenance Model

The B/C-ratio model defined in Eq. 14 was applied to model the maintenance optimization of Pipeline Segment X1 using direct enumeration. The parameters defined for the failure mechanisms (external interference, corrosion, structural defect, and operational error) in Table 1 were used to determine the optimum maintenance schedule for the pipeline segment. The outcome of the maintenance optimization presented in **Figs. 1 through 4** shows that external interference requires preventive maintenance every 2.5 years, corrosion requires preventive maintenance every 3 years, structural defect requires preventive maintenance every 5 years, and operational error requires preventive maintenance every 5.5 years.

The plots show that external interference requires more regular preventive maintenance compared with the other failure mechanisms, while operational error requires the least. This is indeed expected, owing to the fact that external interference and operational error result in the highest and lowest frequency of failure, respectively, among all the failure mechanisms. Similarly, the corresponding B/C ratios and the maintenance costs required to achieve the maintenance cycles are depicted in **Table 2.**

Conclusions

A decision-based model has been presented for integrity maintenance of petroleum pipelines. The model uses structured, expert judgment to predict the frequency of failure for a given pipeline. It has been demonstrated that optimum decision making can be achieved with the use of structured, expert judgment on the basis of the classical model. The model reveals that only three out of the six experts actually contribute to the optimum decision making. In addition, the subjectivity inherent in the model can be minimized through estimation of uncertainties in the expert elicitation and by carrying out maintenance optimization.

The case study revealed some interesting conclusions, which show that location plays a significant role in pipeline integrity because expected costs of failure vary along pipeline segments. For the case study, external interference is found to be the most important failure criterion, representing more than 50% of all failures. The high likelihood of failure by external interference is because of a somewhat high occurrence of acts of sabotage and mechanical damage around the pipeline location. Therefore, increased surveillance along the right of way of a pipeline would help improve pipeline reliability. Maintenance optimization requires that the pipeline segments be subjected to regular preventive maintenance.

The equations and building blocks for maintenance-optimization models—expected cost of failure and B/C ratio—are defined in this paper. However, because of the limited availability of data, the B/C ratio was applied to determine optimum maintenance duration for all the failure mechanisms. For Pipeline Segment X1 in particular, the optimum duration of 2.5, 3, 5, and 5.5 years is found for external interference, corrosion, structural defects, and operational errors, respectively. To minimize the occurrence of failure because of these mechanisms, the pipeline should be maintained, generally, at a duration earlier than the optimum points.

The result also confirms that equal allocation of maintenance resources to pipeline segments may not always be the optimal maintenance decision. For example, in the allocation of maintenance resources for the pipeline under study, Segment X1, with the highest expected failure cost, should receive more attention than the other segments. In addition, Segment X3 will require more maintenance resources than Segment X2. The maintenance manager will find this approach to be beneficial in formulating the annual inspection and maintenance policy for the company's assets. In general, the accuracy of the optimal maintenance interval calculated could be improved further as more pipeline-failure data become available.

Nomenclature

- C_{inc} = incidence cost
- C_r = corrective-maintenance costs
- C_p = preventive-maintenance costs
- N = number of failures
- Q = cost per unit time
- t = time
- β = shape parameter of the failure-intensity function
- θ = scale parameters of the failure-intensity function
- λ = equipment-failure frequency
- τ = single maintenance cycle

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