Warranty Program Engineering

Tom Rooker • Memorex Telex • Raleigh

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ABSTRACT

A process is developed that contributes to the successful engineering of a warranty program. The process utilizes a combination of analytical techniques to define a window of ranges for factors impacting warranty program cost. To create a tighter target, a simulation-based algorithm called Programmed Optimization of Warranty (POWer) is introduced. The POWer algorithm converts factors from production, field service, marketing, and reliability into easily digestible units of dollars. The algorithm uses the Monte Carlo simulation technique to project warranty performance. The results are linked with engineering/economic factors to provide a solution in dollars.

INTRODUCTION

One of the most perplexing aspects of product planning is defining the product warranty program. Just like other elements of the product to be offered for sale, a company wants to make a profit from its warranty program. Often the establishment of a warranty program rests on politics, vague definitions of product reliability, "one-up-manship" in the marketplace, and customer expectations. However, a warranty program based on this approach can just as easily penalize the customer as burden the manufacturer. A better approach would be to utilize a decision process that combines reliability principles with manufacturing and economic factors. A product strategy task team at Memorex Telex successfully managed this challenge. The challenge was handled in three phases: (1) Defining the environment, (2) Developing a feasible range of solutions, (3) Selecting the set of values that produced the best results during simulation.

PHASE 1. NEW PRODUCT ENVIRONMENT DEFINITION

The need arose to examine the warranty program for a new product offering. The product was targeted at the highly competitive 3270 video display terminal (VDT) marketplace. Suddenly, within the marketplace, the old ninety-day warranty was replaced by one- and three-year warranties. Warranty periods had been extended and expected Mean Time Between Failures (MTBF) increased as competitors sought product differentiation. These new one- and three-year warranties were being offered as an additional feature of the VDT. They were being sold to customers in the same way as extended warranties in the automobile industry. They represented both a marketing opportunity and a potential liability. To confront this new warranty feature offering, the product strategy committee initially held discussions centered on MTBF expectations. However, the committee quickly began to see the warranty feature in terms of dollars. They recognized that it was important to price the warranty feature sufficiently high to at least cover the field service cost of unit failures. They also recognized that the total impact on the unit selling price resulting from the warranty feature cost and associated MTBF enhancement costs had to be minimized. The committee concluded that to properly develop a successful strategy to meet the new warranty feature offering, the focus of attention should be placed on the unit selling price. By focusing on the unit selling price, all the other product considerations such as warranty feature cost, MTBF, expected profit per unit, production cost, and field repair cost could be encompassed.

The task of encompassing the new product considerations was given to a new product planning subcommittee. The subcommittee had to determine what the MTBF needed to be to achieve a respectable performance level. They also needed to know how much the new warranty feature should cost. Finally, they needed to define the impact of this new warranty feature on the unit selling price. The expected profit per unit had been firmly established. The answer had to be expressed in a suggested unit price that would incorporate the cost of this new warranty feature. This unit price also had to include the production cost and expected unit markup. In other words, the solution had to give the price to be charged to recover the cost of the new warranty. The optimum solution was one that gave the minimum suggested price but still maintained a satisfactory level of performance.

Several key factors were developed from the study of the previously released VDT. The prior family of VDT achieved its design goal of a 20,000-hour MTBF. More exhaustive research of prior generations of product revealed an apparent contradiction to reliability engineering precepts. Apparently, prior generations had performed at increasing levels of MTBF as the level of design complexity had also increased. A factor was derived that related the MTBF and complexity of different generations of product; that factor was called the "engineering evolution factor." Additional information concerning the engineering evolution factor will be provided later. The typical engineering evolution factor was determined to be 1.6 to 2.0.

The failure profile of the prior VDT had followed the Poisson exponential distribution. The typical repair action in the field on the prior design had been $141.89 per service call. In typical customer usage, the VDT could be expected to be operated for 430 hours each month. This level of customer usage over a three-year warranty period would result in a total of 15,480 hours of operation.

PHASE 2. WINDOW OF FEASIBILITY

After developing an understanding of the new environment, the question revolved around solving for two unknowns. Those two unknowns were the MTBF and the warranty feature cost.

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Due to the complexity of product environment, a range of feasible MTBF hours and warranty cost was required. The process of defining the feasible range of values was composed of three studies.

The first study looked at the impact of various levels of field service calls on the warranty cost and MTBF. Table A was developed to show this impact on a sample population. A sample of one thousand units was assumed. Table A listed a given number of failures that might occur during any three-year warranty period. A pool of warranty-reserved dollars was collected at the time of sale. Each failure event drew funds from the pool. That pool of warranty dollars would have to be at least equivalent to the number of service calls times the cost to return a unit to service. If it were not equivalent, then the three-year warranty feature would be unprofitable. In order to collect the required pool of warranty-reserved dollars, each unit sold would have to be assessed a warranty feature fee or warranty cost per unit.

The MTBF was calculated for each quantity of failures across the three-year warranty period. Table A showed that as the number of failures increased and the MTBF fell, the warranty cost charged the customer would increase.

The second study used probability to define the number of failures that might occur for a given MTBF. The prior VDT family had demonstrated a Poisson exponential distribution failure profile. An assumption was made that the new VDT family would also follow the same type of profile. From that assumption, Table B was developed using the Poisson exponential probability. Table B depicted the likelihood that a unit would survive the entire three-year warranty period. The survival or failure of an individual unit would be independent of the remainder of the population. Subtracting the probability that a unit would survive from one hundred percent yielded the likelihood that a unit would experience a failure. Multiplying that likelihood of failure by the selected sample size generated the expected number of units that would experience at least one failure. The warranty reserve pool required to service all units that experienced a failure was calculated as in Table A. Table B also expressed the warranty cost per unit in a manner similar to Table A.

Table B presented a "best case" representation of the warranty cost per unit. The difference between Table A's and Table B's warranty costs increased as the MTBF decreased. The reason for this is that Table B reported the number of units experiencing failure event. Table B did not reflect multiple failures that a "failing" unit might have experienced. Instead, all failures against a failing unit were counted as being serviced once. Table A, however, effectively counted every failure that might have occurred in a sample population. With these two tables, the "best" and "typical" warranty feature cost per unit were bracketed for various MTBF.

The third study used the engineering evolution factor to establish a range of feasible MTBF values. As previously stated, the MTBF of prior generations of product had increased while the design complexity had increased. This apparent exception could only be explained if the engineering process was somehow compensating to meet this design dilemma. The term developed to explain this action was the engineering evolution factor. In the practical sense, the engineering evolution factor was the result of actions such as derating, implementing hardware redundancy, employing error correction schemes, incorporating fault tolerance and avoidance strategies, and lowering temperature and power dissipation. Such actions offset the adverse impact of design complexity on MTBF.

The first step in calculating the engineering evolution factor was to define complexity. The measure of complexity used was the total number of gates in the electronic design. A proportion relationship between the MTBF and the reciprocal of the square root of the number of functions per chip was assumed to exist (Ref. 1). Using this relationship, a ratio between the new VDT design and the prior design was constructed. Determining the resulting constant of proportionality defined the engineering evolution factor for any MTBF of interest for the new design. Table C displayed the design factor for the range of MTBF hours under consideration. Table C clearly indicated that, with an engineering evolution factor of one, the new VDT would have about a 14,000-hour MTBF.

At this point in the search, it was possible to begin to develop a range of MTBF and warranty cost values. A preliminary MTBF and warranty cost range was calculated by arbitrarily taking 0.9 to 2.25 of the prior generation of VDT's 20,000-hour MTBF. That preliminary MTBF range was from 18,000 to 45,000 hours. From Table A and B, the corresponding range of warranty feature cost was found to be between $40 and $125. Having previously demonstrated an engineering evolution factor of 1.6 to 2.0, a more aggressive 2.5 maximum was assumed. Table C then helped redefine the MTBF range from 25,000 to 35,000 hours. This provided a warranty feature cost range from $51 to $88. The $37 spread in the warranty feature cost range represented an unacceptable risk. Selecting a warranty feature cost at the low end of the range would result in having to support the warranty program at a loss. Selecting the warranty feature cost at the high end of the range might result in lost revenue due to a noncompetitive unit selling price.

PHASE 3. BEST SOLUTION

To obtain tighter control and provide a better solution, another analysis technique was employed. That technique was the POWer algorithm. The POWer algorithm provided three concrete benefits. First, all the user-defined factors were tied together in a relationship. This relationship would yield a noncomplex result in dollars. Second, when implemented on a computer, the POWer algorithm provided the opportunity to optimize the factors. This provided a method to quickly and cheaply evaluate "what if-ing" or sensitivity of the factors. This allowed a "window" of acceptable values for the factors to be tightened. Finally, POWer gave management a set of easily measured thresholds expressed in dollars. This allowed the identification of trends, variances, and forecast.

General Description

The POWer algorithm is composed of six sequential steps: Establishing general assumptions, identifying primary factors and relationships, making product-specific assumptions, selecting a failure model performing simulation technique, and optimizing decision factor. Each of these steps will be subsequently discussed.

POWer's General Assumptions

POWer works under four generalized assumptions (Refs. 2, 3). The first assumption is that the field performance can be modeled by a hazard function or failure frequency density function. The confidence in the profile will vary directly with the maturity level of the product. As the product matures, the actual field failure performance profile can be developed from data. This will also serve to validate the prior profile selection.

The second general assumption is that the failure events are random. A subset of the entire population is randomly drawn and submitted to the simulation process. All members of the total population, regardless of when they are produced, stand an equal opportunity to be selected for the subset. Items that experience zero failures during the warranty period are just as likely to be included in the subset as those experiencing multiple failures.

The third assumption is that all the members of the population experience the same operational profile. Not only do they experience the same stress level, but they all undergo the same length of warranty period. However, the individual items may enter the warranty period according to their own schedule.

The last general assumption implies that sufficient number of samples have been submitted to simulation to clearly demonstrate tendencies. Each sample must be a sizable portion of the total population.

Primary Factors

After accepting the four general assumptions, the next step of the POWer algorithm requires information from four broad areas: product field performance, production activity, logistic support, and marketing. Each area yields inputs in the form of factors and relationships. A factor is expressed as a value or range of values. A relationship is a definition of how a set of factors act. POWer integrates these factors and relationships into a map of the solution. (From this point forward, the use of the term "factor" will imply both factor and relationships.)

One of the first areas in which to search for information is product field performance. The information provided by this area yields a method for distributing the failure population. That method is a probability distribution function. The function is developed from the product's failure profile and reporting process. For the POWer algorithm, the product failure profile must be converted into a cumulative distribution model.

The production activity provides four major factors. The first three are material, labor, and burden cost factors. These three cost factors represent the total cost to design, manufacture, and warehouse the product. The material, labor, and burden cost are combined into one expression of cost per unit basis. The final factor provided by the production activity is the volume of units produced.

The factors from the logistics support area are similar to those cost factors in the production area. They are the spares inventory cost, travel cost, time-on-site cost, and overhead cost. These four cost factors are accumulated and averaged. The unit of logistics support cost is expressed as the average cost to return an item to service.

The final area, marketing, provides factors that bridge the boundary between the manufacturer and the customer. Marketing provides the concrete factors of unit pricing and markup per unit. A less concrete factor provided by marketing is sales volume. Just as importantly, marketing finally provides a conceptualization of the competition's sales strategy. Without this last factor, all the work can easily be superfluous.

Simulation Technique

The POWer algorithm uses the Monte Carlo simulation to define the failure pattern of each unit in a sample or population (Figs. 1, 2). Prior to the actual generation of the failure pattern, failure bins are defined. A failure bin serves as a counter of units which experience the same number of failures. Each failure bin corresponds to a particular probability of a number of failures occurring. The failure pattern for a single unit depends on the spin of the wheel, roll of the dice, or computer generation of a random number. That number is converted into a value between zero and one. This value range effectively represents cumulative probability. That random number links the unit to a failure bin. Each time a unit is assigned to a failure bin, the bin is incremented.

The product performance is defined by the multiple cycles through the random number generator and resulting assignments to failure bins. The accumulation of the artificial unit performance in terms of failures counted provides an unbiased forecast of warranty performance. The entire population of product, a sample, or multiple samples can tested without the first real unit ever being assembled. Multiple large samples can be used to collect a range of warranty failure performance. This performance is then linked to the factors by the defined relationships.

Factor Optimization

The final step of the POWer algorithm is the factor optimization (Fig. 1). The level of activity in this step depends on the number of factors that are rigidly defined. The POWer algorithm permits the testing of the sensitivity of the MTBF and warranty feature cost to the factors originally introduced or assumed. Critical factors such as the dollar per service call, expected profit per unit, and production cost can combine across several ranges of values to yield satisfactory results. This allows the definition of performance thresholds. Multiple runs of large samples provide simulated data yielding worst case and average values of warranty feature costs and unit selling price for corresponding MTBF.

The Application

The POWer algorithm was implemented to tighten the MTBF and warranty cost window. The problem was set up under the general assumptions. The primary factors concerning MTBF, warranty period, production cost, logistics support cost, volume estimate, and markup were developed. A set of problem-specific assumptions was included in the algorithm. This set was composed of four assumptions. The first assumption was that all units experienced the same operation profile. This profile was expressed as the number of power-on hours per month. Second, the production cost was assumed to be an average cost per unit over the entire period of production. Third, logistics support was assumed to be the average total cost to return a failed unit to service. The prior VDT product family was selected as being representative of current design and production processes. That selection, and a review of the field data for it, led to the final assumption. The final assumption was that the product profile would exhibit a Poisson distribution.

To include the "infant mortality" failure population, the area under the curve representing the infant mortality was converted to a rectangular shape (Fig. 3). The length of the rectangle was set equal to the three-year warranty period. This modified area was added to that of the shape represented by the Poisson distribution.

With the assumptions made, programming of the algorithm was undertaken. A workable POWer algorithm was implemented in ten thousand bytes of memory (Figs. 1, 2). This version of the algorithm included a random number generator, user-friendly input and change menus (Fig. 4), and hard-copy options (Fig. 5).

After completion of the programming, the initial factors were entered. Multiple samples of one thousand units were submitted to simulation. Referring to Table C, each increase in MTBF was associated with a corresponding increase in the production cost. The production cost was expressed as material, labor, and burden. The expected profit per unit remained fixed during the entire simulation. The values of MTBF and corresponding production costs were varied within the window of feasible values. Each sample run resulted in a cost per unit incurred by returning failures to service. Coupled with that result was the suggested unit price. That price included the production cost at the trial MTBF, the cost per unit due to the warranty period failures, and the expected increment of profit. After multiple samples, a small band of MTBF demonstrated a tendency to center on the desired warranty cost and unit price. Once that MTBF value had manifested itself, a large set of samples was run using that MTBF to establish a mean and a worst case for the warranty cost and unit selling price.

Results

Table D provides the results of multiple runs of large samples for the typical manifested MTBF. The table provides the highest and average warranty feature cost. With a large number of simulation runs, it was possible to determine the maximum warranty feature cost with a 95-percent confidence. From Table D, 95 percent of the sample runs with a design having the typieal MTBF resulted in a warranty feature cost of less than $67.81.

The $1,332.92 maximum suggested unit selling price was computed in a similar manner. For the typical MTBF, this price reflected the production cost, warranty feature cost, and expected profit per unit. Based on the results of the simulation runs, the confidence that the unit selling price would be $1,332.92 or less was 95 percent. The set of factors that produced the $1,332.92 unit selling price was formed into a set of threshold values. The typical unit selling price and its corresponding set of threshold values formed the recommendation of the new product planning subcommittee. The threshold values recommended suggested that the next generation of VDT would have to achieve a higher level of field performance.

Over the life of the product studied, it has been shown that the new level of field performance was achieved as the algorithm suggested it could. The optimized factors have served as key thresholds. These thresholds have provided an indication of when nonrandom forces are at work in the failure populations. The warranty decision process as described in the example was used to perform trade-off studies between reliability and logistic support strategies.

CONCLUSION

The decision process presented in this paper provides the capability of making unbiased decisions concerning a warranty program. Decisions concerning key new product factors such as production cost goals, logistic support targets, and MTBF can be made long before the first schematic is drawn. The relationship and sensitivity between the manufacturing/economic factors and the expected reliability performance can be demonstrated with the POWer algorithm. Finally, the POWer algorithm provides an unbiased forecast in dollars of the expected new product's performance. Variance from this forecast indicates that a mechanism is acting on the actual population in some nonrandom way.

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BIOGRAPHY

Tom Rooker
Memorex Telex Corporation
3301 Terminal Drive
Raleigh, North Carolina 27604 USA

Tom Rooker is the Reliability Manager of the 3270 Network KOB of Memorex Telex. He has served in that position since 1983. Prior to that time he held positions of increasing product assurance responsibilities at Texas Instruments and Data General. His product assurance experience ranges from cardiac pacemaker integrated circuits to mainframe computers. He is a 1972 graduate of the United States Military Academy and is registered in North Carolina as a professional engineer. He is also certified by the ASQC as a reliability engineer.

TABLE A
Performance Based on Failures Expected to Be Observed

Assumptions:
430 power-on hours per month (typical operating profile)
Field service cost: $87.86 per call (travel + labor + parts)
Sample Population: 1000
15,480,000 Op hours for 1,000 units over 36 months at 430 POH/mon

Service Call	$ All Calls	Warranty Cost $/Unit	MTBF
100	14,189	14	154,800
201	28,520	29	77,000
298	42,283	42	52,000
344	48,810	49	45,000
387	54,911	55	40,000
442	62,715	63	35,000
516	73,215	73	30,000
619	87,830	88	25,000
774	109,823	110	20,000
860	122,025	122	18,000
1,032	146,430	146	15,000
1,191	168,991	169	13,000

TABLE B
Expected Performance Based on Poisson Distribution

Assumptions:
430 power-on hours per month (typical operating profile)
Field service cost: $141.89 per call (travel + labor + parts)
Sample Population: 1000
15,480 Op hours for 1 unit over 36 months at 430 POH/mon
15,480,000 Op hours for 1,000 units over 36 months at 430 POH/mon

MTBF	% Failure Free	Units Failing	$ All Calls	Warranty Cost $/Unit
150,000	90.2	98	13,905	14
77,000	81.8	182	25,824	26
52,000	74.3	257	36,466	36
45,000	70.9	291	41,290	41
40,000	67.9	321	45,547	46
35,000	64.3	357	50,655	51
30,000	59.7	403	57,182	57
25,000	53.8	462	65,553	66
20,000	46.1	539	76,479	76
18,000	42.3	577	81,871	82
15,000	35.6	644	91,377	91
13,000	30.4	696	98,755	99

TABLE C
Comparison Based on Complexity

Assumptions:
Prior Design: 20,000-hour MTBF
Prior Design: 37,439 IC gates
New Design: 73,876 IC gates

New Design MTBF	Engineering Evolution Factor
150,000	10.5
77,000	5.4
52,000	3.7
45,000	3.2
40,000	2.8
35,000	2.5
30,000	2.1
25,000	1.8
20,000	1.4
18,000	1.3
15,000	1.1
13,000	0.9

Engineering Evolution Factor = (MTBFi/MTBFo)/
(Square Root (GATESo)/Square Root (GATESn))
MTBFx = MTBF of either i or o
GATESm = Gate counter estimate of either n or o
i = One of the range of MTBF for New Deisgn
o = Indicates the Prior Design
n = Indicates the New Design Gate Count

TABLE D
Simulation Results Based on Typical VDT Factors for Typical MTBF

1,000	Number of sample runs evaluated
1,000	Units per each sample run
73.36	Highest cost to repair per unit from this set of runs
1,341.41	Highest suggested unit price from this set of runs
62.75	Average cost from this set of runs
1,325.18	Average charge from this set of runs
67.81	Maximum repair cost per unit (95% Confidence)
1,332.92	Maximum suggested unit price (95% Confidence)

FIGURE 1
POWer Algorithm

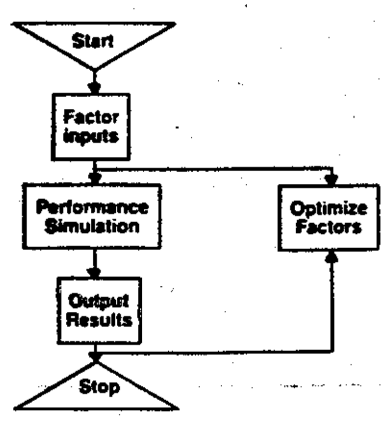

FIGURE 2
Performance Simulation – Discrete Case

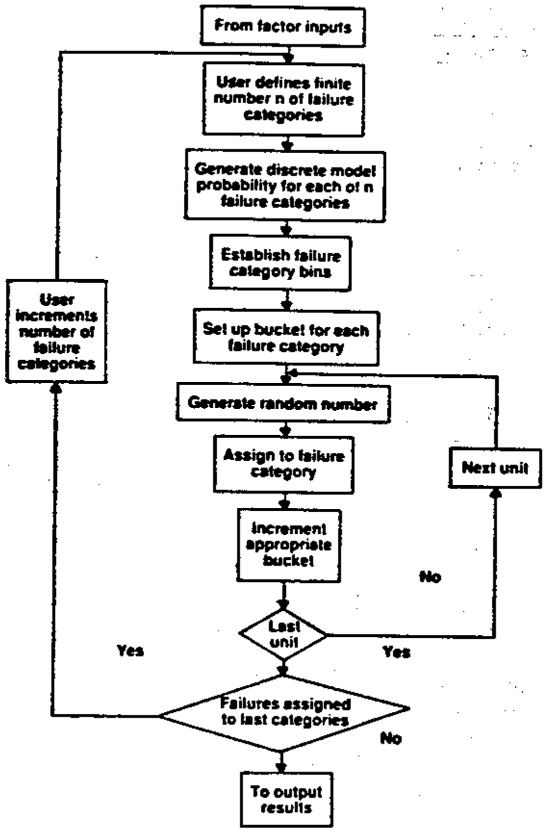

FIGURE 3
Allocation of Infant Mortality Failure Rate to Constant Failure Rate

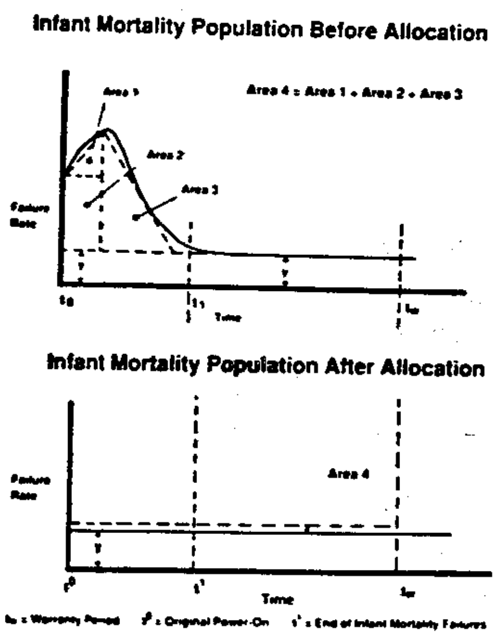

FIGURE 4
Change Screen

Make a selection from the following menu:

A	.... Change the Mean Time Between Failures	35000
B	.... Change the Operating Time	15480
C	.... Change the number of failure bins	10
D	.... Change the number of trials	1000
E	.... Change the random number	13
F	..... Change the material, labor, overhead cost per unit	0.00
G	.... Change the expected mark-up	0
H	.... Change the cost per failure to return to service	141.89
M	.... Change to Monte Carlo Simulation only	
W	.... Change to find the warranty numbers	
O	.... Change to stop printing hardcopies	
P	..... Change to start printing hardcopies	
R	.... Make another run	
Q	.... Quit and return to BASIC	

Enter your selection

FIGURE 5
Result Screen Based on Typical Inputs

640	Units with 0 Failures
292	Units with 1 Failures
56	Units with 2 Failures
11	Units with 3 Failures
1	Units with 4 Failures
0	Units with 5 Failures
0	Units with 6 Failures
0	Units with 7 Failures
0	Units with 8 Failures
0	Units with 9 Failures
0	Units with 10 Failures
441	Total Number of Failures
0.441	The failure rate for the operation period
62573.49	Total cost of repair
62.57	Repair cost to be recovered per unit
1324.91	The suggested unit price

Enter a 'Y' or 'y' to continue