Reliability vs. Total Quality Cost - Part Selection Criteria Based on Field Data, Combined Optimal Customer and Business Solution

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Abstract - **Most privately owned businesses are formed to generate profits. Every year, manufacturers loose a portion of potential profits on covering warranty claims. To minimize warranty costs companies focus on product quality improvements. In this project real historical warranty data of three electronic sensors have been analyzed. Two-parameter Weibull distribution to measure sensors' reliability have been used. Monte Carlo simulations have been implemented to calculate Total Quality Costs (TQC). The results show that cost of improved products may have an adverse impact on business profit – the main business objective. It has been demonstrated how reliability and TQC interact with each other and specified optimum business solutions. A new ratio representing combined business and customer objectives was introduced – Quality Cost Ratio (QCR). A new term has been proposed – Excessive Quality Cost (EQC). Improved process of selection parts and materials were proposed.**

Keywords - **Total Quality Cost, Quality Cost Ratio, Excessive Quality Cost, Warranty, Reliability, Weibull, Monte Carlo.**

I. INTRODUCTION

Warranty claims impact business profits and affect sales volumes due to customer dissatisfaction. To minimize the number of warranty claims manufacturers constantly improve their products' reliability[1]. Although, reliability improvements contribute to lower Failure Costs (FC), they may simultaneously cause an increase in Preventive and Appraisal Costs (PAC). The sum of FC and PAC forms a parabolic shape function called Total Quality Cost (TQC) as shown in Fig.9. FC and PAC are nonlinear functions. As product reliability increases, delta ΔPAC increases but the ΔFC decreases. The TQC function has its local minimum at the intersection of the Optimum Quality Cost (OQC) and the Optimum Quality Level (OQL), that is at the point where ΔFC equals ΔPAC . This point is the optimal business cost solution but not necessarily the optimal customer solution. On the other hand, pure reliability approach though satisfies or even delights the customer, can be detrimental to the main business objective i.e. profits.

In [2] and [3] the authors discuss *Six Sigma* methodology that aim to target a level of 3.4 defects per million opportunities (DPMO). Arthur Schneiderman in [1] tries to target a *zero defects* product at optimum cost. The author claims that product improvement does not necessarily increase costs as the quality level approaches 100%. In fact, product quality improvements lead to higher product costs but not necessarily increases TQC or product price. According to [2], [3] and [6] the TQC exists and is determined by the totals of prevention, appraisal and failure costs. In [7] methods were discussed to estimate the lifetime distribution using warranty data which consist of only failure information. In [8] and [9] based on field data, the authors perform warranty cost estimation, and in particular, the discounted warranty cost and impact of seasonality on warranty budget. In [10] various methods applied to predict reliability of electronic products were discussed. Both, empirical and physics of failure methods were compared. In [11] the author provided practical approaches to reliability analysis and prediction with warranty data by applying various methods. In [4] the author performed Monte Carlo (MC) studies to estimate switching regression models. In [5] the author applied MC results to evaluate accuracy of various statistics working with non normal and incomplete datasets. In [6] the authors determined the number of numerical tests required to provide a solution for a heuristic optimization problem with a user-defined accuracy when compared to a global optimal solution.

In this paper, business and customer objectives were combined to identify methods providing optimal part selection process for product improvements. Analysis of real historical warranty data of three temperature sensors drove findings and conclusions. A new ratio was introduced, combining common business and customer objectives. A new term - Excessive Quality Cost EQC – was introduced and discussed.

An overview of researched parts and analyzed data is provided in the Materials section. Methods applied to estimate and compare parts reliability and calculate TQC are discussed in the Methods section. In the Results section Weibull analysis, MC simulations and response surface results are presented. In the Discussion section results are interpreted; important variables are identified; the problem statement and solution are expanded; the proposed new term and ratio are explained. Proposed process of parts and materials selection is listed, quality cost ratio importance is highlighted

II. METHODOLOGY

A. Materials

Historical warranty data (real field data) of three electronic temperature sensors fitted on track type machines were validated and analyzed. Real Part Numbers (PN) and their technical specifications remained

[1] Reliability is probability that an item performs a required function under stated conditions for a stated period of time and is an integral part of the widely understood quality.

the intellectual property of the manufacturer. Table I contains information about price, number of reported failures and number of censored data.

Table I
PARTS COST AND RECORDED FAILURES

Description	Part Numbers (PN)		
	PN0008	PN0011	PN0015
Price ($)	16.33	3.99	11.53
Reported failures	17	37	8
Right censored data	1403	1403	1403

B. Methods

The sensors reliability was estimated using 2-parameter Weibull distribution. A 95% confidence level hypothesis test was performed to prove that collected data of each part follows a 2-parameter Weibull distribution. In mathematical form, Probability Density Function (PDF) of 2-parameter Weibull was expressed by

$$f(t)=\frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{(\beta-1)} e^{-\left(\frac{t}{\alpha}\right)^{\beta}}, \quad (1)$$

where α is scale parameter (characteristic life), β is shape parameter (slope) and t is failure time. The obtained Weibull parameters α and β shown in Table II were applied with (2) and used in MC simulation to produce failure times. Uniform distribution was used to generate random number r (2),

$$t=\alpha(-\ln r)^{\left(\frac{1}{\beta}\right)}, \quad (2)$$

where r is a random number between 0 and 1. The minimum number of iterations required to obtain results with maximum acceptable error of 2% were calculated according to

$$N=\left(\frac{3\sigma}{\varepsilon}\right), \quad (3)$$

where N is number of iterations, σ is standard deviation of the random variable and ε is the value of the maximum acceptable error. In total 1,200,000 iterations were performed, for 3 parts, 200 runs and 2,000 productions,

$$200\times2000\times3=1200000 \quad (4).$$

Assumptions made to perform MC simulations:

- Production volume = 2,000 machines
- Warranty time =1,000 hours
- Labor cost = $250 and $750 / failure
- Maximum accepted error = 2%

Generated by MC failure times were applied with

$$TQC=Failures\times(Labor+P_{Cost})+\mathrm{Prod}\times P_{Cost} \quad (5)$$

to calculate TQC, where P_{Cost} is the cost of a single part, *Failures* is the number of failed parts, *Labor* is the cost of labor per single failure, *Prod* is the production volume. Failure times and TQC results are shown in Table III.

Factorial Design Of Experiments (DOE) [12] was performed to produce response surface graphs and show how parts cost, labor cost and number of failures impact the TQC.

III. RESULTS

Hypothesis tests with 95% confidence level confirmed that data fits 2-parameter Weibull distribution. Minitab statistical software was used to obtain Weibull results shown in Table II and Fig.1.

Table II
WEIBULL PARAMETERS

DESCRIPTION	VALUES		
PARTS →	PN008	PN011	PN015
β – Slope parameter	1.23627	0.704798	0.784469
α – Scale parameter	140,209	355,851	1,132,914

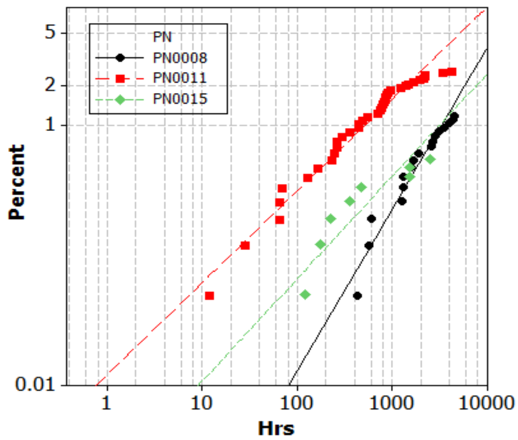

Fig. 1. Results of a 2-parameter Weibull

Microsoft Excel spreadsheet supported with Visual Basic for Applications (VBA) script was created to perform MC simulations and calculate TQC. The minimum number of iterations was calculated according to (3) and results are presented in Table III. Response surface graphs were presented in Fig. 2-7.

Table III
MONTE CARLO RESULTS

DESCRIPTION	VALUES		
PARTS →	PN008	PN011	PN015
Minimum iterations	7	183	19
FAILURES[1]:			
Mean	**4**	**31**	**8**
Minimum	0	18	0
Maximum	11	50	17
Standard deviation	2.2	5.6	2.8
TQC[2] thousands USD:			
Mean	**34**	**16**	**25**
Minimum	33	13	23
Maximum	36	21	28
Standard deviation	0.6	1.4	1.2
TQC[3] thousands USD:			
Mean	**36**	**31**	**29**
Minimum	33	25	25
Maximum	39	39	35
Standard deviation	1.6	3.6	2.4
TQC/Prod [USD]			
Denominator of QCR[2]	16.92	7.91	12.56
Denominator of QCR[3]	17.77	15.81	14.54

[1] 400,000 iterations per part → 200 runs x 2,000 Production
[2] Labor average cost = $250 per failure
[3] Labor average cost = $750 per failure

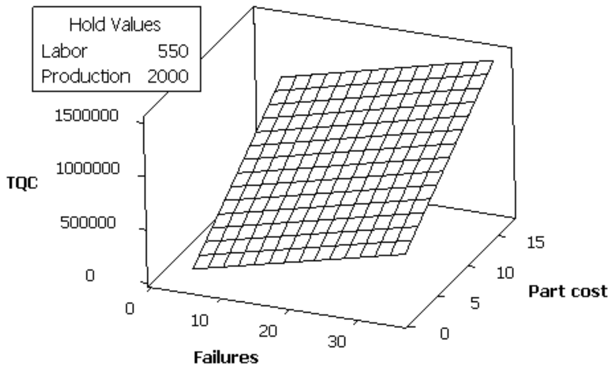

Fig. 2. TQC vs. number of failures, part cost (price)

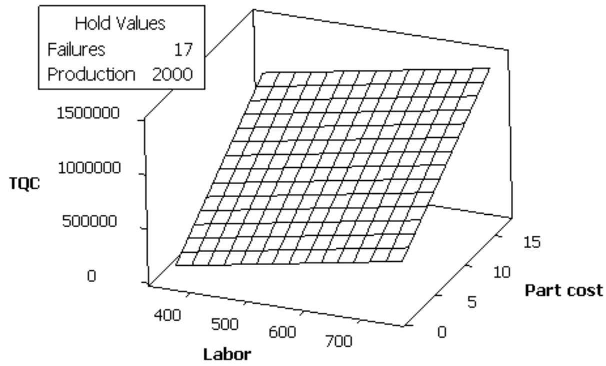

Fig. 3. TQC vs. labor cost per failure, part cost (price)

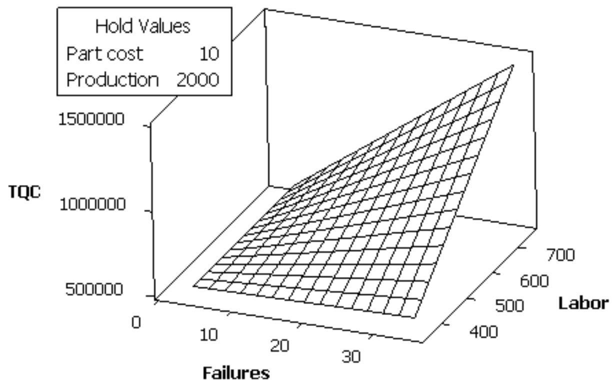

Fig. 4. TQC vs. number of failures, labor cost per failure

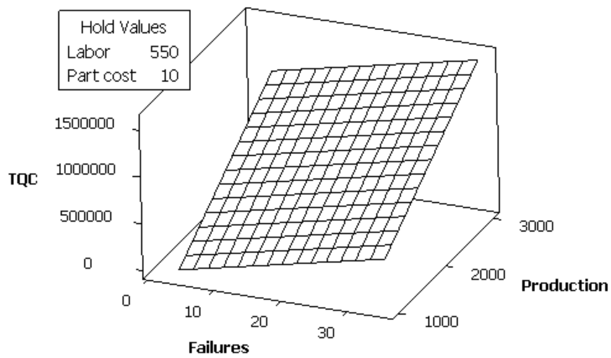

Fig. 5. TQC vs. number of failures, production value

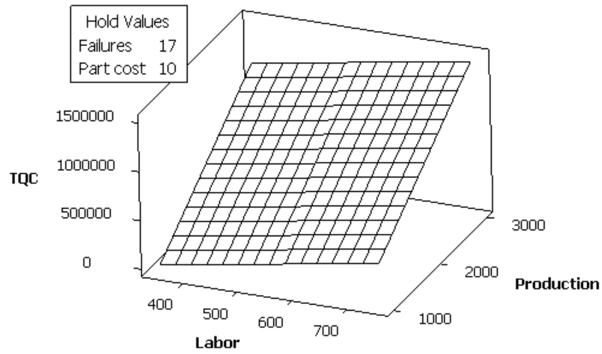

Fig. 6. TQC vs. labor cost per failure, production value

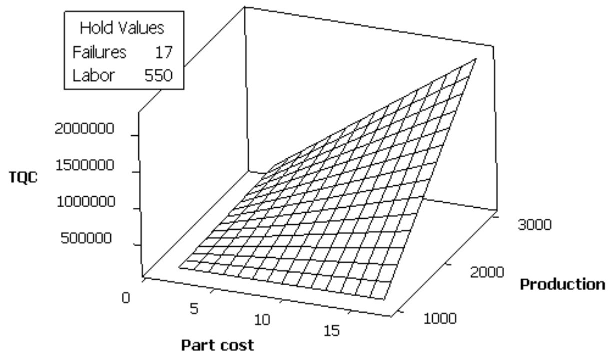

Fig. 7. TQC vs. part cost (price), production value

IV. DISCUSSION

Based only on number of recorded warranty claims presented in Table I, the PN0015 failed the least number of times. Weibull analysis presented in Fig. 1 shows that PN0008 was the most reliable part. Finally, PN0011 was the most profitable part according to the TQC results shown in Table III. The result is three approaches and three different outcomes. Moreover, the most profitable part is the most frequently failing one where TQC is half of PN0008 as shown in Table III. Preferred part selection choices are summarized in Table IV showing how easy is to make a mistake and expose the business to losses.

Table IV
COMPARISON RESULTS

METHOD	RANKING: 1=BEST; 3=WORST		
PARTS →	PN008	PN011	PN015
Count failures (Table I)	2	3	1
Weibull analyzes (Fig.1)	1	3	2
TQC (Table III)	3	1	2

A pure reliability approach is not the best part selection approach unless the customer requirement is to get maximum product reliability regardless of cost, such as for safety and space products. In these specific cases the TQC does not have local minimum, hence no optimal cost solution. For most products targeting zero defects [1] or *Six Sigma* 3.4 DPMO is the right direction to improve products if supported by profitability analysis. Weibull results on its own are enough to judge about a part reliability but not enough to make a judgment on product improvement profitability. Unlike reliability results, the TQC results are expressed in monetary units and provide reliability contribution into business profits. As shown in this paper, decisions based only on reliability results, do not necessarily contribute to the main business objectives and may be detrimental to the business profit. Nevertheless, reliability parameters employed with MC simulations effectively support profitability analyses.

Business objectives are to earn maximum possible profits and provide product that at least satisfies customer requirements. Customer objectives are to get product that at least satisfies their functional requirements and has best Quality-Price Ratio (QPR). Therefore product functionality is a common objective for both, business and customer; and both parties will aim to achieve this objective. Profit and QPR are opposite direction driven objectives and require a compromise between customer and business. As shown in Fig. 8, the optimal solution requires the QCR to remain in a central position to avoid bias towards business or customer objectives. In practice, this can be achieved by equal distribution of profits from increased QCR. Wider area of customer and business objectives can be covered by stretching QCR. This can be achieved by selecting parts and materials with high QCR for specific production requirements. Net Present Value (NPV) and Internal Rate of Return (IRR) can be calculated for better understanding the financial output of the proposed improvement.

$$\frac{\text{Price}}{\text{Cost}} \times \frac{\text{Quality}}{\text{Price}} = \frac{\text{Quality}}{\text{Cost}} = \text{QCR} \qquad (6)$$

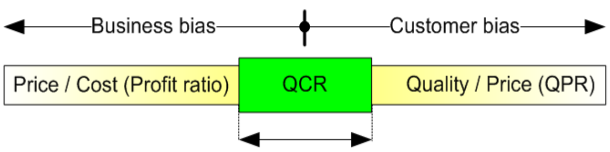

Fig. 8. QCR - business vs. customer objectives

A customer expects that product does not fail during its lifetime cycle. During warranty time, the QCR nominator (quality) remains equal for all parts as any failure is being fixed free of charge to the customer. The QCR denominator (cost) was calculated by dividing TQC by production volume; the results are shown in Table III. Therefore in warranty time for the QCR the denominator value can be compared across parts. For the whole product lifetime cycle, cost of extended warranty need to be added to denominators accordingly while nominators remain equal for all parts. As long as market products are being constantly improved in the process of continuous product improvement (CPI), the satisfactory level of the QCR is changing also. Kano model [2] and [3] explains the process of increasing customer expectations over time.

This new approach combines business and customer objectives into a single factor. The QCR can be applied in more complex quality study which is why the authors used the term quality instead of reliability. The authors recommend applying QCR with goodwill studies.

Cost of Poor Quality (CoPQ) was discussed in [2] and [3]. It occurs when applied quality/reliability is below OQL as shown in point Q_1 of Fig.9, assuming OQL is the quality expected by the customer. In this case more reliable parts can be applied at a lower TQC. That means higher customer satisfaction and higher profits to the business due to lower costs and increased sales. The optimal solution for the business and customer is to apply part from quality range between OQL and Q_3. Applying parts with quality beyond this range will delight the customer but decrease business profits. A new term - Excessive Quality Cost (EQC) is proposed to describe this situation, where any further quality improvements though contributing to higher customer satisfaction, causes detrimental impact to the business profit.

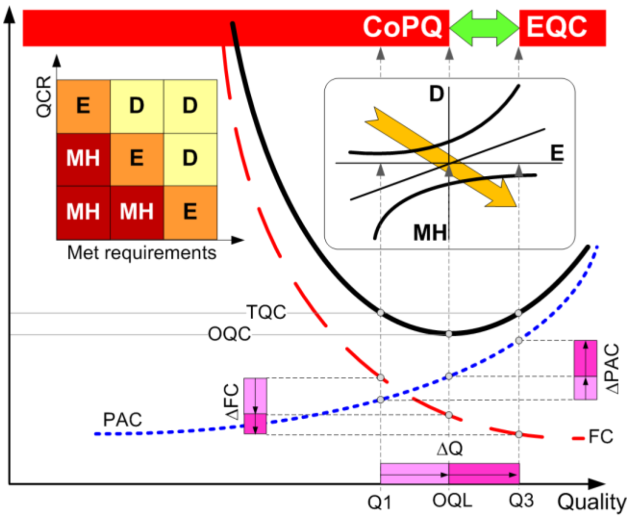

Fig. 9. Relation between TQC, Kano model, reliability and QCR where Q is quality, MH is *Must Haves* E is expected and D is delighting.

Response surface graphs (Fig. 2-7) show that in this model production volumes have a major impact on TQC.

V. CONCLUSION

The true product improvement is achieved if TQC and product prices are not increased. Alternatively, if product price increases, the added value is worth the price for the customer and is not harmful to the business profit.

The optimal business and customer solution is between CoPQ and EQC as shown in Fig. 9. Targeting zero defects [1] or *Six Sigma* 3.4 DPMO [2], [3] is the right direction of product improvements but the targets need to be approved by profitability studies. Uncontrolled focusing on reliability improvements does not truly reflect neither business objectives nor customer requirements. Moreover, it can be detrimental to the business profit due to increased TQC and lowered QCR.

The process of parts and materials selection needs to start with a reliability analysis to exclude parts and materials below minimum customer reliability requirements. It requires MC simulations to estimate number of failures and TQC at specified production volumes, warranty time, parts cost and labor cost. The minimum number of iterations required to obtain results with maximum acceptable error of 2% can be calculated using Equation (3). Also requires to calculate and compare QCR for a specified warranty period and product lifetime cycle. For the product lifetime cycle, cost of extended warranty needs to be added accordingly. NPV and IRR can be calculated for better understanding of the financial output of a proposed improvement.

In a long time perspective, only product improvements contributing to at least one side of the contract and without negative impact on objectives of the other side are beneficial to the business.

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