Ford's Reliability Improvement Process, A Case Study on Automotive Wheel Bearings

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ABSTRACT

This case study presents the structured approach used by Ford Motor Company to identify and implement product design changes to increase product reliability. This nine-step process facilitates the engineering community's ability to make data-driven decisions targeted toward increasing customer satisfaction. This case study contains a review of the quantitative techniques used in the methodology including fitting random variable models to censored data, modeling and predicting automobile warranty claims, and various other product and process improvement methods. Lastly, we present an application of Ford's reliability improvement process to a front wheel bearing to demonstrate the methodology.

1 INTRODUCTION

Engineers at Ford Motor Company continually evaluate current passenger vehicles (automobiles, light trucks and Sport Utility Vehicles) for design changes intended to increase quality and reliability. Historically, these changes were targeted toward preventing failures during the basic warranty period of 3 year 36,000 miles or 5 year 50,000 miles with the intent of reducing warranty costs. However, in the more competitive global automobile market, vehicles must function properly for longer than the basic warranty coverage for manufacturers to retain customers. Ford now defines the useful life or design lifetime of their passenger vehicles – the point at which 95% of vehicles should still function - as 10 years or 150,000 miles.

Ford has developed a standard process to add structure and consistency to product changes intended to improve product reliability. This case study presents the reliability improvement process used by Ford that engineers have successfully implemented to improve product field performance in the time domain. This methodology is presented in general and we illustrate its application in the context of a wheel bearing used in some Ford automobiles. Figure 1 shows the automotive wheel bearing analyzed in this case study. The bearing assembly contains a collection of lubricated steel balls that roll in the outer bearing housing and allow the wheel to rotate. The hub flange provides a large rigid surface used to attach the wheel bearing to the wheel. The bearing cap is made of plastic and covers the portion of the anti-lock brake system (ABS) internal to the wheel bearing. The bearing cap design utilizes a friction seal to prevent contamination ingress between the cap and the outer bearing housing. The wheel bearing contains an ABS sensor that detects wheel rotation and transmits the rate of rotation to the ABS control unit. When a wheel is not rotating - the brakes are locked - the control unit will release the brakes for a very short time interval to allow the wheel to roll again that provides the driver the ability to steer the vehicle. The wheel bearing uses an o-ring to seal the ABS sensor opening and prevent contamination from entering the bearing. These wheel bearings were experiencing a condition that resulted in what customers perceived as excessive noise. This condition affected about 3% of the bearings and was purely a customer inconvenience, i.e., passenger safety was never at risk. Never the less, the bearing was covered by warranty and they were being replaced at company expense. Therefore, warranty and reliability engineers initiated Ford's reliability improvement process to address this noisy failure mode.

The remained of this case study has the following outline. Section 2 describes the nine steps of the Ford reliability improvement process. Section 3 develops the quantitative methods used in the methodology and provides citations for literature containing more details of these specific techniques. Section 4 contains an application of the methodology to an automotive wheel bearing. The application follows the outline of the Ford process and includes supporting data and analysis from the wheel bearing redesign. Section 5 contains conclusions and recommendations on how to effectively use the methodology.

2 APPROACH USED

The Ford reliability improvement process consists of nine phases, which are numbered phase 0 to phase 8 and discussed in Sections 2.0 - 2.8 below. This methodology has the breadth to cover most types of problem resolution, yet is flexible enough to apply to the wide variety of design issues encountered in automobile manufacturing. Each problem is unique and, to a certain extent, requires a specific solution process. The Ford methodology is not intended to be overly rigid and allows the engineer to customize the process to meet their needs. For some steps, the methodology suggests the improvement team select from multiple analytic techniques that further lends to the flexibility.

2.0 Identify Priority Concerns

In the first step of this phase, Ford personnel identify design issues for potential resolution. This step is somewhat open-ended so engineers will not miss potential issues because early identification doesn't fit in the methodology. The Ford process doesn't provide quantitative criteria for problem identification, rather it encourages justifying the issue quantitatively. In general, the identification of issues should be data driven, without any strict guidelines on what constitutes an issue. Engineers can identify a design issue using warranty data, Ford customer survey data, or third party survey data such as *The Initial Quality Survey*[1].

Warranty claims provide a readily available source of data on all vehicles sold to use in the problem identification phase. Warranty and reliability engineers continually receive detailed data on any vehicle repaired under warranty. Unfortunately, vehicles leave warranty coverage before they exceed their useful life, which limits the ability to identify high mileage failures. Warranty claims provide a source for identifying design issues that limit product functionality.

Another source of data is obtained through customer surveys, which Ford sends to each customer purchasing or leasing a new vehicle. Customers have the opportunity to rate items at the system level (e.g., exterior appearance, power train, seats, etc.) on a five level satisfaction scale. The survey also contains space for open-ended or specific comments. Ford also holds inspection clinics, conducted at various locations, which allow customers to show their vehicles to Ford engineers and discuss concerns one-on-one. The data from the surveys and inspection clinics allow engineering and marketing functions to identify customer annoyance issues that may not appear in warranty claim data. External surveys provide similar data to the Ford customer survey, but provides comparisons to vehicles produced from a variety of manufacturers worldwide. This data allows Ford personnel to judge their product's performance relative to their competitors and can lend a different perspective to certain issues.

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[1] *The Initial Quality Survey,* an across manufacturer comparative study of new vehicle quality, is published annually by J. D. Power and Associates, Agoura Hills, CA.

The second step of Phase 0 is to identify a team champion. Warranty and reliability engineers forward their findings to the product line engineering director (or equivalent) for review. If the director decides to initiate the redesign process, they identify a team champion who assumes responsibility for completing the project.

Phase 0 completion activities**:** problem identified, upper management approval for redesign project, team champion named.

2.1 Set-up Team

The team champion establishes a team with the skills required to deliver a solution to the concern identified in Phase 0. This team has a leader (different from the team champion) and consists of a cross functional group (product design engineer, reliability engineer, manufacturing or process engineer, product cost analyst, etc.) with specific product knowledge. The team champion obtains local management commitment for the each member. Before being a member of the team, an employee's immediate supervisor must agree to provide the employee time and resources to work on the design issue.

Phase 1 completion activities: identify team members, obtain management commitment for each team member.

2.2 Detail Failure Modes and Identify Uncontrollable or Noise Variables

This phase, consisting of three steps, represents the detailed analysis of the problem or design issue. At the conclusion of this phase, the team will develop a collection of documents. The documents the team may choose to include: Block diagram, Function Tree, Reliability and Robustness checklist, and Parameter-Diagram.

Step 1:Perform a comprehensive analysis of warranty or survey data. Failures covered under warranty have a direct impact on company profits, therefore warranty claims remain the primary source for data. The Ford process suggests using either Pareto charts or hazard plots of warranty data as supporting evidence of a problem. The team should compare actual field performance with design intent or compare projected warranty costs with budgeted values.

Step 2: Review actual field failures or customer identified annoyance parts. Any part replaced under warranty becomes the property of Ford Motor Company. To receive payment for the repair, the service provider must return the item to the design center making these parts readily available. The purpose of these reviews is to identify failure modes of which Ford defines two types: hard failure (product stops functioning), and soft failure (product function degraded to unacceptable level). Ultimately, the team will propose design changes to eliminate the failures identified in this step. The team also creates a list of noise factors (uncontrollable variables) and control factors (controllable variables) for the product. The team then identifies the range for these variables in the field. For example, if the noise factor is outside temperature, the team needs to identify the coldest and warmed temperatures the product will experience.

Step 3: Determine the best in class (BIC) product. The team conducts an analysis of Ford and competitor products to determine BIC. The team compares the current Ford product to the BIC product focusing on basic design and field performance. The team then initiates a purchase order for enough of the BIC product to do performance testing. The team will use the BIC product as a benchmark for any proposed product changes.

Phase 2 completion activities: problem statement, identify failure mode(s), list of noise factors with range of exposure, list of control factors with range of exposure, communicate failure modes to appropriate design process.

2.3 Analyze Failure Mechanisms

The purpose of this phase is to determine root causes of field failures by drawing on past experience and judgment. In addition, the team utilizes the 8D problem solving process (described in Section 3.3.1) to lend structure to their activities as they uncover various potential causes of the failure modes. The team must also demonstrate the ability to reproduce failure modes in the bench test environment. This step is critical to verifying that new designs have eliminated the failure mode. Some recommended techniques are brainstorming sessions and formal design change reviews. Once failure mechanisms have been fully explored, the team updates the failure mode and effects analysis (FMEA) documentation.

Once failure mechanisms have been identified and understood, the team estimates the associated cost of quality. While these costs can be both direct (warranty repair costs) and indirect (lost customer due to product dissatisfaction), this analysis should focus on direct quantifiable costs that could be saved through product changes. This cost information becomes an input to any future cost / benefit analysis associated with proposed product design changes. Lastly, the team investigates the BIC product for possible solutions to the failure mechanisms.

Phase 3 completion activities: failure mechanisms understood and documented, FMEA update initiated, cost of failure mechanisms quantified, BIC product evaluated for potential solutions.

2.4 Establish System Design Specification (SDS) and Worldwide Corporate Requirements (WCR) compliance

The team reviews and updates design documentation to prevent future designs from containing the failure mechanism. The team reviews the SDS and WCR design guides to compare the current design with the standards and notes any differences. The team also assesses the standards to determine, if completely followed, they would prevent the failure mechanisms identified. Lastly, the team develops a plan for how the product should comply with the design standards.

Phase 4 completion activities: comparison of current design to design standards, plan to achieve design compliance.

2.5 Develop Test and Establish Performance of Current Design

Ultimately, Ford engineers design for a useful life of 10 years and 150,000 miles. However, a bench test will accelerate this usage period to a matter of a few days or weeks. The team needs to translate customer usage (time and mileage) into the metric(s) of the bench test. The team also needs to have a formal definition of hard and soft failures. Ideally, these should be quantitative or objective criteria that can be uniformly applied to many parts by many people. Finally, the team must verify that the bench test can reproduce the failure mode. After establishing a valid test, the team tests the current (failing) design to establish a baseline performance level. This data will provide a benchmark for testing of newly designed or redesigned parts. The team must verify that all the noise variables are represented in the bench test and the bench test meets specified performance criteria.

Phase 5 completion activities: bench test that reproduces failure modes, detailed documentation of bench test, bench test performance of current design.

2.6 Develop Noise Factor Management Strategy

The team develops a strategy, or approach for isolating the product from the adverse affects of uncontrollable (noise) variables. This results in a product design robust to environmental variables that customers can not control or predict, e.g., temperature, wind, or precipitation. The team documents the strategy using the noise factor management matrix.

Phase 6 completion activities: strategy for design robust to noise variables.

2.7 Develop New Design and Verify Using Reliability Disciplines

In this phase, the team produces the new design for the product. This design should be robust to operating conditions, no longer exhibit the failure mode currently encountered in field performance, and function for the useful life of the product. The team conducts bench tests on prototypes of the new design. These tests must show, with statistical significance, that the product will meet the usage criteria while no longer experiencing the failure mode.

Phase 7 completion activities: new product design, FMEA complete.

2.8 Sign-off Design and Update Lessons Learned

This phase represents the conclusion of Ford's reliability improvement process. The team completes final updates of all necessary documentation (FMEA's, system design specs, etc.) and releases the new design into production (following the usual appropriate steps which are not detailed here). The team then updates the lessons learned which facilitates continual improvement through structured corporate memory. Lastly, upper management formally recognizes the team for completing a successful project.

3 QUANTITATIVE ANALYSIS METHODS

The applications of statistical methods in reliability divide into two categories: repairable and non-repairable systems. The appropriate method depends on the characteristics of the product, service, or component under study. Non-repairable systems reliability describes the situation when a single failure, or observation in the data, represents the end of a product or component lifetime. Repairable systems techniques apply when a product can have multiple failures or observations in the data which implies that after repair, products return to some useful state. Thompson (1981) provides a thorough treatment of the use of distribution functions for modeling time to failure of non-repairable systems, and stochastic process models that apply to repairable systems. The Ford methodology applies to automotive components and assemblies and treats them as non-repairable systems.

3.1 Estimating Product Lifetime with Field Data

This case study uses maximum likelihood estimation to fit random variable models to field failure and bench test data. Lawless (1982) and Meeker and Escobar (1998) provide functional forms for random variables often applied to lifetime data, e.g., Weibull, Exponential, and Log-normal. Field failure data often results in partial or incomplete data on lifetimes, which are called censored values. Lifetime data can possess three types of censored data: right censored indicates the product has not yet failed thus placing a lower limit on lifetime, left censored values arise when the product has failed but has an unknown origin and an unknown lifetime, and interval censored that bounds lifetime between two values. Maximum likelihood estimation (mle) allows incorporating the information contained in censored values. To use mle to estimate random variable model parameters for a sample of size n, denote product lifetimes as the random variables $T_1, T_2, \ldots, T_n$, with observed values $t_1, t_2, \ldots, t_n$. Assuming that the n component lifetimes are independent (this is analogous to assuming a random sample) and have probability density function f( ), the likelihood function for complete (uncensored) data is

$$L = \prod_{i=1}^{n} f(t_i) . \tag{1}$$

The maximum likelihood estimates are the parameter values that maximize the likelihood function. To simplify the maximization problem, one can work with the log-likelihood function

$$\log(L) = \sum_{i=1}^{n} \log(f(t_i)) . \tag{2}$$

Fitting random variable models to a population of automobiles using warranty data results in right censored observations (vehicles without warranty claims have not observed a failure but have a know lifetime). To extend maximum likelihood estimation to the case of right censored data, redefine the observed values $t_1, t_2, \ldots, t_n$ to represent either lifetimes or right censored values. In addition, define an indicator variable

$$\delta_i = \begin{cases} 1 \text{ if } t_i \text{ represents an observed lifetime} \\ 0 \text{ if } t_i \text{ represents a right censored lifetime} \end{cases} \tag{3}$$

to denote right censored observations. A right censored observation means that the product lifetime exceeds the observed value which represents the survivor function evaluated at the censor time

$$P(T > t) = S(t).$$

Incorporating right censored data results in the likelihood function

$$L = \prod_{i=1}^{n} [f(t_i)]^{\delta_i} [S(t_i)]^{1-\delta_i} \tag{4}$$

with an associated log likelihood function of

$$\log(L) = \sum_{i=1}^{n} \left[\delta_i \log(f(t_i)) + (1-\delta_i)\log(S(t_i))\right]. \tag{5}$$

3.2 Modeling Automobile Warranty Claims and Costs

Many manufacturers of durable goods, such as automobiles, appliances and personal computers, provide their customers basic warranty coverage, i.e., coverage included in the purchase price. Products that can experience at most one warranty claim can be modeled as non-repairable systems using random variable based cost models. Blischke and Murthy (1994) provide a comprehensive review of warranty cost models. Letting T represent product lifetime and t_c the warranty limit, one can estimate the probability a given product experiences a warranty claim as the cumulative distribution function evaluated at the warranty limit

$$P(T < t_c) = F(t_c). \tag{6}$$

Many authors have suggested models for predicting automobile warranty claims. Kalbfleisch, Lawless and Robinson (1991) develop a Poisson model for predicting automobile warranty claims in the time domain. They extend the model to predict cost by multiplying the expected number of claims (a function of time) by the expected cost per claim (also as a function of time). Moskowitz and Chun (1994) suggest using a bivariate Poisson model to predict claims for a two dimensional warranty. They fit the cumulative Poisson parameter λ with various functions of time t and mileage m. Hu and Lawless (1996) suggest a technique for modeling warranty claims as truncated data that assumes warranty claims follow a Poisson process. Sarawgi and Kurtz (1995) provide a method for predicting the number of product failures during a one dimensional warranty coverage based on bench test data.

To use statistical methods for warranty data analysis, one must define a population for study. Forming populations of vehicles based on time of sale would serve sales, marketing and accounting needs.

However, product design, manufacturing and assembly changes take effect on assembly or manufacturing dates. Therefore, automotive warranty and reliability engineers form populations based on date of assembly that allows them to compare field performance of vehicles before and after an engineering change. Due to the random nature of sales lag – the time from final assembly to customer delivery (see Robinson and McDonald 1991) - a collection of vehicles built on the same day may sell at different times.

Many automobile manufacturers track warranty claims in terms of cumulative repairs per thousand vehicles, which we denote as R(t) (see Wasserman (1992) and Robinson and McDonald (1991)). To obtain R(t) values, first define N_i as the number of vehicles with at least i months in service (MIS), which can decrease as i increases for a given set of vehicles due to sales lag. Let f_i represent the number or frequency of claims observed in month i of service by the N_i vehicles. Then calculate

$$R(t) = \sum_{i=0}^{t} \frac{f_i}{N_i} * 1000 \qquad (7)$$

Wasserman (1992) developed a dynamic linear predictive model for R(t) using data from multiple model years of a product. Singpurwalla and Wilson (1993) developed a bivariate failure model for automobile warranty data indexed by time t and mileage m. They derived the marginal failure distributions and presented a method for predicting R(t) using a log-log model.

Robinson and McDonald (1991) suggest plotting R(t) on log-log paper, fitting a line to the observed data, and using the fit line to make predictions. This approach is used by many automobile manufacturers who track claims using a statistic similar to R(t) defined by equation (7). To apply the technique, the manufacturer takes a log transform of R(t) and fits the simple linear regression model

$$\log(R(t)) = \beta_0 + \beta_1 \log(t) + \varepsilon . \qquad (8)$$

To predict warranty claims through some future time in service t, the manufacturer transforms the value predicted by the fit line as

$$\hat{R}(t) = \exp(\hat{\beta}_0 + \hat{\beta}_1 \log(t)) . \qquad (9)$$

3.3 Analytic methods

Ford's reliability improvement process incorporates many quantitative tools – some widely used techniques and others less well known. This section presents background information and references for many of the methods used in Ford's process.

3.3.1 8D Problem Solving Process

Many organizations use structured approaches to problem solving and Ford is no different in this regard. Ledolter and Burrill (1999) and Pande, Neuman and Cavanagh (2000) show structured approaches to problem solving. Ford uses a methodology they call the 8D Problem Solving Process which consists of eight steps. The following is a synopsis of the process.

D1 - Establish Team

Establish a small group of people with the process and/or product knowledge, allocated time, authority, and skill in the required technical disciplines to solve the problem and implement corrective actions. The group must have a designated champion and team leader. The group begins the team building process.

D2 - Describe the Problem

Describe the internal/external customer problem by identifying "what is wrong with what" and detail the problem in quantifiable terms.

D3 - Develop Interim Containment Action (ICA)

Define, verify, and implement an interim containment action (ICA) to isolate effects of the problem from any internal/external customer until permanent corrective actions (PCAs) are implemented. Validate the effectiveness of the containment actions.

D4 - Define and Verify Root Cause and Escape Point

Isolate and verify the root cause by testing each possible cause against the problem description and test data. Also isolate and verify the place in the process where the effect of the root cause should have been detected and contained (escape point).

D5 - Choose and Verify Permanent Corrective Actions (PCAs) for Root Cause and Escape Point

Select the best permanent corrective action to remove the root cause. Also select the best permanent corrective action to eliminate escape. Verify that both decisions will be successful when implemented without causing undesirable effects.

D6 - Implement and Validate Permanent Corrective Actions (PCAs)

Plan and implement selected permanent corrective actions. Remove the interim containment action. Monitor the long-term results.

D7 - Prevent Recurrence

Modify the necessary systems including policies, practices, and procedures to prevent recurrence of this problem and similar ones. Make recommendations for systemic improvements, as necessary.

D8 - Recognize Team and Individual Contributions

Complete the team experience, sincerely recognize both team and individual contributions, and celebrate.

3.3.2 Accelerated Testing

In many situations, doing life testing of products during development or redesign is infeasible due to the length of time required to perform the test. Manufacturers can compress product usage over time using methods called accelerated tests which may also involve unique statistical models. Lawless (1982), Blischke and Murthy (2000) and Meeker and Escobar (1998) all contain material on accelerated tests.

3.3.3 B5 Lifetime

For product reliability purposes, manufacturers evaluate the lifetime of their products. Due to the random nature of lifetime for a population of products, manufacturers specify a lifetime model, usually a random variable that quantifies customer usage. At Ford, when engineers design automotive components, they predict a lifetime value which they expect 95% of the products to exceed, referred to as the design lifetime. Ford uses an analogous value, the B5 lifetime, to measure field performance. Warranty and reliability engineers measure field performance, often using warranty data, and develop $\hat{F}(t)$, an estimated cumulative distribution function of actual usage. When an observed value exists for each member in a sample, one can construct a histogram from the data. The histogram serves as a graphical estimate of the probability density function f ( ) and the engineer can use this as an input to model selection.

For example, if the histogram possesses the "bell shaped curve" the modeler of the data should consider using a Normal distribution. Blishke and Murthy (2000) provide figures of f( ) for a variety of distributions (exponential, Weibul, gamma, log-normal, etc.) often fit to lifetime data. In the case of censored data, it is not possible to construct a histogram. In this situation, we suggest graphically evaluating the observed lifetime data with a hazard plot (see Lawless 1982). Majeske, Lynch-Caris and Herrin (1997) use this hazard plotting technique to model warranty data for an automotive audio system. A constant hazard function suggests an exponential distribution while increasing or decreasing shapes may suggest a Weibul distribution. Once the engineer has identified a model, they should perform a goodness-of-fit test (see Lawless (1982) or Blishke and Murthy (2000)) to validate model selection. Using $\hat{F}(t)$ -the random variable model fit to the observed data - the warranty or reliability engineer predicts the B5 lifetime as the value they expect 95% of the population to exceed or

$$B5 = \hat{F}^{-1}(0.05)\,. \tag{10}$$

3.3.4 Block Diagram

A block diagram (see Blischke and Murthy 2000) represents a system of assemblies, such as a complete passenger vehicle, or a product subsystem (collection of components), such as the wheel bearing used in this case study. A block diagram contains a block for each component in the assembly. The diagram contains arrows (one-way or two-way) between the blocks to represent relationships between the components. A list of variables (controllable and uncontrollable) that may affect the functionality of the components completes the diagram. As an example, we will develop a block diagram for the automotive wheel bearing. First, we identify the key components for the wheel bearing: anti-lock brake system (ABS) sensor, ABS sensor o-ring, ABS cap, bearing assembly, and hub flange. Next, we list the variables that might affect the functionality of the wheel bearing: dimensional accuracy, outside temperature, thermal aging, internal temperature, weight imbalance, contamination, and road hazards. Lastly, we evaluate the relationships between the components and the variables. Figure 2 shows the block diagram for the automotive wheel bearing.

3.3.5 Function Tree

A function tree is developed in consort with the block diagram (see above). The function tree has a collection of branches for some or all of the components listed in the block diagram. Starting with a component, the first branch answers the question “what function does the component perform”. The next branch gives more details on the how and the last branch answers the question “why does this component function”. To demonstrate the technique, we develop a Function tree for the automotive wheel bearing which appears as Figure 3.

3.3.6 Parameter Diagram

Phadke (1989) presents a parameter diagram (P-diagram) as a graphical technique used to organize the various variables that describe and or affect a product or process. This technique classifies the variables into four categories: response, signal, noise, and control. Response variables are the quality characteristics that describe the product. Signal factors are the variables that are controlled by the customer or user of the product. Noise factors represent variables beyond the control of the customer or manufacturer and can be classified into three groups: external or environmental variables, common cause variation encountered in the manufacturing process, and deterioration attributed to normal usage or wear out. Control factors are the variables that are defined by the product and or process designers. Figure 4 shows the generic structure for a P-diagram. In section 4.2 we develop a P-diagram for the automotive wheel bearing which appears as Figure 8.

3.3.7 Reliability and Robustness Checklist

A great deal of effort has been allocated toward the design of robust products (see Phadke 1989). In a statistical sense, robustness is similar to independence. Saying that a product is robust means that its ability to function or perform is independent of other, usually uncontrollable, variables. When designing robust products there are two perspectives. One is to design a product that is robust to operating conditions and the other is to make it robust to uncontrollable variables in the manufacturing and assembly process. The reliability and robustness checklist is just a listing of all uncontrollable variables, both manufacturing and customer, and how the product will remain robust to their existence and variability.

3.3.8 Failure Mode and Effects Analysis (FMEA)

This technique assists manufacturers in obtaining robust products by identifying the product’s potential failure modes and attempting to prevent them. Pande, Neuman and Cavanagh (2000) provide a simple five-step approach to performing a product FMEA. Breyfogle (1999) gives a much more thorough treatment of the FMEA including how to incorporate the technique in the design process. The Automobile

Industries Action Group (see AIAG 2001) - a consortium of Daimler-Chrysler, Ford and General Motors tasked with developing common procedures for the domestic automobile industry – has documented an FMEA procedure specifically for the automobile industry.

4 DATA & ANALYSIS

This section presents the Ford reliability improvement process as it was applied to a redesign of the automotive wheel bearing that appeared as Figure 1. The case study will follow the outline of the Ford methodology discussed in Section 2.

4.0 Identify Priority Concerns

Ford reliability and product design engineers continually review warranty and customer survey data to identify opportunities for design changes. As part of his regular duties, a reliability engineer identified abnormally high warranty claim rates for a particular wheel bearing. The warranty claims were for the replacement of the bearing, a rather expensive repair, resulting in warranty costs far exceeding target and budget values. The wheel bearing was identified as a candidate for redesign by constructing Table 1 with data available at 21 months in service (MIS). Table 1 shows data for the case study bearing, two other Ford wheel bearings, and the target or budget values for three quality measures: R(21), repairs per thousand vehicles at 21 MIS, calculated using equation (7), average wheel bearing warranty cost per vehicle or unit (CPU) in dollars, and the B5 life of equation (10) which represents the predicted useful life. The reliability engineer identified that the case study bearing had warranty and cost rates well in excess of the other two Ford products.

A second technique used in the analysis was to compare actual field performance with the design lifetime of 10 years and 150,000 miles. Based on prior experience and product knowledge, wheel bearing designer engineers assumed wheel bearing lifetime (MIS) followed an Exponential distribution, with cumulative distribution function

$$F(t) = 1 - e^{-\lambda t},$$

with $\lambda = 0.0004274$. Thus, the design engineer assumed the wheel bearing would meet, but not exceed, the useful life criteria, i.e., $F(120) = 0.05$. To model actual field performance, the reliability engineer fit random variable models – using the right censored data maximum likelihood estimation approach outlined in section 3.1 – to the warranty claim data. The engineer fit four parametric models to the data (exponential, weibul, log-normal and normal) and used a likelihood ratio test (see Meeker and Escobar 1998) to compare the relative fit of pairs of models. The engineer concluded that a normal distribution, with mean 50 MIS and standard deviation 12 MIS, provided the best fit to the data. Figure 5 compares the normal distribution fit to the observed data (predicted lifetime) with the exponential distribution used as the lifetime model during product design (predicted lifetime). It is apparent from Figure 5 that the field performance of the wheel bearing falls far short of the designers intent and suggests that the design engineers lifetime model (the exponential distribution) did not provide a good forecast of field performance.

The reliability engineer forwarded the data of Table 1 and Figure 5 to upper level management suggesting that they initiate Ford's reliability improvement process. Based on the high cost and poor field performance, Ford management identified a team champion and began the redesign process for the wheel bearing.

4.1 Set-up Team

Team formation for the wheel bearing issue was complex and delicate. Ford purchased the wheel bearing from a tier 1 supplier and the bearing was treated as a "black box" component by Ford. The tier 1 supplier purchased one of the critical components from a tier 2 supplier, thus involving three companies in the design, manufacturing and assembly of the wheel bearing. The team champion decided that the team should include representatives from both the tier 1 and tier 2 suppliers. Initially, both suppliers were hesitant to be included on the team, fearing they be tasked with unrealistic assignments without support from Ford. The team champion assured the suppliers they would be treated as equal partners on the team – sharing the success of the redesign as well as the blame for current failures – and they agreed to join the team. In addition to the champion, the team consisted of 8 people: 4 from Ford, and 2 from each of the suppliers. The Ford product design engineer took the role of team leader, being assisted by the reliability engineer who first identified the issue.

4.2 Detail Failure Modes and Identify Noise

A common technique used by Ford in the problem identification process is to stratify field data by geographic location. Using this technique, initial analysis of the warranty data showed that failures in wheel bearings appeared to vary by state. Figure 6 shows the warranty claim rates for six states - the three states with the highest failure rate and the three states with the lowest failure rates – and includes a line showing the average across all 50 states. Notice that the three states with the lowest failure rates are warm weather states (California, Florida and Texas), while the three states with the highest failure rates are cold weather states (Michigan, New Jersey, Ohio). From this analysis, the team concluded there was some type of a weather effect in the failure.

The team then began the review of field failures repaired under warranty that had been returned to Ford. While all components repaired under warranty become the property of Ford, due to space constraints, they do not keep all the individual parts. The team contacted the storage facility and was able to obtain a sample of 18 bearings. They measured and recorded data on 27 different quality characteristics. During this process, the team noted that many of the wheel bearing exhibited a discoloration in the grease that indicates contaminants entering the wheel bearing. Upon further review, the team noted that 10 of the 18 wheel bearings showed contamination ingress from the inboard side of the wheel bearing. The team then completed page one, the problem description, of the problem solving worksheet that appears as Figure 7.

Next, the team initiated a best in class (BIC) study of wheel bearings. The team contacted the purchasing department for assistance who completed a benchmark study of 7 wheel bearing suppliers. This study rated suppliers on overall quality and technical capability. After reviewing the purchasing department study, the team identified five wheel bearing to include in the BIC study: 2 used in Ford products and 3 in non-Ford products. The team evaluated the various designs focusing on the ability of the design to prevent contaminants from entering the bearing. The wheel bearing selected as BIC has two major design differences form the current product. First, the BIC bearing has an integrated Anti-lock Brake System (ABS) sensor. This design eliminates a possible contaminant entry point to the bearing. Second, the BIC bearing has a metal interface in the plastic seal. The team felt that a metal to metal seal could be more effective in preventing ingress than the plastic to metal seal of the current design. The bearing identified as BIC is currently used on some Ford products which allowed the team to compare failure rates and costs of the BIC bearing to the current design. Table 2 adds the BIC bearing to Table 1 shown previously. Notice that the repair rate and costs of the BIC bearing are about 1/50th of the case study bearing.

The last step of this phase is to identify the noise factors and error states. The team used a combination of brainstorming sessions, meetings and informal conversations to develop a list of possible noise factors. The team placed these noise factors into five categories. To organize and present this information, the team used a Parameter or P-diagram that appears as Figure 8.

4.3 Analyze Failure Mechanisms

The team then began to identify possible root causes. An analysis of the warranty claim data suggested that customers initially complained about noise in their vehicle. Based on the review of field failures, the replaced wheel bearings had rusted and quite possibly were making noise. The presence of contaminants, specifically water, was indicated by the grease discoloration. The root cause identification then focused on potential ingress in two locations. The team concluded that the contaminants could be entering the bearings through the ABS cap to bearing mating surface and / or the ABS sensor to cap interface.

The team initiated the Ford's formal 8 step design change process and completed the first four steps. Having the design change process underway will allow them to quickly implement design changes later in the reliability improvement process. The team then began the process of updating the Failure Mode and Effects Analysis (FMEA). Specifically, the team added the noisy failure mode observed in the field and increased occurrence and detection values on items related to the contamination ingress identified on the failed wheel bearings. The team also completed component level Design FMEA's for the Bearing, ABS Cap and the Sensor.

The team performed an analysis of warranty costs and set targets for design changes. Using the data available at 21 MIS, the team fit the log-log R(t) regression model of equation (8). Using equation (9), the team forecast the bearing would reach 48.3 repairs per thousand (R/1000) at 36 MIS with a predicted cost per unit of $11.63. The team set a goal of a 50% reduction in R/1000 and Cost per unit. Therefore, before implementing any design changes, the team will need to demonstrate (via bench test data) that they will reduce failures covered under warranty by 50%. Unfortunately, the team did not identify any fast track solutions and moved on to the next phase of the process.

4.4 Establish System Design Specification (SDS) and Worldwide Corporate Requirements (WCR) compliance

By reviewing historical design documentation, the team concluded that the current bearing would satisfy the current bench verification tests. This suggested that the existing apparatus – which tested two bearings at a time - did not induce the failure modes occurring with bearings in the field. The team then tested two production bearings on the bench test, running them 20 days (a simulated 200,000 miles). Neither of these bearings failed, confirming that the original bench test did not induce the failure mode experienced in the field. Rather than develop a new bench test, the team decided to modify the existing test to create failure modes caused by contamination ingress into the bearing.

The team analyzed the current bearing and determined that it met all design standards. The team also noted that to Ford, the wheel bearing is a black-box component. Therefore, the design standards are very broad and generic. At this stage the team concluded that they should leave the standards as written, because from a Ford perspective, the details of the design aren't as important as the functionality of the wheel bearing. Ultimately, the bearing must function for the design lifetime in all climates where they operate and must maintain a satisfactory level of customer satisfaction.

4.5 Develop Test and Establish Performance of Current Design

The existing bench test for the bearing utilized two factors to replicate field usage: rotation and temperature. Each rotation of the bearing is equivalent to driving a distance equal to the circumference of the tire, therefore, a direct relationship exists between the bench test and driving distance and varying temperature simulates environmental conditions. Notice that modeling and prediction of field failures occurs in the time domain while the bench test replicates usage in mileage. This seemingly inconsistent strategy is driven by the needs of the various functional groups. Financial managers need to evaluate cash flows in the time domain while the engineering community leverages the ability to accelerate mileage. The team then modified the test to include a contamination component. The team added a pump and movable hoses that could squirt fluids on the bearings while they rotate. The bench test then consisted of rotating the bearings in alternating heat and cooling cycles while exposing the bearing to fluids. During the bench test, bearings are measured once every twenty-four hours.

The response variable measured on the bearing bench test is in units of Vg, a combined noise – vibration reading. A new production bearing reads in the 10 – 20 Vg range and the design standard stated that a bearing was considered functional under 200 Vg. However, the team measured some returned field failures and obtained readings in the 50 Vg to 60 Vg range. The team concluded that once a bearing hit 50 Vg it exhibited the field failure and lowered the bench test failure criteria from 200 Vg to 50 Vg. To verify contamination as the root cause, the team purposefully contaminated bearings in an attempt to reproduce the failure mode. The team injected a set of bearings with a muddy water solution. These bearings were placed on the test and at 10 days (100,000 simulated miles) began to deviate from the 10 – 20 Vg range. Since the field failures occurred at much lower mileage, the team determined that muddy water ingress did not cause the failure mode. Next, they injected a pair of bearings with a salt-water solution. After one day on test these bearings exceeded the revised bench test criteria of 50 Vg. The team concluded that they would use a salt-water solution (squirted on the bearing with the new pump) to simulate the salt melted snow encountered in some cold weather states.

The team then conducted a designed experiment (DOE) to study the cap to bearing interface, the most likely source of the contamination ingress into the bearing. The team identified two factors for the DOE: roundness of the cap, and interference of the cap. The team utilized a 2 by 2 full factorial design (see Montgomery 2001) augmented with current production parts and BIC parts that resulted in six runs. Since the bench test could only accommodate two bearings, and a full test cycle lasted 20 days, each replicate of the experiment could take up to 60 days. The team decided to use 4 replicates; however, they decided not to randomize the runs. Rather, they prioritized the runs that might allow them to confirm factor effects prior to completing the study. Table 3 shows the DOE design with the priorities.

The team obtained a sample of 100 caps and bearings and had them measured. From this sample they identified the 16 cap – bearing pairs that would satisfy the design. After completing testing on 9 wheel bearings (one bearing test was considered invalid), the team had observed 5 failing bearings and 4 that did not fail (see Table 4). The team noticed that all four bearings with roundness at the “worst” level had failed, only one of three with “best” roundness had failed, and neither of the two control parts had failed. Due to the long time span of the bench test, the team concluded they had verified the failure mode and suspended testing, recognizing that they may need to return to this phase at a later date.

4.6 Develop Noise Factor Management Strategy

The team evaluated alternative methods to control the noise factors, i.e., contamination ingress into the bearing. One approach would be to design a bearing that is robust to contamination that would preclude the need to prevent contaminants from entering the bearing. The team ruled out this approach as cost ineffective. A second approach would be to design a bearing that prevents contamination ingress. The team concludes that they will manage the noise factor (contaminants) by preventing them from entering the bearing.

4.7 Develop New Design and Verify Using Reliability Disciplines

The team decided to utilize a two step approach to the product redesign. In the short-run, they would make changes to the exiting design intended to prevent the water ingress through the cap to bearing interface and in the long-run they would completely redesign the wheel bearing. Through brainstorming, the team developed a list of 11 possible short-run design changes. For each change, the team identified advantages and disadvantages and then ranked the ideas. The top ranking idea was to add a groove and an o-ring in the cap to bearing interface area. This approach had many advantages (a proven sealing design, short implementation time, and inexpensive) but also had a few disadvantages (additional assembly step, and the inability to detect damaged o-ring). The team implemented the design change and will track the performance of these bearings in the field relative to the old design. For a long-run solution, the team utilized a design similar to the BIC wheel bearing identified in phase 2 of the methodology. This design utilizes an integrated ABS sensor that eliminates one potential ingress point. It also uses a metal to plastic seal on the cap. However, it will take approximately two model years for this new bearing to be designed, fully tested and implemented into production vehicles.

4.8 Sign-off Design and Update Lessons Learned

The team signed-off on the long term redesign strategy and forwarded the documentation to the appropriate design functions. They left the bench test in working order so that product develop personnel could utilize it for testing prototypes of the new wheel bearing. The team updated the lessons learned so that in the future, other Ford employees could benefit from their experiences. Lastly, the team was formally recognized for a job well done.

5 CONCLUSIONS AND RECOMMENDATIONS

Engineers continually bring quantitative methods to bare on product and process related problems. This case study demonstrates how engineering and product development functions can bring more structure and quantitative methods to the re-engineering process. This case study is not intended to be a "cook book" approach that can be used for any type of product re-engineering. Rather, we show this methodology as an example of how organizations can add more structure to the re-engineering process.

We recommend that manufacturers of all products, and possibly even service providers, utilize a structured methodology to continually improve product reliability. We do not intend to intimate that the methodology contained in this case study will work for everyone. Rather, this serves as an example or an outline of how one might develop such an approach for their particular business. To develop a methodology for your company, we recommend that you start with the 9 step approach outlined in Section 2. Work through each step and evaluate its applicability to your specific product line or service. If the step is relevant to your situation, modify the content to meet your specific needs. This will include changing wording to match the jargon or terminology of your business, assessing specific analytic techniques to verify that they are consistent with the tools commonly used by your personnel, and verifying the completion activities will support your business processes. As you work through the 9 steps you may find that some of them can be removed or that you need to add additional steps. As you tailor the general approach, keep in mind that the key elements of success for this methodology are not over constraining the problem identification criteria and allowing the flexibility to modify the approach to solve specific problems.

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EXERCISES

1. Truncated data models represent another method for modeling field failure or warranty data by only including failed parts. How would this affect the definition of a population, and the conclusions you would draw from the analysis.

2. How would you modify the 9 step approach to apply this methodology to a service organization.

3. The failure appears more prevalent in cold weather states. What would be the pros and cons of having location dependent products.

4. This approach used the log-log repairs per thousand vehicles R(t) – a non-parametric technique - for modeling lifetime. What limitations do non-parametric techniques place on the analysis of lifetime data?

5. The bench test did not incorporate a vehicle. What are the advantages and disadvantages of not using complete products in reliability testing?

6. One factor limiting the ability to rapidly implement design changes was determining who should bear the cost for tooling changes. How would you suggest manufacturers and suppliers resolve these types of issues.

7. Develop a Block Diagram, Function Tree and Parameter Diagram for a product or assembly of your choice.

FIGURES AND TABLES

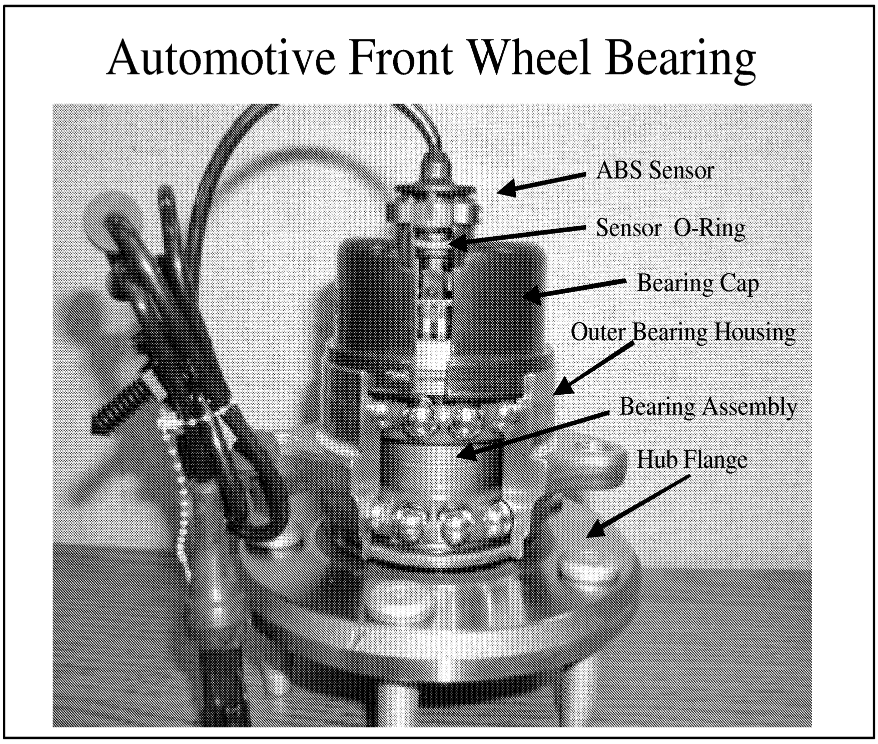


Figure 1: Automotive Wheel Bearing

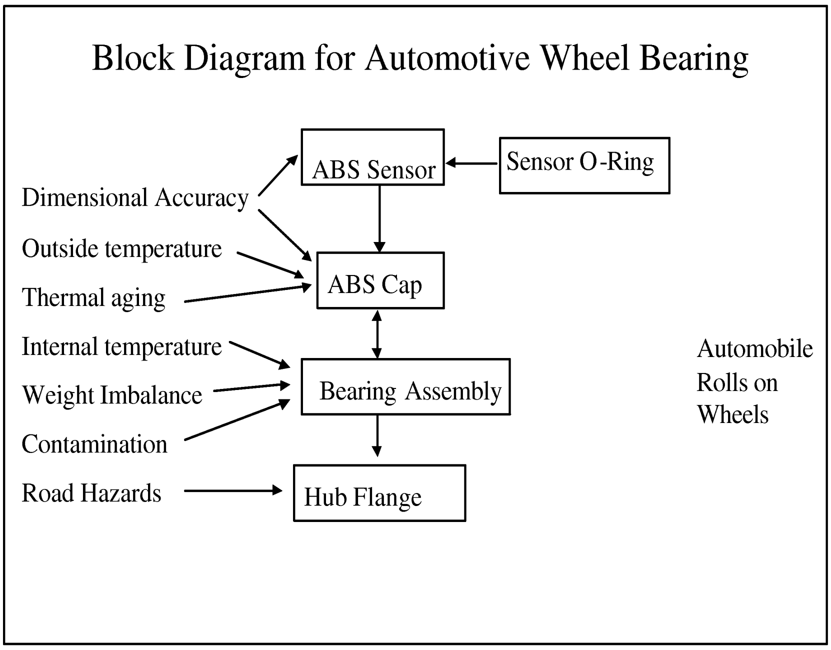


Figure 2: Block Diagram for Automotive Wheel Bearing

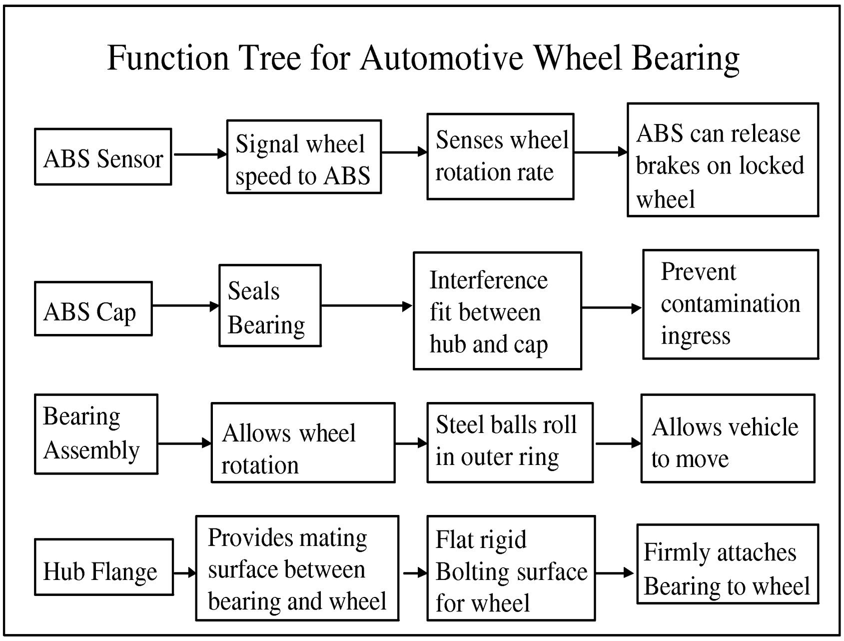


Figure 3: Function Tree for Automotive Wheel Bearing

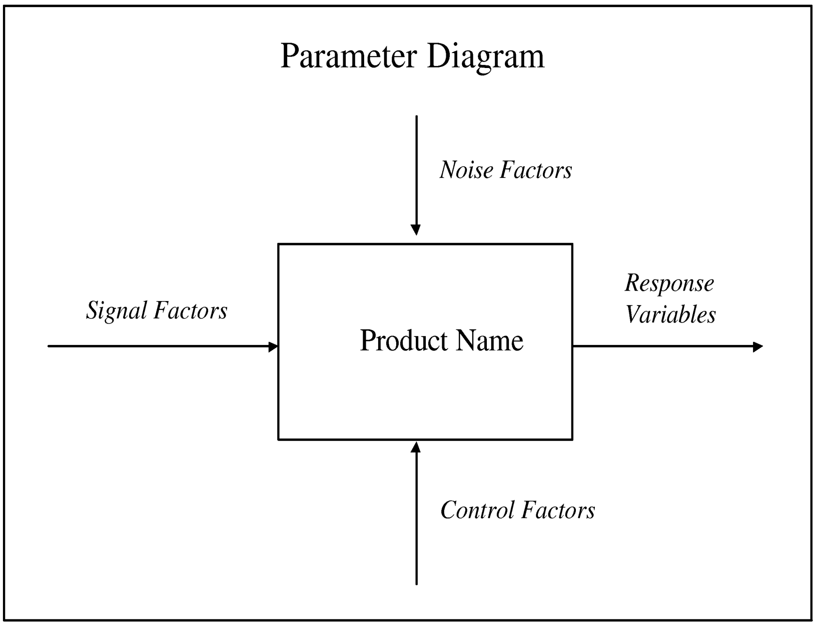


Figure 4: Parameter Diagram Structure

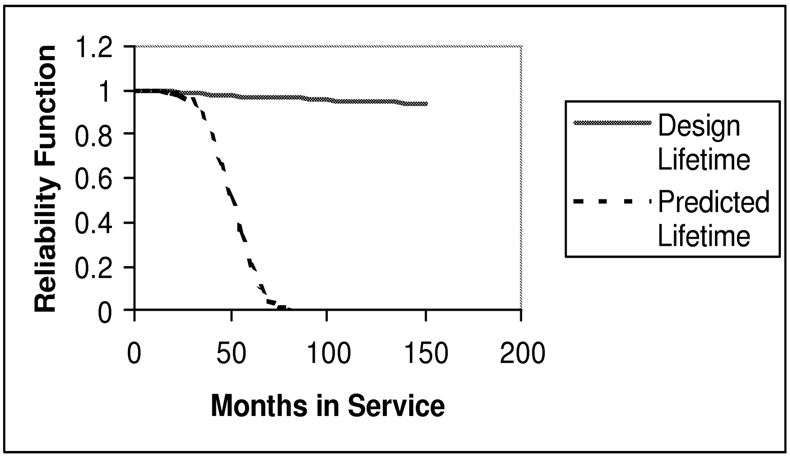


Figure 5: Wheel Bearing design lifetime and field performance.

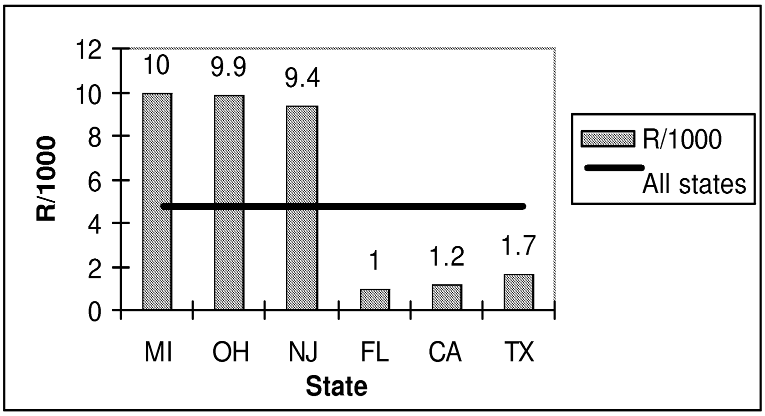


Figure 6: Wheel Bearing warranty claim rates by State.

PROBLEM SOLVING WORKSHEET

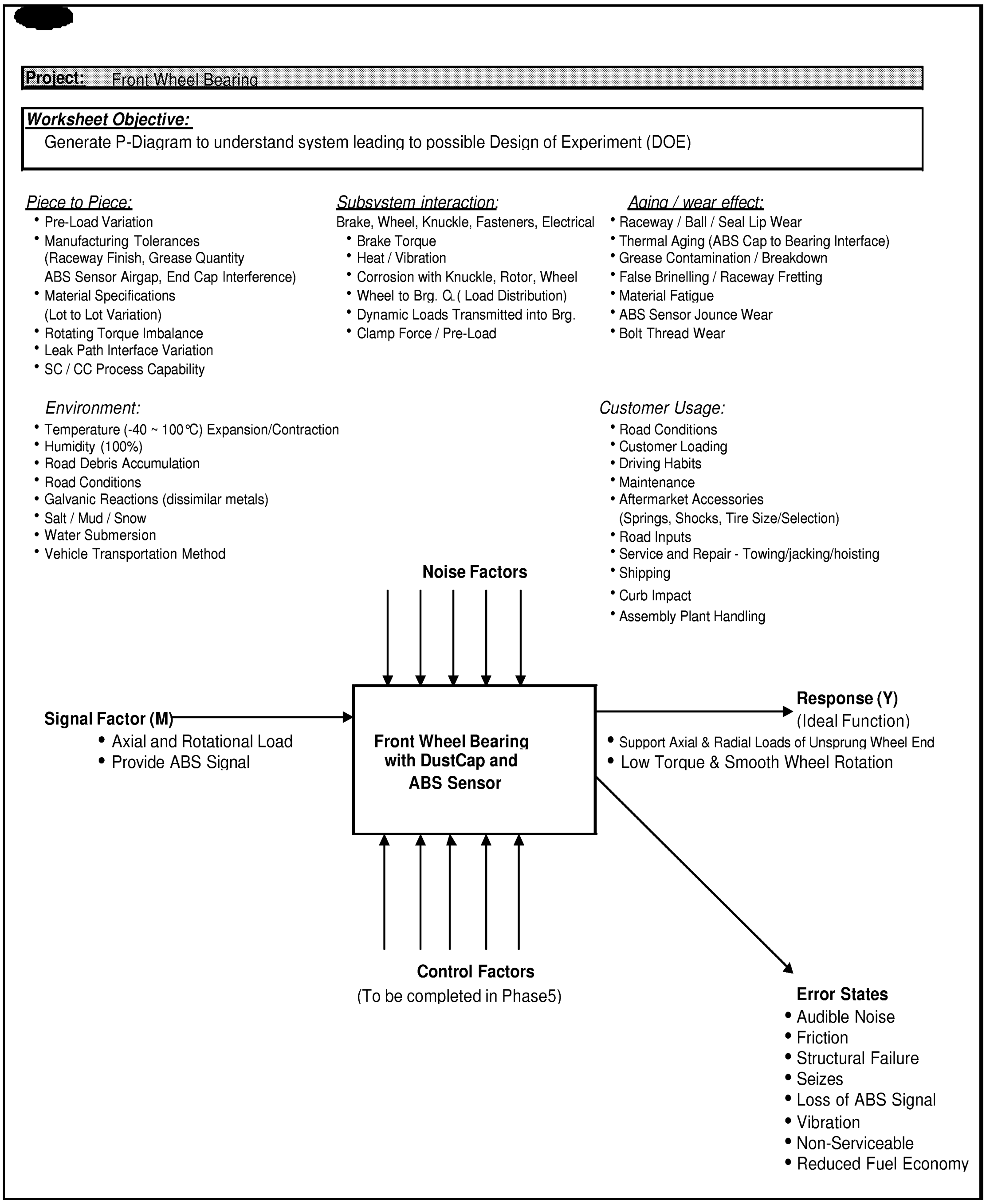
1 of 4

Problem Description

Problem Statement: **Front Wheel Bearing is Noisy**
(What's wrong with what)

Problem Description		**IS**	**IS NOT**	**Get Information**
WHAT	1.	Object Front Left & Right Wheel Bearing	Rear Bearing Brake Noise (worn/loose pads) Contact / Rubbing	Team is collecting AWS Data for Rear bearing.
	2.	Defect Noisy	Loss of Pre-Load / Endplay Lack of Grease Fatigue Failure Vibration	Based on data compiled from initial batch of customer returned parts
WHERE	**3.**	*On Object* Inboard Side Raceways	Outboard Side Raceways	Based on field return noise data
	4.	*First Observed* R-310 Durability for Base Program	Lab Test	
	5.	*Seen since* Seen in all markets predominately in Northeastern States	Predominate in Southern & Western States	Based on AWS Data
WHEN	**6.**	First Seen Customer Vehicles w/ more than 3000 miles	Customer vehicles with less then 3000 miles	
	7.	*What pattern since* Increasing Failure Rate		
	8.	*How many affected* 13.73 R/1000 at 19 MIS	< 13.73 R/1000	
	9.	*Defects per object* 1	Greater or less then 1	
	10.	*Trend* Increasing	Decreasing, Random, Cyclic	

Figure 7: Wheel Bearing Problem Description Worksheet.



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Project: Front Wheel Bearing

Worksheet Objective:
Generate P-Diagram to understand system leading to possible Design of Experiment (DOE)

Piece to Piece:
- Pre-Load Variation
- Manufacturing Tolerances
  (Raceway Finish, Grease Quantity
  ABS Sensor Airgap, End Cap Interference)
- Material Specifications
  (Lot to Lot Variation)
- Rotating Torque Imbalance
- Leak Path Interface Variation
- SC / CC Process Capability

Subsystem interaction:
Brake, Wheel, Knuckle, Fasteners, Electrical
- Brake Torque
- Heat / Vibration
- Corrosion with Knuckle, Rotor, Wheel
- Wheel to Brg. ℄ (Load Distribution)
- Dynamic Loads Transmitted into Brg.
- Clamp Force / Pre-Load

Aging / wear effect:
- Raceway / Ball / Seal Lip Wear
- Thermal Aging (ABS Cap to Bearing Interface)
- Grease Contamination / Breakdown
- False Brinelling / Raceway Fretting
- Material Fatigue
- ABS Sensor Jounce Wear
- Bolt Thread Wear

Environment:
- Temperature (-40 ~ 100℃) Expansion/Contraction
- Humidity (100%)
- Road Debris Accumulation
- Road Conditions
- Galvanic Reactions (dissimilar metals)
- Salt / Mud / Snow
- Water Submersion
- Vehicle Transportation Method

Customer Usage:
- Road Conditions
- Customer Loading
- Driving Habits
- Maintenance
- Aftermarket Accessories
  (Springs, Shocks, Tire Size/Selection)
- Road Inputs
- Service and Repair - Towing/jacking/hoisting
- Shipping
- Curb Impact
- Assembly Plant Handling

Noise Factors

Signal Factor (M)
- Axial and Rotational Load
- Provide ABS Signal

Front Wheel Bearing with DustCap and ABS Sensor

Response (Y)
(Ideal Function)
- Support Axial & Radial Loads of Unsprung Wheel End
- Low Torque & Smooth Wheel Rotation

Control Factors
(To be completed in Phase5)

Error States
- Audible Noise
- Friction
- Structural Failure
- Seizes
- Loss of ABS Signal
- Vibration
- Non-Serviceable
- Reduced Fuel Economy

Figure 8: Wheel Bearing P-diagram.

	R(21)	CPU	B5 Life
Target or Budget value	7	$1.40	120 MIS
Case Study Wheel Bearing	31.16	$7.49	38 MIS
Wheel Bearing 2	8.28	$1.50	79 MIS
Wheel Bearing 3	13.73	$2.40	47 MIS

Table 1: Warranty rates and costs for various wheel bearings

	R(21)	CPU	B5 Life
Target or Budget value	7	$1.40	120 MIS
Best in Class (BIC)	**0.62**	**$0.62**	**152 MIS**
Case Study Wheel Bearing	31.16	$7.49	38 MIS
Wheel Bearing 2	8.28	$1.50	79 MIS
Wheel Bearing 3	13.73	$2.40	47 MIS

Table 2: Warranty rates and costs for various wheel bearings

DOE Run	Roundness	Interference	Description	Priority
1	Best	Best	Optimum condition	B
2	Worst	Best	Roundness test	A
3	Best	Worst	Interference test	D
4	Worst	Worst	Worst case	F
5	N/A	N/A	Case Study Bearing	C
6	N/A	N/A	BIC Bearing	E

Table 3: Runs for Designed Experiment

Bearing	DOE Run	Roundness	Interference	Bench Test Result
1	2	Worst	Best	Failed at 3 days
2	2	Worst	Best	Failed at 3 days
3	1	Best	Best	Failed at 6 days
4	2	Worst	Best	Failed at 6 days
5	2	Worst	Best	Failed at 4 days
6	1	Best	Best	Did not fail
7	5	Case study Bearing		Did not fail
8	3	Best	Worst	Did not fail
9	5	Case study Bearing		Did not fail

Table 4: DOE bench test results