A Quality-Based Business Model for Determining Non-product Investment: A Case Study From a Ford Automotive Engine Plant

Bimal Nepal, Purdue University-Fort Wayne
Ratna Babu Chinnam, Wayne State University
John Petrycia and Eric Brush, Ford Motor Company, Windsor Casting Plant, Ontario, Canada
Colin Chisholm, Ford Motor Company, Essex Engine Plant, Windsor, Ontario, Canada
Mark Hearn, Ford Motor Company, Oakville Assembly Plant, Ontario, Canada
Michael Meixner, Russell A. Farrow, Ltd., Windsor, Ontario, Canada

Abstract: This paper presents an innovative approach for determining non-product investment in the maintenance of manufacturing facilities using quality-based statistical principles. Degradation of process capability (Cpk) over time with respect to key part specifications is analyzed using a regression model to predict the need for investment. While the preferred approach is to track process capability at all stations in a production line, this becomes prohibitively expensive and impractical in many industries, including engine manufacturing plants. By modeling the trend in Cpk values from only the end of the production line, using subject matter experts (SMEs) when necessary, one can still identify production stations/areas of weakness in a manufacturing facility with reasonable effectiveness. We propose such a method to help plant managers prioritize their limited maintenance resources. The methodology is validated using a case study from an automotive engine plant of Ford Motor Company. It is being disseminated as a “best practice” to other manufacturing facilities at Ford.

Keywords: Process Capability, Machine Health, Capital Investment, Business Model, Weibull Plot, Warranty

EMJ Focus Areas: Quality Management, Quantitative Methods & Models, Economics of Engineering

Machines deteriorate through age, lifecycle duty and environmental factors. In order to keep machines usable and to support the product value-streams, it is important to make routine financial investment in their maintenance as well as in their upgrading. The investment made on goods and services in the areas of improvement, maintenance, repair and operations is commonly referred to as a non-product related expenditure in manufacturing industries (Boer, Harnik and Heijboer, 2002). The objective of non-product investment is not only to maximize the availability of manufacturing facilities but also to ensure production of the right quality and capability (Dekker, 1996).

The problem of maintenance management is becoming more challenging with the modernization of manufacturing facilities and the need for reducing non-product investment. In this regard, Dhillon (2002) cites a startling statistic: “Each year over $300 billion are spent on plant maintenance and operations by the U.S. industry, and it is estimated that approximately 80% of this is spent on correcting chronic failure of machines, system and people.” This clearly indicates the pressing need to reduce these non-product investments, and, in particular, maintenance costs in manufacturing facilities. Another important aspect of non-product investment, especially in the automotive industry, is that monies are typically made available to manufacturing plants to upgrade or overhaul critical equipment and tooling only if the plants are receiving new product models. For example, at Ford Motor Company, historically, if an engine plant is not slated to receive any new engine models for years to come, its non-product investment budget is dramatically reduced. In such plants, it becomes important to carefully utilize the limited budget resources available to selectively upgrade or overhaul equipment and tooling. The non-product investment model proposed in this article addresses this issue.

Although the field has been researched quite extensively, there are hardly any non-product investment and maintenance management models that can be applied universally (Scarf, 1997). The earliest form of maintenance models dates back to the 1950s and 1960s, when preventive maintenance (PM) concepts originated to reduce equipment failures and downtime (Dekker, 1996). Traditional PM plans were largely based on a combination of recommendations from manufacturers, legislatures and company-specific standards; very few plans were based on maintenance data (Rausand, 1998). In the 1970s the condition-based maintenance (CBM) concept evolved and proved to be more effective than preventive maintenance programs based largely on time (Dekker, 1996). In CBM programs, the maintenance decisions are made by monitoring the actual state of equipment, such as lube-oil debris analysis and vibration monitoring. The other major shift in maintenance practice occurred during the late 1980s—the notion of reliability-centered maintenance (RCM). Introduced in the airline industry as early as the 1960s, some twenty years later it became popular in other industries as well (Fonseca and Knapp, 2000). The purpose of RCM was to minimize the PM cost by focusing on the most critical functions of the system, leaving out the other functions that are not critical in terms of their reliability (Rausand, 1998; Crocker and Kumar, 2000).

One challenge of managing non-product investment, particularly maintenance, is precisely modeling the equipment deterioration data. Universal statistics such as average failure rate are more appropriate for complete replacement and thus may not be useful for most maintenance actions. More importantly, the data should capture the actual status of individual equipment.
with respect to the failure mechanisms. Analyzing data without knowing the underlying failure mechanism can lead to a completely wrong conclusion. Maintenance information systems mainly store accounting information on events, and there is a wide concern about the value of their data for engineering decision making (Dekker, 1996). In many cases the failure log books are not updated on a timely basis, which makes failure tracking very difficult, if not impossible. As stated earlier, the tracking or monitoring of equipment in manufacturing facilities is critical for the effective utilization of the limited non-product investment and maintenance budget resources available to these facilities; however, the data acquisition system itself should not become an economic burden to the company.

While the CBM approach is preferred over traditional PM models in dealing with critical equipment, a prerequisite for adopting these techniques is special sensing/data acquisition hardware, such as lube-oil particle sensors and vibration transducers as well as signal processing and decision support software for monitoring the condition of the equipment. Given these prohibitive costs, technical constraints such as network bandwidth for collecting data over networks, and complexity that often involves sophisticated algorithms which analyze sensor data in time-, frequency- and mixed-domains, in general CBM can only be justified for monitoring a very small fraction of manufacturing assets. Furthermore, even the most sophisticated technologies and software currently available in the marketplace still lack the effectiveness to be deployed on a wide variety of equipment. More importantly, despite considerable advances over the last two decades in terms of hardware and software algorithms, online condition monitoring and diagnostics are still largely reserved for only the most critical system components and have not found their place in mainstream machinery and equipment health management (Kaczynski and Roemer, 2000). If one were to talk about proactive and predictive maintenance technologies, in particular prognostics, no robust methods exist for even the most critical system components (Baruah and Chinnam, 2005; Camci and Chinnam, 2005).

Prognostics has traditionally been defined as the ability to detect and sometimes isolate a faulted component and/or failure condition. Prognostics builds upon the diagnostic assessment and is defined here as the capability to predict the progression of this fault condition to component failure and estimate the remaining useful life (RUL). Also, very little attention has been paid to make the business models comprehensible to practitioners. In addition, many existing methods do not integrate the other business functions and data sources, such as quality/warranty and financial investment data, to predict the future non-product investment necessary for maintaining and improving the health of manufacturing facilities. Furthermore, little or no attention has been paid to developing structured approaches to real-world plant data analysis, where data acquisition and management is not very systematic. For example, in conducting this research, surprisingly, we routinely encountered production and assembly lines in the automotive industry that lacked up-to-date machine-specific data; in addition, the data were often noisy and needed significant clean-up.

The objective of this article is to present an innovative business model that determines optimal non-product investment in a manufacturing facility with relatively constant product routings by monitoring quality data from the end of the line. As an alternative to the expensive and complex CBM techniques, this paper suggests using the quality based data such as Cpk as an indicator to prioritize the maintenance budgeting and planning. The advantages of this are technically simple and economical to implement. More specifically, we monitor the degradation of actual process capability levels (i.e., $C_{pk}$), for key part print specifications over time, and using a linear regression model we predict when a machine/station is likely to compromise the business and financial objectives of the plant through factors such as poor quality, excessive rework and large machine downtimes. This provides the plant management with a data-driven and time-based methodology to identify areas of weakness. These areas of weakness can then be prioritized and planned for budget allocations. Because the framework mostly employs SPC data to determine machine health, there will be no additional cost for utilizing this model. The paper also describes a structured procedure to handle unclean data typically available in large manufacturing plants. The methodology is validated through cost-productivity-quality relationships as well as capital investment budget (CIB) to $C_{pk}$ relationships, based on a case study from an automotive engine plant of Ford Motor Company.

The remaining sections of the paper are organized as follows: Section 2 describes the theoretical framework to determine non-product investment in manufacturing facilities using quality-based statistical principles. In section 3, we present a business model for implementing the proposed framework. The Essex engine plant case study, including the data acquisition and refinement issues, are discussed in section 4. Section 5 outlines the benefits and limitations of the proposed business model. In section 6, we analyze how a low value of $C_{pk}$ drives the quality, customer satisfaction and warranty issues, and their potential impacts on non-product investment. Finally, section 7 discusses conclusions along with some important lessons learned from this project.

A Framework for Non-Product Investment in a Manufacturing Facility

In this article, the scope of non-product investment under consideration entails resources necessary to maintain and/or upgrade machines and stations in manufacturing facilities. An analogy from failure theory explained by the “bathtub curve” of the instant failure rate is the theoretical basis of this research. If $f(t)$ denotes the lifecycle or, conversely, the failure distribution of components/equipment, the instantaneous failure rate, (also known as the failure-hazard rate) is defined as:

$$\lambda(t) = \frac{P(t < (t + \Delta t) \setminus T > t)}{\Delta t}$$

Given that by definition reliability at any instant $t$, $R(t)$, is:

$$R(t) = \int_0^\infty f(x) \, dx \forall t \geq 0 ,$$

one can easily arrive at the following relationship between reliability and instantaneous failure rate:

$$R(t) = \exp \left[-\int_0^t \lambda(\xi) \, d\xi\right].$$

The Weibull distribution has been traditionally used to model $f(t)$ for a wide variety of mechanical and electrical systems (Ekings, 1988; Kayener and Sandborn, 2005). It has the ability to effectively represent a broad range of failure rate profiles, and is also used to develop design criteria and recommended operating conditions to meet reliability targets. In this research, we promote a similar analogy for machine failure prediction by focusing on
the approximate linear section of Phase III of the failure rate bathtub curve (Exhibit 1).

Exhibit 1. A Plot of (Typical) Instant-Failure-Rate Profile for Failures

Another concept used in this study is process capability analysis—an engineering study that predicts how well the process holds the tolerances. In other words, it determines how good the measurements are when compared to the product specifications (Montgomery, 2000). It assists product developers/designers in selecting or modifying a process and is also used for specifying the performance requirement for new equipment. Quantitatively, the capability of a process is defined as process capability index which is computed as:

\[
C_p = \frac{(USL - LSL)}{6\sigma}
\]

where, USL = upper specification limit, LSL = lower specification limit, and \(6\sigma\) = process width. The \(C_p\) is known as potential capability index and works well only for centered process. For an off-centered process an actual process capability index (\(C_{pk}\)) is calculated. Mathematically,

\[
C_{pk} = \min\left(C_{pu}, C_{pl}\right)
\]

where, \(C_{pu} = \frac{(USL - \mu)}{3\sigma}, C_{pl} = \frac{(\mu - LSL)}{3\sigma}\), and \(\mu\) and \(\sigma\) are the process mean and standard deviation, respectively.

The process capability index is used to find out the percentage of measurements that are out of specification. Typically, manufacturing industries set a \(C_{pk}\) standard of 1.33 and have a goal of 2 when the equipment is new. If it is less than 1.33, every effort is made to bring it into quality compliance. On the other hand, if \(C_{pk}\) is less than 1, then 100% inspection has to be instituted because there will be some out-of-specification product coming out of the process under study (Smith, 2004).

The main idea here is to use quality data, in particular process capability index (\(C_{pk}\)) data, and analyze its trend over time to predict potential problems in the corresponding manufacturing operations. The following sections describe the various hypotheses developed and tested to support this research. The hypotheses are about the "cost-productivity-capability" relationship and "\(C_{pk}\) to total cost" relationship, and are validated through data from the Essex engine plant of Ford Motor Company. The company’s sensitive data are protected in the paper to maintain confidentiality.

Cost-Productivity-Quality Relationship

One of the areas least explored relating to machine maintenance and machine downtime is the quality aspect of the component part being produced over time as a predictor of the remaining useful machine life (or how much useful machine life remains). Over the lifecycle of a machine, a definite financial timeline exists. Exhibit 2 illustrates just such a profile from an automotive engine manufacturing plant, that includes the initial investment for machine procurement and installation as well as subsequent maintenance expenditures. Productivity typically follows a flat trend after initial launch, except for favorable performance right after investment is made. As additional monetary resources are invested in the machine over the years, it would be expected that the quality measure or capability would at least in the short run increase with each expenditure, while declining in general due to wear and tear.

As can be seen from the cost productivity (measured in jobs per hour)/capability relationship (Exhibit 2), the initial cost of the machine was assigned a dollar value. At that time, JPH (jobs per hour) and capability were both zero. As the machine was commissioned, additional funds were spent to get it running according to its capacity. Productivity as measured by JPH took three years to reach a steady state, during which incremental spending was used to make improvements. It may be noted that the \(C_{pk}\) and productivity mirror the cost line. As expenditures were made to retrofit the machine, the \(C_{pk}\) and JPH went up, as illustrated in Exhibit 2.

Exhibit 2. Cost-Productivity-Capability Relationship From a Station in an Automotive Engine Manufacturing Plant

In addition, the relationship shows that machines do not have a very long “memory” for expenditures; in other words, once a piece of machinery has reached steady state, maintenance expenditures will simply bring it back to the way it was. During year six, the effects of capital budget expenditures have made a short-term improvement, but the trend of declining \(C_{pk}\) and JPH continues shortly thereafter. The plant under study is approaching the 23-year mark on much of their equipment. In other words, most of the equipment is at phase III (old age or wear-out stage) of the bathtub curve. By examining the \(C_{pk}\) JPH and cost data of an actual piece of machinery at the plant, a model can be generated and used as a predictor of potential machine failures. The model can then be used to prioritize the necessary resources in the plant. Thus, focusing attention and expenditures on critical areas can reduce wasted expenditures.

Despite being intuitive, the cost-productivity/capability relationship may not always be statistically significant in the real world. Exhibit 3 shows one such example from an Essex engine manufacturing plant where, although a relationship appears to exist, in actuality there is some inconsistency between \(C_{pk}\), scrap and financial activity.

Conceptually, it is evident that \(C_{pk}\) and scrap are highly related because a lower \(C_{pk}\) value by definition means that the machine is more likely to produce an out-of-specification or scrap part (Booker, Raines and Swift, 2001; Mayer and Nusswald,
2001). Therefore the alternative hypothesis of no correlation was rejected, as the correlation between $C_{pk}$, quality and scrap was well established (Montgomery, 2003) and not in dispute. Based on this proven relationship we concluded that the given data were excessively noisy and hence could be attributed to chance correlation.

Further, to validate our assumptions, we brought up these issues with the subject matter experts (SMEs) in the plant, and they suggested the following potential reasons for the above anomaly:

a. The scrap records were not entered in the same month as when the scrap was generated.
b. The measurements for $C_{pk}$ were not made in the same month as when the part was manufactured.
c. The months, which contained a shutdown period, generated a volume of rejects. This trend was not normal for the other periods. This was due to maintenance set-up activities.
d. With respect to this example (Exhibit 3), the data from pre-2000 included many variables such as program-funded capacity and program tooling changes (1996), and eventually a fully new product (2001). In such cases, there was no way to sort out the old data, as they were considered to contain too much noise.

In order to remove the noise effects from such data sets, we recommend the following general “data-cleaning” guidelines for automotive engine plants:

a. Eliminate data collected during a shutdown period; such data typically include excessive maintenance resulting from project or program actions in that period.
b. To address minor data integrity and/or sample size problems, data should be aggregated into multi-period buckets (e.g., two months). The $C_{pk}$ measure should not be the average for individual periods but rather recalculated over the multi-period bucket.
c. Carefully scrutinize erratic behaviors in the data before consideration for modeling. Process logs and SMEs can often explain such erratic behavior.
d. Eliminate the data that are clearly outliers. There is no value in keeping data with an erroneous value. This will cause any future decisions such as linear regressions and/or predictions to be skewed. We suggest the existing statistical rules for elimination of outliers.

$C_{pk}$ and Cost Relationship

We next examine the correlation between $C_{pk}$ and cost. Although the correlation looks intuitive and straightforward, this is not reflected in real-world data (Exhibit 3), largely because of how industries conduct their business. For example, at Ford, the fundamental issue is that the company expects each of its plants to report year-over-year cost reductions. Essentially, each year a plant has a smaller budget allocation than the year prior. There are several ways plants typically cope with such demands and requirements. One approach is that engineers let machines limp along until the next product program funding opportunity. Another practice is for engineers and maintenance personnel to use excessive monies in times of plenty, and simply waste less when the budget is rolled back. In this case, there is also a reliance on product program funding to rehabilitate machinery from other parts of the plant while retooling certain sections for the new product. Some of these side appropriations may also not be fully accounted for in the ledgers. These sorts of practices tend to skew the data and falsely suggest phantom correlations that do not exist in reality.

The objective here is to establish the following correlation:

$$C_{pk} = -\alpha \times \text{Total Cost}$$ 

where $\alpha$ denotes the correlation constant.

The underlying logic behind the above correlation is as follows:

$$C_{pk} - \alpha \text{ Scrap} = \alpha \text{ Machine Health}$$ 

$$\text{Scrap} = \alpha \text{ JPH}$$ 

$$\text{JPH} = \alpha \text{ Total Cost}$$

As mentioned earlier, there is a proven relationship between $C_{pk}$ and scrap (Montgomery, 2000). Also, it is intuitive to presume that scrap is an indicator of poor machine health; for example, scrap is mostly attributed to poor capability and not calibration and operational errors. In auto industries the $C_{pk}$ is used as a key indicator of worn components or malfunctioning machines. Further, the scrap-to-JPH correlation is also rational. For instance, in high volume machining transfer lines, if a piece of work is removed for scrap, then that piece is not available to count toward the JPH. Moreover, the transfers are synchronous with little or no
buffering. Hence, if there is any time delay in either clearing the scrap from the machine or getting the machine functional after the generation of scrap, then a delay in the movement of the line will occur. In most cases, stoppages on the transfer machine can be modeled to JPH as follows:

\[ \Delta \text{JPH}_{\text{VAC}} = \epsilon \times \left( \frac{\text{Seconds Lost}}{3600} \right) \text{JPH}_{\text{VAC}} + \text{Daily Engine Count} \text{Hours Worked} \]

The purpose of these formulations is to use an objective or data-driven basis for establishing the above mentioned correlations about machine health and projected remaining useful life; however, in the case of the \( C_{pk} \)-JPH-Cost correlation, as explained, there are some doubts as to what extent the data will reveal the true underlying relationships when plants are required to show year-over-year spending reductions. It would be counterintuitive when considering this model to assume that in light of year-over-year reductions in spending that quality and/or productivity would ever go up. This is because in current accounting practice, the product spending and capacity improvement budget are not considered part of the plant budget although these monies are spent on plant equipment. Therefore, given all these reasons, it can be concluded that financial data do not necessarily represent true machine health. This finding has motivated us to examine the \( C_{pk} \) data in order to predict the status of a machine.

\( C_{pk} \) versus Machine Life

In order to establish a relationship between \( C_{pk} \) and machine life for the purpose of predicting the health of a machine, we must first define what constitutes “health”: namely, a machine’s ability to hold or maintain the blueprint specification of the parts it produces. It is logical to say that as the machine fails, the quality of the components made on that machine will decline, as will the machine’s \( C_{pk} \) as it nears the end of its service life. \( C_{pk} \) is a capability index, the inverse of the machine’s failure rate. Thus, the fundamental assumption of this research is that \( C_{pk} \) is inversely proportional to machine failure, and that for machines near the end of their useful lives, a linear regression of the declining \( C_{pk} \) is inversely proportional to the first derivative (slope) of the instantaneous failure rate at that time. It is logical to use this analogy because if we were to examine the bathtub curve and take the derivative of the slope of the curve of the failure line, we would get a linear approximation of the failure rate (see Exhibit 1, Phase III).

Predicting useful machine life using \( C_{pk} \)

The next question is how we can use \( C_{pk} \) to predict the state of machine health. The \( C_{pk} \) index has been used exclusively as a measure of the machine’s capability to produce parts that are to the blueprint’s specifications. By considering a machine as a subset of component operations, the blueprint features are generated as a result of a series of operations by the individual machines. As the operation wears or begins to fatigue, the dimensions of the finished detail will begin to drift until the machine starts to make parts that no longer meet the blueprint’s specifications. Using the \( C_{pk} \) data plotted over time, it can be determined whether the \( C_{pk} \) is generally increasing or decreasing over time. If the \( C_{pk} \) is decreasing and the machine is far enough along on Phase III of the bathtub curve, then the \( C_{pk} \) can be approximated as the proportional inverse of the instantaneous failure rate curve for that machine.

The linear regression model used for this purpose is in the form \( Y = B + mX \), where \( B \) is the intercept and \( m \) is the slope, the intercept being applied at time zero such that the \( C_{pk} \) at time zero is equal to the intercept value. If the model is statistically significant and the slope of the line positive, that would imply that the \( C_{pk} \) is increasing. This means that the machine is being well maintained, and in many cases no work is required on the equipment. By evaluating the slope, the process engineers can make a decision on the machine’s health. Thus, the intercept is an approximation of the machine’s \( C_{pk} \) at time zero, and the slope is the trend that the machine is following. There are several scenarios that can follow, depending on the slope and intercept. Exhibit 4 explains the four possible outcomes of a statistically significant regression model. Depending upon the model outcomes, an appropriate recommendation is made for each case.

**Type I:** This is the ideal category, high \( C_{pk} \) with increasing slope. This means that the operation is in good health and is getting better over time. There is generally no action required for Type I.

**Type II:** This is also good, as it has high \( C_{pk} \) with decreasing slope. \( C_{pk} \) is decreasing, and the time until the \( C_{pk} \) intersects with 1.00 is calculated as minimal risk. Depending on the slope, this prediction can be several years, in which case, with the SMES’ concurrence, the recommendation would be to do nothing. In some cases, if failure is imminent, the slope may be steep. In this case action would be required.

**Type III:** \( C_{pk} \) is low, but slope is increasing. It is suggested to examine two things: (1) why the \( C_{pk} \) is low, and (2) if its positive trend will continue even if no action is taken. Often if the machinery is in the process of being fixed, or if it was recently fixed, the linear regression may display a Type III curve.

**Type IV:** This demonstrates low \( C_{pk} \) with negative slope, which means that the capability is low and is predicted to get worse. Action is required.

**Selection of Model Reference Points**

The linear regression model presented in the previous section has two parameters, viz. \( B \), the intercept, and \( m \), the slope. The intercept represents the \( C_{pk} \) value at time zero and the slope explains the \( C_{pk} \) trend over time. Similarly, there are two points of reference in the model which are: time zero and the threshold value of \( C_{pk} \). Selection of these reference points will have direct impact on the way we interpret the results. The following subsections describe in brief the selection of each reference point.

**Selection of Time Zero**

Time zero is the point of time when predictions are made. In the process of determining the time until the machinery fails, it is critical to determine time zero. This time can be chosen and set to a certain date, or the default can be set to “today.” If the objective is to compare several pieces of equipment with a goal of determining when a given piece of machinery will fail, then it is often advantageous to pick a time zero and use a common time zero for all machines.

As outlined earlier, the scope of this study is to provide plant managers with a guideline about their machines’ health and estimated time of failure. A critical assumption behind this study is that the machine is climbing up the “failure side” of the instantaneous failure rate bathtub curve. Thus, by taking the derivative of the failures and taking the limit as time approaches zero, we can approximate a portion of the curve linearly. Likewise, as failures of the machine increase, the capability or \( C_{pk} \) of the
machine is decreasing. The trend line of $C_{pk}$ over time is expressed in the form of $y = B + mX$. Thus, if we let the $y$ value be the $C_{pk}$ value, one may solve for time if we know the value ($C_{pk}$), which is considered to be a failure or unacceptable process capability. For the purposes of this research, failure is defined as the time at which the expected $C_{pk}$ drops below 1.00.

The choice of a time zero is critical. If time zero is set to “today” or a reasonable approximation of today, then the $C_{pk}$ offset (the intercept) will be equal to today’s average running $C_{pk}$. If the time zero is set in the past, then the intercept will naturally be the $C_{pk}$ value for that time. It is less valuable to know what the $C_{pk}$ was five years ago than the current value; for this reason, it is recommended to use a time zero that is close to today. Another reason to use time zero of today is that since the intercept is equal to today’s average running $C_{pk}$, if that value is below 1.00, then it is readily apparent that the machine is deficient and in need of immediate repair. The formulations of the linear regression model is not affected by time zero, but it appears to be more intuitive to have time zero as today; thus, time in the past is “negative,” and the future is “positive.”

**Selection of Threshold Value for $C_{pk}$**

The $C_{pk}$ data are linearly extrapolated from the time zero point across the future of the time line until it passes below a threshold level of $C_{pk}$. Once the $C_{pk}$ is equal to or less than the threshold value, it is defined as a failure. The threshold level may vary across companies and the nature of their manufacturing operations. For example, in an engine plant at Ford Motor Company, a process with a $C_{pk}$ level of 1.33 or higher is considered an acceptable process; one with a $C_{pk}$ level between 1.33 and 1.00 is called a marginal process; and any process with a $C_{pk}$ level below 1.00 is known as an unacceptable process; therefore, for the Ford engine plant, the threshold value for $C_{pk}$ is 1.00.

Similarly, the $C_{pk}$ value of 1.33 can also be considered an excellent warning signal that action must be taken. By monitoring the performance of the operation, it is possible to see it decline over time as the equipment ages. Using this value as the warning indicator allows time to define the root cause and to identify the corrective actions, and it provides the appropriate lead time to let the revision occur before the outgoing product reaches an unacceptable level. Furthermore, the operation may be repaired at a reduced cost since the damage to the equipment should not be as great as when the equipment is left to degrade over long periods of time. This aligns with the preventative maintenance concept that has been widely adopted across the industries. Any equipment operating below the threshold $C_{pk}$ value should be addressed immediately and containment action implemented until its level is brought above the threshold value. Exhibit 5 shows a sample output of the declining $C_{pk}$ over time with the warning level and failure level indicated. The time between these two levels (T1 and T2) is the time the user is allowed to address the problem. Depending on the rate of decline of the $C_{pk}$ level, this could be months or years. The negative numbers on the X-axis show the times prior to time zero.

**Exhibit 5. Failure and Warning Levels – (T1-T2 = Allowed Correction Period)**

![Exhibit 5](image)

**Implementation of Proposed Business Model**

Exhibit 6 shows the flow diagram of a proposed business model for predicting the needs for non-product investment in a manufacturing facility. There are seven steps involved in the implementation of the proposed framework. While the steps are explained with respect to an automotive engine plant, they are generic and transferable to any other manufacturing facility with a minimum level of customization.

**Step 1: Select the Subject Matter Expert (SME)**
The first step of the proposed business model is to identify the SMEs who have in-depth knowledge about the manufacturing equipment and the corresponding operations under study. Our experience has shown that in a complex manufacturing environment such as the auto industry, the role of SMEs is pivotal to successful implementation of any innovative problem-solving approach. Yet in the operations management literature, it is difficult to find a formal process for selecting a suitable SME. In this research, the following guidelines are proposed for selecting SMEs:

a. At least 10 years of experience in the relevant field
b. Well versed in design and manufacturing; one or two SMEs may have been promoted to management from machine operators and engineering
c. Familiar with the nature of product changes (e.g., due to results of design improvements or programinduced changes)
d. Familiar with capital and expenses spending
e. Proven track record

**Step 2: Determine Key Performance Indicator Variables (KPIVs)**
The key to successful implementation of the model lies in the proper identification of the key performance indicator variables (KPIVs)
that have the most impact on the critical blueprint specifications. There may be several stations that act in series to manufacture a finished dimension on a part. Examples might include the process sequence of drill, ream, counter-bore, tap or rough cut, grind and polish. Therefore, in the second step, we ask the SMEs to properly identify the characteristic blueprint dimensions that are best suited to determine the health of corresponding machine(s). For example, in the case of an automotive engine, the diameter of a drilled oil feed-hole in a crankshaft may not be a good indicator of machine health, whereas a ground or milled journal diameter on the subject crankshaft may be a better choice. Obviously there are key factors unique to each of the components that better determine their KPIVs. The initial step is to determine the part print specifications that are the most critical to the quality of the part.

As an illustration, a simple manufactured component (Exhibit 7) consisting of two manufacturing holes, a datum and a hole located by a dimension with respect to the two datums, will be analyzed. The hole has two characteristic features: its diameter and its position relative to the datums and/or manufacturing holes. By checking the location of the feature hole, much can be determined about the process because operations completed before the hole is drilled have an effect on the final location of that hole. If the manufacturing hole is not in the right location, then the final hole will not be in the desired location.

**Step 3: Process of Grouping and Aligning**

Once the key dimensions have been identified, the next step is to establish a regression line of $C_{pk}$ vs. time, as well as confidence interval curves for that feature. The $C_{pk}$ trend analysis can be done in two ways depending upon data availability. If station-wide data are available, one can directly move to the next step of data filtering, followed by establishing the linear regression of $C_{pk}$ on time. On the other hand, if station-specific data are not available, then the machines or operations that impact the key dimensions need to be lumped together in a group for further analysis. The series of operations will generate the finished dimension with the understanding that if any of the machines are not working properly, then the finished dimension will not have as high a $C_{pk}$ as it would otherwise. Through interviews with the manufacturing SME, one can group all the operations together that contribute to the final part print specification. Once a grouping is created, by reviewing the declining $C_{pk}$ rates across the component, one can determine which areas need to be addressed and in what priority; however, it may be noted that the grouping process does not allow for resolution down to a specific machining station since the data are not collected on a station-by-station basis. If station-specific $C_{pk}$ data exist, this would enhance the process and allow a much clearer resolution on what areas to address.

**Step 4: Filter the Unclean Data**

This step is also conditional in the sense that if the SMEs feel the data are maintained on a regular and real-time basis, then filtering is not required; however, despite regular maintenance, there may be some scenarios such as plant shut down that skew the data significantly. In reality, however, real-time data management does not happen unless the plant has an automated data management system. Therefore, in order to gain desired correlations between $C_{pk}$, cost, and time, it is necessary to filter the data to exclude variability from any extraneous factors that can distort the data. Here are some basic guidelines:

- Account for plant “idling” or shutdown periods and eliminate and/or clean the data appropriately.
- Eliminate and/or clean variation in data that can be attributed to clearly identifiable extraneous or special factors that do not represent the routine operations.
- Exercise caution in using data too old for any valid discrepancies that cannot be explained.

**Step 5: Establish Linear Regression**

This is the main model of the proposed framework. In step 5, we fit the regression line between $C_{pk}$ data and time to predict future degradation of $C_{pk}$ over time. In order to support the hypothesis that $C_{pk}$ degrades over time, we have demonstrated the other
supporting hypotheses such as the relationship between Cpk and scrap rate, and also the phenomenon of machine aging. The four possible outcomes of regression analysis and the recommendation for dealing with them have been explained earlier in Exhibit 4.

**Step 6: Review the Results with the SMEs**
The sixth step in this framework is to review the results with the SMEs. The review process consists of two steps: (a) understanding the data, and (b) reviewing with the SMEs. The first step is to review the trend lines of the Cpk data for each KPIV being studied. It is important to ensure that any mistakes in the data are corrected and the trend lines are clearly understood. Once we are familiar with the data, we should prepare a proposal by highlighting the suggested problem areas (Type IV), as well as noting the areas that do not need to be addressed (Type I, II and III), as shown in Exhibit 4. It is also suggested a proposed solution be included so that the review with the SMEs flows well and remains on track.

After the preparation is complete, in the second phase, one should review the proposed solutions and Cpk trend lines with the SME(s). The results of the studied KPIVs should be reviewed in detail one at a time. It is also important to not just review the areas that are an immediate concern but also areas that are operating at an acceptable level. We need to confirm that their trend lines are accepted as well as highlight KPIVs that are at an acceptable Cpk level, but have a declining slope. While these characteristics may not be an issue today, with the aid of the estimated timeline to failure, one ought to include them in medium and long-term planning to ensure that they do not become issues in the future.

**Step 7: Establish a Prioritized List (What to Repair, Rehabilitate, and Refurbish)**
Finally, after the review process with the SMEs is complete for each component, a prioritized list can be developed. The purpose of the list is to aid the engineers, production support staff and managers in determining what areas of the plant require funding so that improvements can be made. For instance, if the quality data for a particular department reveal that operations 100 to 150 are producing parts with a declining Cpk and are currently at or below the threshold value, then the plant should consider spending some funds on those operations. The details of what items to address for any specific operation should come from the SMEs and engineers in the area. Sometimes, the decision may be in favor of a more in-depth capability study on each individual operation. This can be done to improve the resolution of the model. In any event, the purpose of the prioritized list is to only give a macro view of the manufacturing plant and areas that require improvements within a given time frame.

**Essex Engine Plant - A Case Study**
The proposed model for determining non-product investment was demonstrated at Ford Motor Company’s Essex Engine Plant (EEP). The EEP facility was of particular interest given the age and duty cycle of the equipment. At EEP some of the machines dated back to the plant launch in the year 1981 and were nearly 23 years old. Other machines had been maintained through preventive maintenance programs typical of Ford facilities, and some equipment was newer because of recent product programs where modifications or additions were required. During the past 23 years, the equipment in the plant has manufactured and assembled over twelve million 3.8L, 3.9L, and 4.2L V-6 engines in front-wheel drive and rear-wheel drive configurations for automotive and truck customers primarily in North America. In 2003, it was anticipated that an additional one million engines needed to be produced before its lifecycle ended after the 2008 model year. Furthermore, the plant management requested that the plant be prepared to respond to what significant non-product spending would be required to maintain or extend production capabilities beyond the 2008 model year, if needed.

The proposed business model was implemented at various departments of EEP. For the purpose of demonstration of the model, we present two analyses, one each for the connecting rod (CR) and the crankshaft departments (CD). Like most typical large manufacturing plants, the process monitoring data at EEP were kept in several different formats, and thus were not easily transferable into a standardized format; therefore, we had to begin our work with data acquisition and management methods at EEP to provide the plant with a standardized data sheet/table. The purpose of this sheet was to simplify the data analysis in the future. By considering the skills sets of the users, macros were written in Microsoft Excel to analyze the regression model and plot Cpk trend lines with 95% confidence intervals. The data standardization helped to automate the regression analysis using Excel macros.

**Plant Analysis - Connecting Rod Department**
Much of the current equipment in the CR department at EEP had been in operation since 1995. As with most of the machining operations at EEP, the CR department had twin lines for the majority of its operations, as illustrated in Exhibit 8.

From a number of review meetings with the SMEs of the CR department, it was determined that there were four KPIVs or print dimensions critical to proper engine function. These dimensions were:
- KPIV #1—diameter of the piston wrist pin bore
- KPIV #2—diameter of the crankshaft pin bore
- KPIV #3—thickness of connecting rod
- KPIV #4—centerline distance of the crankshaft bore to piston wrist pin bore

For each KPIV, the monthly quality data were collected and inputted into the Excel macro for generating respective Cpk graphs (regression lines) over time. Exhibit 9 illustrates that there is a slight downward trend for Cpk of the part print dimension of bore diameter of the piston wrist pin. In other words the department was in a Type II situation with respect to KPIV #1. Data from the past 1.5 years showed that there had been a continuous improvement in Cpk for this dimension. We reviewed the final data with the SMEs and process engineer. It was explained by the process engineer that in the previous 175 to 354 days, an extensive preventive maintenance (PM) program had been undertaken. Because the required volume was high, it allowed the department to work on this equipment and spend time inspecting and replacing some of the finer components for the operations responsible for connecting rod thickness. Small inexpensive details such as rest pads, locators and fixture details were inspected and replaced when required. The last five data points on the graph indeed show the benefits resulting from carrying out the PM work. These five points show a continuous improvement of Cpk over time even though the overall trend was negative. During the review process, the process engineer and SME agreed that the data and model accurately showed what was occurring on the production floor.

The other three dimensions shown in Exhibits 10, 11 and 12 depict upward trends with a similar continuous improvement
trend for the last 175 to 354 days. Referring back to the four situations shown in Exhibit 4, KPIVs #2, #3 and #4 (Exhibits 10-12) all exhibit Type III situations. These results were reviewed with the relevant SMEs. It was agreed that no significant capital investment budget was needed on any of the operations that contributed toward making the final part print dimensions for diameter of the crankshaft pin bore, thickness of the connecting rod, centerline distance (crankshaft pin bore to piston wrist pin bore) and diameter of the piston wrist pin bore.

Based on the previously mentioned results and consequent concurrence from the SMEs in the CR department, a number of conclusions were drawn. The first conclusion was that the proposed model and processes were valid for predicting the machine health condition for the purposes of making capital investment decisions. The next conclusion was that the current health of the equipment in the CR department was high and that no major capital investment was required for the remainder of the life of the engine program. The department was advised to continue with

Exhibit 8. Connecting Rod Department Layout at Ford’s Essex Engine Plant

Exhibit 9. KPIV #1—Piston Wrist Pin Bore Diameter
Exhibit 10. KPIV #2—Crankshaft Pin Bore Diameter

Rolling 5 Month Average For Cpk With Confidence Intervals

Exhibit 11. KPIV #3—Connecting Rod Thickness

Rolling 5 Month Average For Cpk With Confidence Intervals

Exhibit 12. KPIV #4—Centerline Distance Crankshaft Pin Bore to Piston Wrist Pin Bore

Rolling 5 Month Average For Cpk With Confidence Intervals
the PM processes and procedures it developed and implemented approximately 175 to 354 days ago. Lastly, a separate check on the cost accounting procedure in the connecting rod department validated the earlier developed thought regarding how looking at capital investment alone did not provide the proper resolution or correlation to equipment wellness. For example, the money that was spent by the department for preventive maintenance on rest pads, fixtures and locating details was not captured by the capital investment tracking system. This was because the purchasing of those components did not increase the value of the equipment; therefore, the money used to purchase the components and the labor hours required to install them would not be captured.

**Plant Analysis — Crankshaft Department**

After consulting with the SMEs, the following four KPIVs were identified for crankshaft department.

- KPIV #1 — diameter of the main journals
- KPIV #2 — diameter of the pin journals
- KPIV #3 — run out of the flange end (rear)
- KPIV #4 — run out of the post (front)

These KPIVs were key to proper functioning of the component as well as important in determining the condition of the manufacturing machine. In the next stage, the grouping of stations was done based on the KPIVs as well as the conformance audit data that existed on the dimensions over a long period of time (Exhibit 13). The data analysis for each dimension was processed through an Excel macro written for automating the data grouping and establishing the linear regression process; however, a user had to remove the outliers manually. One of the criteria used in this paper for identifying the outliers was by using six sigma limits of normal distribution. In addition, we also used the data cleaning procedure explained earlier in this paper for filtering the data corresponding to special circumstances, such as shut down period and so forth.

After completing the data cleaning process, regression lines were developed for each KPIV. The $C_{pk}$ regression lines for main journal and pin journal diameters are shown in Exhibits 14 and 15. The $C_{pk}$ data were analyzed and the results reviewed together with production department personnel. Both main journal and pin journal diameters were identified as problem areas or Type IV. In both cases, the $C_{pk}$ levels were below the warning value of 1.33, in some case even below the threshold value of 1.00 (see Exhibit 14). The data showed that the main journal $C_{pk}$ had been below 1.00 since year 2000 and that the pin journal $C_{pk}$ had been below 1.00 since 2001. Both cases were recommended

---

**Exhibit 13. Crankshaft Department Layout and KPIVs**
for immediate actions. The SMEs agreed with the data as they had already suspected the same for the main journal diameter and had been trying to find a way to address that equipment. In order to analyze the more recent trend, we added three additional data points as shown in the shaded area of Exhibit 14. This data confirmed that the machine was still operating at an unacceptable level. The department process engineer investigated the stations in the grouping and determined one operation to be the root cause of the problems. Based on this investigation, actions were taken to obtain additional funding to refurbish the machine.

Exhibit 14. Crankshaft Main Bearing Journal Diameter Graph

![Crankshaft Main Bearing Journal Diameter Graph](image)

Further, it was reported that a major program was under way to revise the stroke of the crankshaft by one millimeter. It revised the engine displacement from 3.8L to 3.9L. That action had occurred since June 1, 2003 (data cut-off date used in this research) and drove changes to most of the machining in the Pin Diameter Journal grouping (Exhibit 15). Due to this revision in the grouping, the SMEs believed the latest Cpk data would be at an acceptable Cpk level.

To verify the situation, we gathered and analyzed the most recent Cpk data that were collected during the capability study sign-off runs on the reworked machine. These data were taken machine by machine across 30 parts and was much more accurate than the monthly conformance audit data used to create earlier regression lines. The more machine specific data gave better resolution into the actual status of the machine after the 3.9L changes. Figure 16 shows the Cpk level prior to the 3.9L program, as well as after the revisions were made. As can be seen, the Cpk level has been raised to a more than acceptable Cpk level of 5.62; this area, now a Type I, no longer needs to be addressed.

Similarly, the third KPIV or the flange (flywheel mounting) end run out was also investigated. The Cpk data gathered from the monthly quality conformance audits experienced much variation. Several attempts were made to interpret the data, but no correlation could be found. The data were reviewed one point at a time and it was noted that the normal variation seen in the data from 1996 through 1998 disappears in 1999 and then returns halfway through 2000. We investigated if a specification had changed during this time period or if any program action that had occurred might have influenced the data. No single reason was evident for this variation. Based on this we approached the SMEs as well as the production department; however, no one could explain the drastic change in the data attributes during that time period. Exhibit 17 shows the magnitude of the change in the data. We determined this data to be corrupt. No conclusions could be based on the corrupt data; thus, no recommendations were made to the production department. We instead had to rely on the sole opinion of the SMEs as a special case in which the SMEs stated the machine was working well and that no action was required for this characteristic.

The final dimension investigated was the post (damper pulley) end run out. Exhibit 18 shows the post end run out data. The Cpk value was very high at 7.0; therefore, no action was required at that time or was classified as a Type I. The slope was also at a very slight angle, which would likely indicate the Cpk level will not approach 1.33 for a number of years. We reviewed these data with the SMEs and all agreed no action was required in this area. The SMEs stated that the data were representative of production, and they had extremely good control of this dimension.

**Impact of Non-Product Funding on Customer Satisfaction and Warranty**

In this research, the motivation for basing a decision on a station’s Cpk value was that it was foremost a quality measure, not just a manufacturing deliverable. Further, the use of Cpk directly linked the manufacturing equipment status with the quality of the outgoing product. After identifying the status of Cpk level for KPIVs, the next step was to investigate the effect of ‘out-ot-
Exhibit 16. Crankshaft Pin Journal Diameter $C_{pk}$ – Before and After the 3.9L Program

No Further Action Required. The 3.9L Crankshaft Program resolved the issue.

Exhibit 17. Corrupt Flange End Run Out Data

Removed bad data Points due to Special Cause.

Exhibit 18. Crankshaft Post Run Out Data

Cpk at good level. No action required.
specification’ parts in the field. In other words, we wanted to explore if the customer was being impacted through warranty or raising the issue as a dissatisfied customer due to poor performance of equipment on KPIVs. The purpose of this effort was to establish a more appropriate rationale for prioritizing the maintenance funding. If one can determine a direct link of an operation’s status to the field, then one can estimate the costs associated with this impact and use them to justify a request for additional funding for fixing the equipment to improve its \( C_{pk} \) back to an acceptable level. This article utilized the following means to establish a link between KPIVs and customer satisfaction.

The first step was to look at the KPIVs identified by the SMEs and determine what failure modes were associated with them. In this case, one can look at both process and design failure mode and effects analyses (PFMEA & DFMEA); however, in each case, the end customer may be different in the sense that for PFMEA, the end customer would be the next assembly operation, whereas for DFMEA it may be the actual customers in the field. Although not presented in this article, a detailed DFMEA was developed and customer satisfaction survey data were analyzed during this research. The key finding in DFMEA was that there was a clear relationship between customer satisfaction and the KPIVs.

Upon identification of potential failure modes, the next step was to determine if there was any issue with the KPIVs in warranty. In the current practice, the automobile warranty system is broken into many categories. Most of the categories are based on component part numbers. When a claim is made on behalf of a customer against a specific part, it is processed in the system through the component part number; however, some categories are very generic in nature, such as replacement of an engine. An engine replacement could happen for a number of different reasons. The problem could have been one of many parts internal to the engine (crankshaft, piston, spin bearings, contamination, etc.) or could have been a result of a subsystem that feeds the engine (oil cooler, low coolant, poor fuel, etc.). In such cases, the resolution of the analysis is drastically reduced. It becomes impossible to identify if the component being investigated caused the failure, or what percent of the failed population was related to the component. In many cases, it may be possible to estimate the impact of KPIV failure modes on the warranty. Even if one cannot estimate the hard dollar values, knowing the KPIV-customer satisfaction-warranty relationship alone will help the plant managers in prioritizing their limited budget in a more informed way.

Several methods are used in industry to estimate a dollar value that can be associated to a specific failed part that contributes to the total failure amount in a generic “binned” classification. The most widely accepted is the Six Sigma = TGW or \( R/1000 \); however, in these tight financial times, there is no longer a single accepted reason for project funding requests, so these must be accompanied by additional evidence. Even in this case study, warranty data analysis for Essex V6 engine failure revealed a relationship between the engine teardowns and the KPIVs identified in the early part of our analysis. The intent of the additional analysis of \( C_{pk} \) beyond the manufacturing operation level is to provide the management with an insight about the broader effect of the non-product investment—in other words, an additional evidence to prioritize their budgetary needs.

**Benefits and Limitations of the Proposed Model**

The benefits of the proposed business model can be summarized as follows:

- The model allows the process engineers to highlight the areas in a manufacturing facility that need to be addressed based on quality indicators instead of bias or personal opinion.
- It presents a structured way to clean and analyze the real world (typically noisy) plant data to draw a data-driven conclusion.
- The model can be used to determine a timeline for when a particular group of operations may fail.
- It aids management in developing a prioritized list for expenditures and developing corrective action plans.
- The analysis is also extended to issues such as customer satisfaction and warranty and how they can drive the need for non-product investment in the manufacturing facility.
- The macro used to execute the model is easy to use and creates all the required graphs and results.
- The model is generic and transferable and, thus, can be used at other manufacturing plants.
- The \( C_{pk} \) degradation trend can be considered an indicator for condition-based-maintenance (CBM). Unlike the other CBM techniques, it does not result in substantial additional cost of data collection, since it mostly employs existing statistical process control (SPC) data.

Like any other approach, however, there are limitations with the proposed business model. Some of the limitations were identified at the beginning of the research during its development, while others were identified as the model was applied to the machining departments at EEP during the pilot implementation plan. The limitations of the model are outlined as follows:

- The model assumes that linear regression is adequate for short-term forecasting of machine health for non-product investment needs.
- The resulting analysis from the model is limited to giving the user an idea of which operation or groups of operations to investigate further. For maintenance of a specific station, one needs to consult with SMEs and conduct further studies.
- The model cannot be used to calculate the actual amount of non-product investment associated with areas that may be highlighted as requiring repairs. Investment can only be estimated by utilizing meetings with departmental personnel and the selected SMEs.

**Conclusions and Future Work**

In this paper a framework has been presented for determining the need for non-product investment in manufacturing facilities using statistical quality control data. The proposed business model was recognized by SMEs of Ford’s Essex engine plant as a valid tool for predicting and prioritizing the non-product investment in their manufacturing facilities. In the two cases from EEP departments presented, the CR department showed a healthy state of machines, whereas the CD machines represented a state of poor \( C_{pk} \), hence demanding immediate attention. The proposed framework is generic—thus transferable to other types of manufacturing plants that employ relatively fixed product routings. It does not result in substantial additional cost of data collection since it mostly employs existing statistical process control (SPC) data. The successful pilot implementation of the model at EEP implies that the limitations of this methodology identified earlier do not hinder its need or diffusion throughout other manufacturing plants beyond an automotive engine plant. Furthermore, as in condition-based maintenance practice, the lower \( C_{pk} \) value (below
threshold) can provide a ground for investigation of the relevant machines to improve their performance. Further, in this article, the $C_t$ trend analysis was extended to correlate with customer satisfaction and warranty analyses.

Based on the lessons learned from the Essex case study, the following recommendations are made for more effective use of the model in the future. If data are recorded manually, then it is labor intensive to input the data into electronic form; therefore, when this process is adopted, all part print dimensional data should be recorded electronically to reduce effort required to perform an analysis. During the implementation process at EEP, this issue was found to be a roadblock due to reduced manpower in the quality department. As a way to work around this problem, a standard data-gathering sheet was developed in an Excel spreadsheet format. The accuracy and validity of the model and process is limited in that it is only as good as the data that have been recorded. The resultant analysis provided by the model should not be taken on its merit alone. The results produced by the model must be reviewed by the local departmental personnel and selected SMEs as a reality check. The stronger the selected SMEs, the more useful the analysis from the model becomes due to their input into the final results. The confidence intervals that are calculated and plotted become more ineffective the further they are projected from the sample data set; therefore, if the confidence intervals are projected no more than a year from the last data point in the sample set, they will be useful to the user. Once they are projected for more than a year from the last data point in the sample data set, the range that is given is so large that they become useless to the user. Future work will significantly focus on developing the data collection mechanism. As mentioned earlier, a standardized database management system with timely updating is critical to success of this framework. Another area of concentration will be on formalizing the selection process of SMEs. A quantitative framework needs to be developed with proper assignment of weight to each selection criterion.

Acknowledgments
The authors are thankful to all the anonymous reviewers for their constructive comments to improve the quality of the article.

References
Crocke, J., and U.D Kumar, “Age-Related Maintenance versus Reliability Centered Maintenance: A Case Study on Aero-

About the Authors
Bimal P. Nepal completed his PhD in industrial engineering from Wayne State University in 2005. He is currently working as assistant professor of Industrial Engineering Technology at Purdue University-Fort Wayne. His areas of research interests include product architecture, new product development, systems engineering and applied operations research. He has worked on a number of R&D projects with Ford Motor Company and Visteon Corporation. He also holds a masters degree in IE from Asian Institute of Technology, Bangkok, Thailand, and a bachelors degree in ME from Malaviya National Institute of Technology, Jaipur, India.

Dr. Ratna Babu Chinnam is an associate professor with the Department of Industrial & Manufacturing Engineering at Wayne State University. He is the author of over 50 technical publications in the areas of smart engineering systems, autonomous diagnostics & prognostics, advanced quality & reliability engineering, and supply chain management. He is associate editor for the International Journal of Modeling and Simulation. Most of his research is funded by the National Science Foundation. He has carried out extensive collaborative research with Ford Motor Company and DaimlerChrysler.

John P. Petrycia is the senior manufacturing engineer at the Ford Windsor Engine Plant. He has worked for
Ford Motor Company since 1994. John holds a bachelor of applied science from the University of Windsor and a masters in engineering management from Wayne State University.

**Eric G. Brush** is the resident engineer at the Ford Essex Engine Plant. He has worked for both Ford Motor Company and General Motors. Eric has worked in both product development and manufacturing roles as well as launched power train upgrades. Eric holds a masters in engineering from Wayne State University.

**Colin A. Chisholm** is lead engineer for V8 engine assembly at Essex Engine Plant. He is a Six Sigma Black Belt and has held previous positions as a process and test engineer. Colin holds a bachelors degree in mechanical engineering from Dalhousie University and a masters degree in engineering management from Wayne State University.

**Mark Edward Hearn** is the power train resident engineer at the Ford Oakville Assembly Plant in Oakville, Ontario. Mark holds a mechanical engineering degree from Carleton University (1986), a masters of engineering from Wayne State University (1996) and a masters of engineering management (2004) from Wayne State University.

**Michael Meixner** is the Director, International Logistics at Russell A. Farrow Ltd. He has held numerous positions in the construction, manufacturing and supply chain disciplines over the past 19 years. Michael holds a bachelors of science degree in business administration from Lawrence Technological University, and a master of science degree in engineering management from Wayne State University.

**Contact:** Ratna Babu Chinnam, Department of Industrial and Manufacturing Engineering, Wayne State University, 4815 Fourth, Detroit, MI 48202; phone: 1-313-577-4846; fax: 1-313-578-5902; r_chinnam@wayne.edu.

**Footnotes**

1. These guidelines developed for automotive engine plants have to be adapted to other individual manufacturing plants based on the type/frequency of activity.
2. Care should be exercised here to accurately compensate for any time lags in either recording the scrap data or evaluating the quality of the parts.