Advanced Maintenance in Manufacturing: Costs and Benefits

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ABSTRACT

The costs of maintenance and the potential effect on maintenance costs from adopting predictive maintenance techniques is not well documented at the national level. A number of data items need to be collected to estimate the costs and losses associated with maintenance. This paper examines the current literature on maintenance costs as it relates to advanced maintenance techniques and discusses the feasibility of collecting data to measure the relevant costs and losses. Discussions with manufacturing maintenance personnel suggests that manufacturers are willing and able to provide estimates or approximations of the data needed for estimating the manufacturing costs/losses relevant to advanced maintenance techniques. However, some discussants expressed uncertainty about the willingness to provide some of the data. Some items were not tracked; however, most believed that an approximation could be provided in these cases. In order to estimate maintenance cost for the manufacturing industry as a whole , a sufficient sample size is needed. Depending on the standard deviation, confidence interval, and accepted margin of error, a needed sample size of 77 is estimated, but could reasonably be as low as 14.

1. INTRODUCTION

Trade associations and public research efforts in manufacturing have benefits to both producers and consumers of manufactured products. That is, research efforts improve the efficiency in both the production and use of products. Costs and losses are reduced for manufacturers (i.e., efficiency in production), while consumers have reliable long-lasting energy efficient products at lower prices (i.e., efficiency in product function). Manufacturing research efforts can and often are described in varying ways, such as improving quality, reliability, improving the quality of life, or even competitiveness, but these descriptors, generally, amount to reducing resource consumption for producers and consumers.

An enabling research effort to advance manufacturing process efficiency is ongoing at the National Institute of Standards and Technology (NIST) where personnel are engaged in creating standards that ultimately reduce the costs and losses associated with maintenance within manufacturing environments. This effort aims to promote the adoption of advanced maintenance techniques that harness data analytics. According to the Annual Survey of Manufactures, in 2016, US manufacturers spent $50 billion on reported maintenance and repair, making it a significant part of total operating costs. This estimate, however, does not create a complete picture, as it includes only outsourced maintenance. Also, it aggregates machinery and building maintenance together, making it difficult to examine the benefits of improved machinery maintenance. Maintenance is also associated with equipment downtime and other losses including lost productivity. Currently, there is limited data on the total cost of manufacturing equipment maintenance at the national level. National data collected by the Census Bureau and Bureau of Labor Statistics does not create a complete accounting of maintenance costs (Census Bureau, 2016a; Census Bureau, 2016b). Additionally, there is very limited data on the extent of downtime at the national level, such as the downtime caused by reactive maintenance.

Manufacturing environments are continually changing with new technologies and standards being developed rapidly. Firms create competitive advantages using their knowledge, skills, supply chains, and processes to create superior products at lower prices. In such a competitive environment, efficient maintenance methods can mean the difference between a thriving profitable firm and one that loses money and sales. Maintenance can affect product quality, capital costs, labor costs, and even inventory costs amounting to efficiency losses to both the producer and consumer. Understanding these costs and investing in advanced maintenance methods can advance the competitiveness of US manufacturers. NIST efforts in maintenance research seeks to create standards that reduce the costs and losses associated with maintenance in manufacturing environments. It aims to facilitate the adoption of advanced maintenance techniques, including determining the most advantageous balance between predictive, preventive, and reactive maintenance methods. Reactive maintenance occurs when a manufacturer runs their machinery until it breaks down or needs repairs and preventive maintenance is scheduled based upon pre-determined units (e.g., machine run time or cycles). Predictive maintenance is scheduled based on predictions of failure made using observed data such as temperature, noise, and vibration.

This paper investigates the data available from public sources and in the literature on the total cost of manufacturing maintenance, including data on separating those costs into planned and unplanned maintenance. It also investigates the feasibility of collecting data to measure maintenance costs and separate costs by firm size. This area of investigation includes identifying whether manufacturers can provide information to estimate and separate maintenance costs. This effort requires consulting literature on the data collected at manufacturing facilities and consulting industry experts.

2. LITERATURE AND DATA OVERVIEW

Below is a discussion of the data available on maintenance costs, benefits of predictive maintenance, and current maintenance practices. To understand the effects of adopting advanced maintenance techniques, it is necessary to understand the current costs of maintenance, how it is impacted by new maintenance techniques, and the current maintenance practices.

2.1. Maintenance Costs

Manufacturing maintenance costs are estimated to be between 15 % and 70 % of the cost of goods produced, as shown in Table 1; however, some portion of these costs include non-maintenance expenditures such as modifications to capital systems (Mobley and Keith, 2002; Bevilacqua, 2000). Alsyouf (2009) estimates that in Sweden 37 % of the manufacturing maintenance budget is salaries for maintenance staff with spare parts being another 32 %, as seen in Figure 1. Komonen estimates that industrial maintenance is 5.5 % of company turnover (i.e., sales); however, it varies from 0.5 % to 25 %, as shown in Table 1 (Komonen, 2002). Another paper showed that maintenance is 37.5 % of the total cost of ownership, which is also in the table (Hermann et al, 2011). Eti et al. estimates that in the chemical industry annual maintenance cost is approximately 1.8 % to 2.0 % of the replacement value of the plant and in "poorly managed" operations it could be as high as 5 % (Eti et al., 2006). It is estimated that, approximately, one third of maintenance costs are unnecessary or improperly carried out

Table 1. Characteristics of Maintenance Costs from a Selection of Articles, Various Countries/Industries. ([a]Mobley, 2000; [b]Bevilacqua and Bralia, 2000; [c]Komonen, 2002; [d]Hermann et al., 2011; [e]Eti et al., 2006; [f]Tabikh, 2014)

	Maintenance	
Description	Low	High
Cost of Goods Sold[a,b]	15.0%	70.0%
Sales[c]	0.5%	25.0%
Cost of Ownership[d]	37.5%	
Replacement Value of Plant[e]	1.8%	5.0%
Cost of Manufacturing[f]	23.9%	
Percent of Planned Production Time that is Downtime[f]	13.3%	

(Mobley, 2002). For instance, preventive maintenance is estimated to be applied unnecessarily up to 50 % of the time in manufacturing (Vogl, 2016). Tabikh estimates from survey data in Sweden that downtime costs (i.e., costs resulting from a halt in production) amount to 23.9 % of the total cost of manufacturing (Tabikh, 2014). He also estimates that the percent of planned production time that is downtime amounts to 13.3 % (Tabikh, 2014).

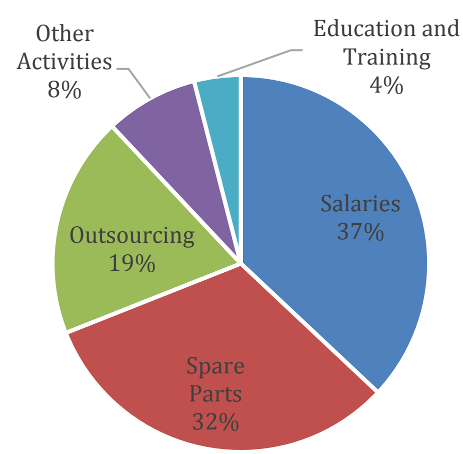

Figure 1. Manufacturing Maintenance Budget Distributions, Sweden (Alsyouf, 2004).

2.2. Benefits of Predictive Maintenance

Some implementations of advanced maintenance techniques (i.e., predictive maintenance) have been shown to have a range of impacts on a number of areas, as shown in Figure 2 (Nakajima, 1988; Ahuja and Khamba, 2008; Federal Energy Management Program, 2010). Ahuja and Khamba suggest that most companies can reduce their maintenance costs by one-third through advanced maintenance techniques (Ahuja and Khamba, 2008). Barajas and Srinivasa identify that investment in advanced maintenance techniques has had a return on investment of 10:1 (Federal Energy Management Program, 2010; Barajas and Srinivasa, 2008). The cost characteristics of different maintenance types is characterized in Table 2, which is drawn from Barajas and Srinivasa and two papers by Jin et al.

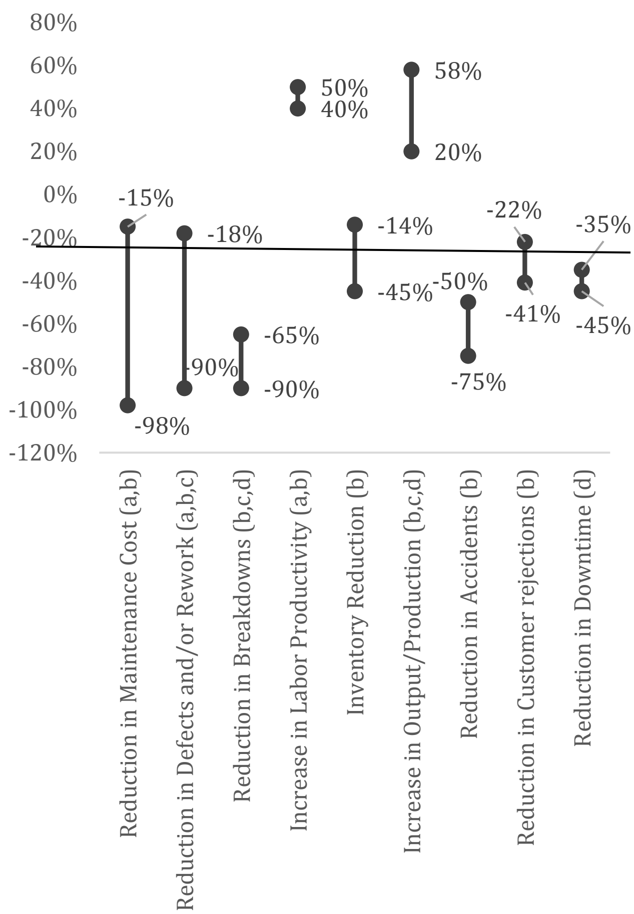

Figure 2. Range of Impacts Identified in Various Publications from Implementing Advanced Maintenance Techniques ([a]Nakajima, 1988; [b]Ahuja and Khamba, 2008; [c]Chowdhury, 1995; [d]Federal Energy Management Program, 2010).

Reactive maintenance has high labor and parts cost. It is considered not cost-effective. Predictive maintenance has relatively low maintenance labor and medium parts costs along with having significant costs savings (Barajas and Srinivasa, 2008).

A case study by Feldman et al. estimated a return on investment ratio of 3.5:1 for moving from reactive maintenance to predictive maintenance on a multifunctional display system within a Boeing 737 (Feldman et al., 2008). Although this is not maintenance on manufacturing machinery, it is a piece of equipment where there is regular use and reliability is important. An examination of train car wheel failures showed a potential cost savings of up to 56 % of the associated costs when switching from a reactive maintenance approach to a predictive maintenance approach (Drummond and Yang, 2008; Yang and Letourneau, 2007). Again, this is not maintenance on manufacturing machinery, but it is a piece of machinery that is expected to perform regularly and there are significant losses when it fails.

Piotrowski estimates that for pumps, reactive maintenance costs $18 per horsepower (745.7 watts) per year while preventive maintenance was $13, predictive was $9, and reliability centered maintenance was $6, which combines predictive techniques with other methods (Piotrowski, 2007). Additionally, the Environmental Protection Agency (EPA) estimates that predictive maintenance can result in 15 % to 25 % increase in equipment efficiency (EPA, 2011).

A case study, where advanced maintenance techniques were adopted along with revising changeover standards, had a total investment cost of $1.35 million (Smith and Mobley, 2008). A team was developed by the plant manager to address reliability problems. Before the implementation of the project, quality losses were 9 % of production and the plant was operating at 57 % of its true capacity. After adopting advanced maintenance techniques, maintenance costs increased in the first year by 10 % but decreased in the following years. The project increased capacity to 94 % and quality losses were brought down to 4 %. This project resulted in a $17.22 million increase in revenue in the first two years. Another case study at a paper mill in Sweden, invested in advanced maintenance where annual costs increased by $45 500 on average per year. The savings from this effort amounted to $3 million in addition to $358 000 in additional profit on average annually (Al-Najjar and Alsyouf, 2004).

Bo et al. identify a number of benefits of prognostics and health management, a component related to predictive maintenance, which include (Sun et al., 2010):

- Safety: Advance warning of failure and avoiding a catastrophic failure
- Maintainability: Eliminating redundant inspections, minimizing unscheduled maintenance, and decreasing test equipment requirement

- Logistics: Improving and assisting in the design of logistical support system
- Life-cycle costs: Reducing operational and support costs
- System design and analysis: Improving design and qualifications along with improving reliability prediction accuracy
- Reliability: Making products more reliable

Jin et al. identified through surveys that safety, availability, and reliability are the most highly rated maintenance objectives while productivity and quality were also considered important (Jin et al., 2016a; Jin et al., 2016b).

Table 2. Characteristics of Maintenance by Type. (Barajas et al., 2008; Jin et al., 2016a; Jin et al., 2016b)

	Maintenance Type		
	Reactive	Preventive	Predictive
Frequency	On Demand	Scheduled, Timed, or Cycle Based	Condition Based
Labor Cost	High	High	Low
Labor Utilization	High	Low	Low
Parts Cost	High	Medium	Medium
Throughput Impact	High	Medium	Very Low
Urgency	High	Low	Low
ROI	Low	Medium	High
Initial Investment	Low	Medium	High
Profitability	Not cost effective	Satisfactory cost-effectiveness	Significant cost savings
Cost effectiveness	Labor intensive	Costly due to potential over maintenance or ineffective & inefficient maintenance	Cost-effective due to extended life and less failure-induced costs

2.3. Current Maintenance Practices

A study by Helu and Weiss examined the needs, priorities, and constraints of small-to-medium sized enterprises through a series of case studies (Helu and Weiss, 2016). The results suggest that small and medium firms might rely more heavily on reactive maintenance with limited amounts of predictive maintenance while larger firms seem to rely on preventive maintenance; however, these results are based on anecdotal evidence (Helu and Weiss, 2016). Barajas and Srinivasa suggest that the automobile industry has been engaged with advanced maintenance technologies for some time (Barajas and Srinivasa, 2008). A survey of Swedish firms shows that the most prevalent maintenance strategy is preventive maintenance when asked about failure-based maintenance (i.e., reactive maintenance), preventive maintenance, condition-based maintenance (i.e., maintenance based on monitoring), reliability-centered maintenance (i.e., process to maintain system function), and total productive maintenance (i.e., maintenance process to eliminate breakdowns, defects, and other issues). Condition-based and failure-based maintenance was tied for the second most cited (Alsyouf, 2009). Swedish firms also revealed that 50 % of their maintenance time is spent on planned tasks, 37 % on unplanned tasks, and 13 % for planning. Approximately 70 % considered maintenance a cost rather than an investment or source of profit.

Companies, generally, compete either on cost or quality (quality is often referred to as differentiation or a portion of it). A survey in Belgium provides insight into how competitive priorities (e.g., cost competitiveness) might influence maintenance strategies (Pinjala et al., 2006). In addition to cost and quality, this survey had a third category labeled flexibility. Table 3 provides the number of respondents that indicated that they have a high, medium, or low level of each of the different maintenance types with the respondents being categorized by their competitive priority. For instance, in the top of the cost column (i.e., the third column) in the table, it indicates that four respondents are classified as cost competitors and have a low level of corrective maintenance. Moving down to the next row, it indicates that three respondents are cost competitors and have a medium level of corrective maintenance. The next row indicates that seven have a high level, resulting in a total of fourteen companies that are cost competitors, which is indicated at the bottom of the cost column. The same respondents also indicate their level of preventive maintenance and predictive maintenance in the next six rows, which also each sum to fourteen. Companies that focus more on cost competition tend to favor corrective maintenance, as half of the respondents (7 of the 14 respondents) prioritize cost competitiveness indicated they have a high level of corrective maintenance (i.e., reactive maintenance) and 73 % (8 of the 11 respondents) that focus on flexibility indicated they had a high level of corrective maintenance. Meanwhile only a third of those that focus on quality have a high level (see Table 3). Approximately 52 % of companies that focus on quality indicated that they have a high level of predictive maintenance. Moreover, Table 3 shows that cost competitive companies along with those focusing on flexibility tend to favor reactive maintenance while those pursuing quality as a competitive priority favor preventive and predictive maintenance.

Jin et al. (2017a and 2017b) found in a survey that companies are starting to consider predictive maintenance techniques with a majority of their respondents having active projects in manufacturing diagnostics and prognostics. The respondents also identified that they have had both successes and failures in the area of diagnostics and prognostics. A little more than a quarter of the respondents indicated that they were mostly using reactive maintenance techniques.

Table 3. Maintenance Type by Competitive Priority, Numbers Indicate the Numaber of Respondents out of a Total of 46 (Pinjala et al., 2006)

Maintenance Type	Level	Competitive Priority: Cost	Quality	Flex.	TOTAL
Corrective Maintenance (i.e., reactive maintenance)	Low	4	5	0	9
	Med.	3	9	3	15
	High	7	7	8	22
Preventive Maintenance	Low	5	5	3	13
	Med.	5	5	8	18
	High	4	11	0	15
Predictive Maintenance	Low	5	5	3	13
	Med.	5	5	8	18
	High	4	11	0	15
TOTAL		14	21	11	46

The majority of research related to predictive maintenance focuses on technological issues and, although there are some studies that incorporate economic data, these represent a minority of the literature (Grubic et al., 2009). Many of the economic assessments are individual case studies, personal insights, and other anecdotal observations. A limited number of them cite prevalent economic methods that are used for investment analysis. Numerous papers present methods for examining maintenance costs, focusing on the technological aspects; however, many do not provide data or examples. This gap in the literature suggests that the potential benefits of widespread adoption of predictive maintenance are largely unknown or are based on anecdotal observations.

2.4. Relevant Data

There are a number of sources for aggregated data on manufacturing relevant to maintenance costs. These sources include the following:

- Annual Survey of Manufactures (Census Bureau 2018)
- Economic Census (Census Bureau 2018)
- Occupational Employment Statistics (Bureau of Labor Statistics 2018)
- Economic Input-Output Data (Bureau of Economic Analysis 2018)

The Annual Survey of Manufactures provides statistics on employment, payroll, supplemental labor costs, cost of materials consumed, operating expenses, value of shipments, value added, fuels and energy used, and inventories. The Economic Census is a survey of all employer establishments in the U.S. Both the ASM and the Economic Census use the North American Industry Classification System (NAICS); however, prior to NAICS, the Standard Industrial Classification (SIC) system was used (Census Bureau, 2017a; Census Bureau, 2017b). NAICS and SIC are classifications of industries, which are based primarily on the product produced (e.g., automobiles, steel, or toys). The categories include both intermediate and finished goods.

The County Business Patterns series provides payroll and the number of establishments by employee by industry that can be used to adjust data collected through surveys.

The Occupational Employment Statistics program at the Bureau of Labor Statistics provides data on employment and wages for over 800 occupations categorized by the Standard Occupation Classification SOC) system and by NAICS code. Since the data is categorized by both occupation and industry, it is possible to estimate the amount of manufacturing maintenance labor by industry.

Annual input-output data is available from the BEA for the years 1998 through 2016. The input-output accounts provide data to analyze inter-industry relationships. It contains the purchases that manufacturing industries make from establishments categorized as NAICS code "811300: Commercial and industrial machinery and equipment repair and maintenance." These purchases represent the value of outsourcing for manufacturing maintenance.

3. METHODS FOR MEASURING COSTS

There are multiple methods that could be used to measure the different cost/loss components related to adopting advanced maintenance techniques. Below is a description of methods.

3.1. Direct Maintenance and Repair Costs

There are two methods that could be used to estimate direct maintenance costs. The first is to survey manufacturers and ask them to estimate these costs. The responses would then be scaled-up using industry data on payroll. The scaling would match the company size and industry to corresponding national data:

$$DMC = \sum_{i=1}^{I} \sum_{s=1}^{S} \frac{\sum_{x=1}^{X} EM_{x,s,i}}{\sum_{x=1}^{X} PR_{x,s,i}} PR_{s,i} \qquad (1)$$

where
DMC = Direct maintenance costs
$EM_{x,s,i}$ = Estimate of maintenance costs for establishment *x* with size *s* within industry *i*
$PR_{x,s,i}$ = Estimate of total payroll for establishment *x* within industry *i* with size *s*
$PR_{s,i}$ = Estimate of total payroll for industry *i* with size *s*

The challenge in doing so, is in acquiring enough responses to provide an accurate estimate, assuming that manufacturers even track this type of information. The number of establishments could replace payroll in the equation. Repair costs would need to be assessed in a similar fashion, replacing estimated maintenance costs ($EM_{x,s,i}$) in the above equation with estimated repair costs ($ER_{x,s,i}$). Since repairs are largely associated with reactive maintenance they are considered separately.

An alternative to surveying costs is using input-output data. The BEA Benchmark input-output tables have data for over 350 industries (Bureau of Economic Analysis 2014), including "NAICS 8113: Commercial and Industrial Machinery and Equipment Repair and Maintenance." This data includes Make tables, which show the production of commodities (products) by industry, and Use tables, which show the use of commodities required for producing the output of each industry. The data is categorized by altered codes from the North American Industry Classification System (NAICS). The tables show how much each industry (e.g., automobile manufacturing) purchases from other industries; thus, it shows how much "Commercial and Industrial Machinery and Equipment Repair and Maintenance" services were purchased by each industry. However, this does not reveal internal expenditures on maintenance and it also includes repairs. Internal expenditures for maintenance labor could be estimated using the Occupational Employment Statistics and estimating the additional costs using the data on "NAICS 8113: Commercial and Industrial Machinery and Equipment Repair and Maintenance." Maintenance costs could be estimated using the following method:

$$DMC = PM\left(\frac{RM}{MO_{RM}} * MO_I + (PI * RM)\right) \qquad (2)$$

where
DMC = Direct maintenance costs
RM = Total value added for NAICS 8113: Commercial and Industrial Machinery and Equipment Repair and Maintenance
MO_{RM} = Estimated compensation for maintenance occupations within NAICS 8113: Commercial and Industrial Machinery and Equipment Repair and Maintenance
MO_I = Estimated compensation for maintenance occupations within the industry of interest
PI = Proportion of value added from NAICS 8113 that is purchased by the industry of interest
PM = Proportion of maintenance and repair that is maintenance (i.e., maintenance activities that are not repairs)

3.2. Downtime Costs

There are three means for estimating downtime costs; however, each of them requires gathering data from manufacturers. The first involves a survey that asks a manufacturer to estimate the lost revenue due to downtime for maintenance. This data would then be scaled-up using national industry data on payroll:

$$DWC = \sum_{i=1}^{I}\sum_{s=1}^{S}\frac{\sum_{x=1}^{X} ED_{x,s,i}}{\sum_{x=1}^{X} PR_{x,s,i}} PR_{s,i} \qquad (3)$$

where
DWC = Downtime costs due to maintenance
$ED_{x,s,i}$ = Estimate of downtime costs for establishment *x* with size *s* within industry *i*
$PR_{x,s,i}$ = Estimate of total payroll for establishment x within industry *i* with size *s*
$PR_{s,i}$ = Estimate of total payroll for industry *i* with size *s*

The second method uses flow time. Manufacturing flow time can be thought of as water flowing into a bucket. Products flow through the assembly line and out of an establishment at a specific rate. Using data on the downtime due to maintenance that would be gathered using a survey, lost revenue could be estimated:

$$DWC = \frac{VA_i}{52.14 Hr_{Plnt,i}} * DWN_i \qquad (4)$$

where
$Hr_{Plnt,i}$ = Average plant hours for industry *i* per week in operation from the quarterly Survey of Plant Capacity Utilization
VA_i = Value added for industry i
DWN_i = Average number of hours of downtime for industry i gathered from survey data

The third method involves examining flow time. Downtime has an impact on the efficiency of capital use, which is often measured using flow time and inventory turns. The calculation for flow time can, again, be thought of as water flowing through a hose into a bucket. The cost of goods sold ($COGS$) is the total amount of water that runs into the bucket over a period of time and the inventory values are the amount of water in the hose at any given time. Since we know the total amount of water that flowed out of the hose (i.e., the amount in the bucket or $COGS$), we can estimate how many times the hose was filled and emptied over that period of time (inventory turns or TRN in the equation below) by dividing the amount in the bucket by the volume of the hose. If one takes the number of days in a year and divides it by the number of inventory turns TRN, the result is the flow time FT, which represents the time it takes to move from the beginning to the end of the hose. This method makes the assumption of first-in first-out (FIFO) where the oldest goods on hand are sold first (Meigs and Meigs, 1993). Industry inventory time can be characterized into four categories (i.e., material goods, work-in-process down time, work-in-process, and finished goods) (Census Bureau, 2017C;

International Standards Organization, 2014). For this reason, a ratio is included in the calculation to account for each category. The proposed method for estimating flow time for materials and supplies inventories, work-in-process inventories, and finished goods inventories for a particular industry, represented by NAICS codes, is:

$$FT_{IND,Total} = \frac{(INV_{IND,i,BOY}+INV_{IND,i,EOY})/2}{(INV_{IND,Total,BOY}+INV_{IND,Total,EOY})/2} \times \frac{365}{TRN_{IND,Total}} \qquad (5)$$

where
$FT_{\text{IND,Total}}$ = Total estimated flow time for industry IND
i = Inventory item where i is materials and supplies (MS), work-in-process (WIP), or finished goods (FG) inventories.
$INV_{\text{IND,Total,BOY}}$ = Total inventory (i.e., materials and supplies, work-in-process, and finished goods inventories) for industry IND at the beginning of the year
$INV_{\text{IND,Total,EOY}}$ = Total inventory (i.e., materials and supplies, work-in-process, and finished goods inventories) for industry IND at the end of the year
$TRN_{\text{IND,Total}}$ = Inventory turns for industry IND (defined below)

This equation calculates, for each industry, the flow time for types of inventory flow time by taking the average inventory for the type divided by the total inventory and multiplying by the total flow time, which the number of days in a year divided by the number of inventory turns per year. Calculating each of these stages is useful in identifying the source of the flow time (i.e., inventory time vs. work-in-process time). Downtime relates to work-in-process inventories; thus, it is necessary to calculate the flow time for this stage. The total industry flow time can be simplified to:

$$FT_{IND,Total} = \frac{365}{TRN_{IND,Total}} \qquad (6)$$

The days that a dollar spends in each of the inventory categories is being calculated by taking the total number of days in a year and dividing it by the number of inventory turns TRN. This is then multiplied by average inventory of type i divided by the total inventory. Finally, the summation of all types of inventory is calculated for industry IND.

Inventory turns, TRN_{Total}, is the number of times inventory is sold or used in a time period such as a year (Horngren et al., 2002; Hopp and Spearman, 2008; Stickney and Brown, 1999). It is calculated as the cost of goods sold, COGS, which is the cost of the inventory that businesses sell to customers (Horngren et al., 2002), divided by the average inventory:

$$TRN_{Total} = \frac{COGS}{\left(\frac{INV_{Total,BOY}+INV_{Total,EOY}}{2}\right)} \qquad (7)$$

where
$COGS = AP + FB + MAT + DEP + RP + OTH + (INV_{\text{Total,BOY}} - INV_{\text{Total,EOY}})$
AP = Annual payroll
FB = Fringe benefits
MAT = Total cost of materials
DEP = Depreciation
RP = Rental payments
OTH = Total other expenses

Inventory turns is usually stated in yearly terms and is used to study a number of fields, such as distributive trade, particularly with respect to wholesaling (Hopp and Spearman, 2008). The data for calculating $COGS$ is from the Annual Survey of Manufacturing. In the previous two equations, inventories are calculated using the average of the beginning of year inventories and end of year inventories, which is standard practice (Horngren et al., 2002).

Flow time for work-in-process inventories (i.e., FT_{N} where in this case N is work-in-process) consists of two components: the time that a good is in work-in-process while the factory is open and the time that a good is in work-in-process while the factory is closed. Breaking out these two is useful for understanding where the flow time occurs. The time when the factory is closed can be estimated by multiplying the total flow time for work in process by the ratio of total hours that the plant is open:

$$FT_{WIPD} = \left(1 - \frac{Hr_{Plnt}}{168}\right) \times FT_{WIP} \qquad (8)$$

where:
FT_{WIPD} = Flow time for work-in-process downtime when the factory is closed
Hr_{Plnt} = Average plant hours per week in operation from the quarterly Survey of Plant Capacity Utilization
FT_{WIP} = Flow time for work-in-process

The value of 168 is the total number of hours in a week. Breaking the flow time for work-in-process into time when the factory is open and closed aids in understanding the activities that are occurring during flow time.

A decrease in downtime would increase the number of inventory turns, reduce the work-in-process flow time, and improve the capital utilization. It could also have the indirect effect of reducing the amount of material inventory and/or finished goods inventory that is maintained. Data could be collected from establishments to calculate inventory turns and flow time. A regression analysis could then be used to estimate the impact that various forms of maintenance have on flow time while controlling for other factors (e.g., management style). Equation 4 could be applied to estimate the dollar impact.

3.3. Lost Sales Due to Delays/Quality Issues

Estimating the lost sales due to delays or quality issues requires gathering this data through a survey. There is also the potential for large error in this estimate, as it is unlikely that there is official tracking of this information. The information would be scaled similar to previously discussed methods:

$$TLS = \sum_{i=1}^{I} \sum_{s=1}^{S} \frac{\sum_{x=1}^{X} LS_{x,s,i}}{\sum_{x=1}^{X} PR_{x,s,i}} PR_{s,i} \tag{9}$$

where
TLS = Total lost sales due to delays or quality issues
$LS_{x,s,i}$ = Estimate of lost sales for establishment *x* with size *s* within industry *i*
$PR_{x,s,i}$ = Estimate of total payroll for establishment *x* within industry *i* with size *s*
$PR_{s,i}$ = Estimate of total payroll for industry *i* with size *s*

3.4. Rework and Defects

In addition to lost sales, there are products that are scrapped or reworked as a result of defects. The cost of rework can be estimated by estimating the proportion of employee labor dedicated to rework, represented as:

$$RWK = \sum_{i=1}^{I} \sum_{s=1}^{S} \frac{\sum_{x=1}^{X} FTE_{RW,x,s,i}}{\sum_{x=1}^{X} FTE_{Tot,x,s,i}} PR_{s,i} \tag{10}$$

where
RWK = Cost of rework
$FTE_{RW,x,s,i}$ = Estimate of the full time equivalent employees dedicated to rework that is preventable through maintenance at establishment *x* with size *s* within industry *i*
$FTE_{Tot,s,i}$ = Estimate of total full time equivalent employees at establishment *x* with size *s* within industry *i*
$PR_{s,i}$ = Estimate of total payroll for industry *i* with size *s*

The lost revenue associated with defects can be approximated by estimating the ratio of output that is defective and can be represented as:

$$DEFLR = \sum_{i=1}^{I} \frac{OUT_i}{(1-DEF_i)} - OUT_i \tag{11}$$

where
$DEFLR$ = Lost revenue associated with defects
DEF_i = Estimated average proportion of output in industry *i* that is discarded due to defects that are preventable through maintenance
OUT_i = Output for industry *i*

3.5. Breaking Down Predictive, Preventive, and Reactive Maintenance Costs

Separating maintenance into predictive, preventive, and reactive categories requires gathering the data through a survey. There is the potential for large error in this estimate, as it is unlikely that there is official tracking of this information. It is likely that this estimate will be based on the opinion or perspective of the person completing the survey. The following information would need to be gathered by establishment to estimate the potential savings from predictive maintenance:

- Scaling
  - Total payroll and number of employees in the plant
  - Industry NAICS code
- Direct costs of maintenance
  - Method 1: Collect direct cost data through survey and scale up
    - Maintenance and repair costs
    - Proportion of maintenance that is maintenance vs. repair
    - Proportion of direct costs for predictive, preventive, and reactive maintenance
    - Proportion of repair costs associated with reactive maintenance
  - Method 2: Use industry data and supplement with survey
    - Proportion of maintenance costs that are maintenance vs. repair
    - Proportion of direct costs for predictive, preventive, and reactive maintenance
    - Proportion of repair costs associated with reactive maintenance
- Downtime
  - Method 1: Collect downtime costs directly in a survey
    - Costs/Losses of downtime, including lost revenue, increased overtime, increased inventory, and lost sales from delivery delays or quality issues
  - Method 2: Use national flow time estimates and supplement with survey
    - Average factory operating hours per week
    - On average, the amount of downtime for a production line
    - Proportion of downtime due to predictive, preventive, and reactive (unplanned) maintenance
  - Method 3: Gather data on inventory turns with survey
    - Inventory turns per year or, alternatively, the following data to calculate it
      - Cost of goods sold (i.e., sum of annual payroll, fringe benefits, total cost of

materials, depreciation, and total other manufacturing expenses)
        - Beginning and end of year inventories (or average inventory) for materials, work-in-process, and finished goods
    - Requires establishment level maintenance costs
        - Maintenance and repair costs
        - Proportion of maintenance costs that are maintenance vs. repair
        - Proportion of direct costs for predictive, preventive, and reactive maintenance
        - Proportion of repair costs associated with reactive maintenance
    - Competitive focus: cost competitiveness or differentiation (e.g., quality)
    - Primarily a push (i.e., make to stock) or pull (i.e., make to order) strategy of production
    - Primary management style
        - Autocratic: Decisions are made at the top with little input from staff
        - Consultative: Decisions are made at the top with input from staff
        - Democratic: Employees take part in decision making process
        - Laissez-faire: Management provides limited guidance
- Replacement costs, if any, due to damage that could be prevented using preventive or predictive maintenance
- Rework and defects
    - Full time equivalent employees needed for rework that could be prevented through maintenance
    - Output that was discarded due to defects that could be prevented through maintenance
- In the case where it is believed to be cost-effective to switch from current practice to predictive maintenance, what is the estimated:
    - Total investment cost of switching to predictive maintenance as a percent of current maintenance cost
    - The potential percent increase in revenue, if any, due to increased quality and/or decreased delays from switching to predictive maintenance
    - Percent change in annual maintenance and repair costs from switching to predictive maintenance
    - Percent change in replacement costs, if any, due to switching to predictive maintenance
    - Percent decrease in total downtime due to switching to predictive maintenance

3.6. Sample Size for Data Collection

Many of the methods previously discussed require collecting data through a survey. This study is, generally, estimating the mean of a population, which can be represented as (NIST, 2013):

$$Sample\ Size = \left(\frac{z\sigma}{e}\right)^2 \tag{11}$$

where
σ = Standard deviation
e = Margin of error
z = z-score

The Annual Survey of Manufactures estimates the total value of manufacturing maintenance was \$49.5 billion for 292 825 establishments with a sample size estimated at approximately 50 000, resulting in a standard deviation of 75 627, as calculated by:

$$\sigma = \frac{RSE}{100} * \frac{M\&R}{EST} * \sqrt{SPL} \tag{12}$$

where
RSE = Relative standard error from the Annual Survey of Manufactures
$M\&R$ = Repair and maintenance services of buildings and/or machinery from the Annual Survey of Manufactures
EST = Number of establishments in manufacturing from the County Business Patterns data
SPL = Approximate sample size of the Annual Survey of Manufactures

Assuming a 10 % margin of error and a 95 % confidence interval (i.e., z = 1.96), a sample size of 77 is calculated. Various sample sizes required at different confidence intervals and margins of error can be calculated with the standard deviation equaling 75 627. With a margin of error of 20 % and a confidence interval as low as 90 %, as few as 14 samples are needed.

4. FEASIBILITY OF DATA COLLECTION

Individual insight was sought out from staff at manufacturing firms to assess the feasibility of data collection. Conversations occurred with seven individuals with five being employed at manufacturing firms and two were employed by change agent organizations, which includes trade associations and research organizations. These discussions assessed whether the individual believed the following data items could be collected:

1. NAICS code
2. Payroll
3. Factory operating hours
4. Expenditure on maintenance and repair (M&R)
5. Separating maintenance from repair and estimating replacement
6. Separating M&R that are due to predictive, preventive, and reactive maintenance activities
7. Lost revenue and increased overtime due to maintenance issues
8. Total downtime and related costs/losses

9. Separating downtime into predictive, preventive, and reactive maintenance activities
10. Identifying instances where it would be cost effective to switch to advanced maintenance, including estimating increased revenue, reduction in costs, and reduction in downtime
11. Inventory turns per year
12. Competitive focus: cost competitive vs differentiation
13. Push vs pull strategy
14. Management style
15. Defect and rework rates

- The discussions indicate that it is reasonable to expect manufacturers to be willing to provide information on these items:
  - However, there was some uncertainty about the willingness to provide payroll and inventory turns.
  - In terms of ability to provide data, there were some reservations, as some items are not specifically tracked.
  - Generally, however, it was believed that an approximation could be provided in cases where data was unknown.
- All individuals indicated that they were willing and able to provide the NAICS code, factory operating hours, competitive focus, push/pull strategy, and management style.
- Individuals indicated that they would be willing and able to provide an estimate for maintenance and repair expenditures with one indicating they would have to approximate it.
- It was also indicated by some that separating out maintenance from repair and associating portions to predictive, preventive, and reactive maintenance might require approximating or "guestimating."
- It was uncertain whether an estimate for lost revenue and increased overtime due to reactive maintenance could be provided and one indicated that they were unable to approximate it.
- Individuals indicated that they could provide an estimate of downtime and could approximate the amount of time that is associated with predictive, preventive, and reactive maintenance.
- Multiple individuals indicated that they could identify instances where it would be cost effective to switch to advanced maintenance techniques but estimating the costs and benefits of doing so was a little more uncertain with one indicating they were unable to make an estimate.
  - One explained that the costs of implementing advanced maintenance techniques are customized solutions; thus, estimating the cost would require tracking individual labor activities and materials.
- Each of the individuals indicated that they believed a blind survey would be better than a confidential one and they would be more likely to respond.

They also indicated that being promised a copy of the report would make them more likely to respond, but it did not seem like a necessity.

5. SUMMARY

This article investigates the data available from public sources and in the literature on the total cost of manufacturing maintenance, including data on separating those costs into planned and unplanned maintenance. It also investigates the feasibility of collecting data to measure maintenance costs and separate costs by firm size. This area of investigation includes identifying whether manufacturers can provide information to estimate and separate maintenance costs. This effort requires consulting literature on the data collected at establishments and consulting industry experts.

The data available in the literature and from statistical agencies could facilitate making estimates of US maintenance costs along with the potential benefits of moving toward advanced maintenance techniques; however, the estimate for benefits of advanced maintenance techniques would require strong assumptions that result in a high level of unmeasurable error. For instance, one would need to assume that the findings in studies of other industrialized countries apply to the US and across multiple US industries. It would also require the insight of a few experts accurately represents industry activity. This estimate would be low cost but have low accuracy, making it an estimated order of magnitude. A more reliable estimate requires data collection.

Manufacturers are, generally, willing to provide data; however, the data needed is often not specifically tracked or documented. Experienced maintenance managers and professionals, however, have indicated that they are able to provide an estimate for these cost items. A great deal of the uncertainty occurs in separating out maintenance and repair costs/losses into different categories.

Future efforts will focus on data collection and analysis. It is intended that a survey will be developed to collect the data discussed and used to better understand the economics of adopting advanced maintenance techniques.

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