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An Experiment To Assess The Utilization Of Adaptive Control Technology On A Cnc Lathe To Reduce Energy Consumption During Machining: A Step Towards Environmentally Conscious Manufacturing

Dean L. Bartles

Indiana State University

AN EXPERIMENT TO ASSESS THE UTILIZATION OF ADAPTIVE CONTROL TECHNOLOGY ON A CNC LATHE TO REDUCE ENERGY CONSUMPTION DURING MACHINING: A STEP TOWARDS ENVIRONMENTALLY CONSCIOUS MANUFACTURING

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Dean L. Bartles

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COMMITTEE MEMBERS

Committee Chair: Ronald Woolsey, Ph.D.

Professor, Industrial Management

University of Central Missouri, Warrensburg, Missouri

Committee Member: Gerald Cockrell, Ph.D.

Professor, Technology Management

Indiana State University, Terre Haute, Indiana

Committee Member: Troy Ollison, Ph.D.

Associate Professor, Industrial Management

University of Central Missouri, Warrensburg, Missouri

Committee Member: Jeff Ulmer, Ph.D.

Associate Professor, Industrial Management

University of Central Missouri, Warrensburg, Missouri

ABSTRACT

Global warming is a well-documented concern. If left unabated, many scientists believe that global warming could potentially have devastating impacts to life on earth. Current research points to greenhouse gas emissions caused by the burning of fossil fuels to produce electricity as one of the primary causes of global warming. The more electricity produced and consumed the more greenhouse gas emissions are released to the atmosphere. Industry is one of the most significant consumers of electricity. Within industry, manufacturing accounts for a significant majority of all energy consumed with machine tools being one of the largest consumers. Machine tool builders need to develop ways for machine tools to use less energy in producing the same amount of product.

The literature contains suggestions on how a manufacturer can approach reducing the amount of energy consumed by machine tools in manufacturing. However, there is paucity in the literature related to how “adaptive control” might be employed to reduce the amount of energy consumed by machine tools in manufacturing. This study examined the possibility of employing “adaptive control” to minimize the amount of energy consumed by machine tools during machining.

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I dedicate this work and this accomplishment to my three sons, Joshua, Caleb, and Jacob, who make me want to strive to be a better father, a better husband, and a better person.

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CHAPTER 1

Introduction

Manufacturing is an important part of any nation's economy and security. The President's Council of Advisors on Science and Technology July 2012 report on "Capturing Domestic Competitive Advantage in Advanced Manufacturing" states that:

> The United States has long thrived as a result of its ability to manufacture goods and sell them to global markets. Manufacturing has supported our economic growth, contributing to the Nation's exports, and employing millions of Americans. Manufacturing has driven knowledge production and innovation in the United States by supporting two-thirds of private sector research and development (R&D) and by employing scientists, engineers, and technicians to invent and produce new products (Holdren & Lander, 2012, p.1).

Further support for the importance of manufacturing is evidenced by the National Association of Manufacturers who report that "US manufacturing produces $1.7 trillion of value each year, or 11.7 percent of U.S. GDP" ("Facts about manufacturing," n.d.).

Although manufacturing, as indicated above, is an extremely important economic sector to the US, it comes with a price. Offsetting the positive attributes of its contribution to US Gross Domestic Product, job creation, knowledge production, etc. is the toll that US manufacturing has taken on the environment. Rahiimiifard (2007) found that the manufacturing industry is one of the biggest sources of negative environmental impact. The environment in general is receiving increasing attention especially as it pertains to “climate change” and “Global Warming” (Gupta & Lambert, 2008, p. ix). Manufacturing has a significant role to play in the area of climate change mitigation. This research focuses on one aspect of manufacturing’s potential contribution.

Background

“Environmentally conscious manufacturing” (“ECM”), according to Gupta & Lambert (2008, p. ix), is “an emerging discipline that is concerned with developing methods for manufacturing new products with as little negative impact on the environment as possible.” Other terms somewhat synonymous to ECM are “green” manufacturing and “sustainable” manufacturing as well as “environmentally friendly manufacturing” and “environmentally benign manufacturing”. Not since the evolution of “lean” manufacturing has a strategic concept for an approach to manufacturing been introduced with the same velocity as “green” manufacturing or “environmentally conscious manufacturing”. A “Google” search on various types of manufacturing conducted on July 18, 2012 reflects the frequency of the following terms appearing on the World Wide Web listed in order of prevalence:

1. "lean manufacturing" - About 6,110,000 results
2. "advanced manufacturing" - About 3,640,000 results
3. "flexible manufacturing" - About 884,000 results
4. “green manufacturing” - About 809,000 results
5. "Just In Time manufacturing" - About 713,000 results
6. "additive manufacturing" - About 495,000 results
7. "environmentally friendly manufacturing" - About 417,000 results

8. "sustainable manufacturing" - About 386,000 results
9. "rapid manufacturing" - About 354,000 results
10. "intelligent manufacturing" - About 281,000 results
11. "competitive manufacturing" - About 244,000 results
12. "agile manufacturing" - About 227,000 results
13. "six sigma manufacturing" – About 220,000 results
14. "smart manufacturing" - About 83,000 results
15. "environmentally conscious manufacturing" - About 62,000 results
16. "reconfigurable manufacturing" - About 49,700 results
17. "subtractive manufacturing" - About 48,900 results
18. "environmentally benign manufacturing" - About 24,200 results

"Green" manufacturing, arguably a more recently coined term than the others, is already fourth in the list and more than likely will move to third in the near future. Clearly, manufacturers of all types and all sizes will be looking to embrace the attributes of "green" manufacturing going forward.

According to the Environmental Protection Agency ("EPA"), "earth's average temperature has risen by 1.4°F over the past century, and is projected to rise another 2 to 11.5°F over the next hundred years" ("Climate change basics," 2012). They also say that "small changes in the average temperature of the planet can translate to large and potentially dangerous shifts in climate and weather" ("Climate change basics," 2012). One of the primary causes of the aforementioned temperature escalation is human activities that have released large amounts of carbon dioxide and other greenhouse gases into the atmosphere ("Climate change basics," 2012). The EPA also reports "the majority of greenhouse gases come from burning fossil fuels to produce energy" ("Climate change basics," 2012). These "greenhouse gases act like a blanket around Earth, trapping energy in the atmosphere and causing it to warm" ("Climate change basics," 2012). Lastly, the EPA goes on to say that "the buildup of greenhouse gases can change earth's climate and result in dangerous effects to human health and welfare and to ecosystems" ("Climate change basics," 2012).

According to the US Government's Energy Information Administration ("EIA"), manufacturing "accounts for about 80 percent of industrial energy consumption", and manufacturing "also accounts for about 80 percent of industrial energy-related carbon emissions" ("Energy-related carbon emissions, 2000"). When you consider that industrial energy consumption represents approximately 40 percent of all energy consumed in the US according to the EIA ("What are greenhouse gases?, 2004") and, as stated above, manufacturing accounts for about 80% of that, it becomes abundantly clear how important it is for manufacturers to focus some of their efforts towards reducing their greenhouse gas emissions by reducing the amount of energy they consume in making their respective products.

According to Richter (2009), "reducing the amount of energy the motors on a metal cutting machine tool use is one way for a manufacturer to increase its competitiveness…while "greening" its operations". Richter points out that the majority of energy consumed by manufacturers is in motor energy consumption on machines. Therefore targeting methods to reduce the amount of energy consumed by motors on machine tools is an effective approach to becoming a more sustainable or "greener" manufacturer.

Problem Statement

Global warming is a well-documented concern. If left unabated, many scientists believe that global warming could potentially have devastating impacts to life on earth. One of the primary causes of global warming is thought to be greenhouse gas emissions caused by the burning of fossil fuels to produce electricity. The more electricity produced and consumed the more greenhouse gas emissions are released to the atmosphere. Industry is one of the most significant consumers of electricity. Within industry, manufacturing accounts for about 80 percent of all energy consumed, as cited above. Manufacturers need to develop ways to use less energy in producing the same amount of product.

Need for the Study

The literature contains suggestions on how a manufacturer can approach reducing the amount of energy consumed by machine tools in manufacturing, such as replacing single speed motors with variable speed motors, replacing older motors with new, more energy efficient motors, etc. (Richter, 2009). However, there is paucity in the literature related to how "adaptive control" might be employed to reduce the amount of energy consumed by machine tools in manufacturing.

According to Drozda & Wick (1983, p. 5-70), "adaptive control" is a "method using automatic means to change the type and/or influence of control parameters to achieve near optimum processing performance". The authors go on to say that it "is used to optimize independent parameters such as speeds and feeds to be consistent with processing constraints such as quality of surface finish and cutter life" (Drozda & Wick, 1983, p. 5-70). This study examined the possibility of employing "adaptive control" to minimize the amount of energy consumed by the machine tool during machining.

Purpose of the Study

This study encompassed field research directed at reducing the amount of energy consumed by machine tools in manufacturing through the employment of "adaptive control" technology. “Adaptive control” was the primary influencing independent variable researched. In addition to “adaptive control,” other influencing independent variables explored included feed rate, spindle speed, depth of cut, coolant temperature, coolant flow volume, and tool condition. The dependent variable that was the focus of this research was the amount of energy used during a chosen machining cycle measured in kilowatt hours which is a common unit of measure for energy found in other research such as Ulmer and Ollison (2008).

Research Questions

The following questions proposed by the researcher were examined during this study:

1) Are there significant differences in energy used based on levels of the independent controlling variables in predicting energy used?
2) Do the independent variables described above have a relationship with energy used? Can a predictive model using these variables be built that will explain a significant amount of the variability in energy used, and provide an accurate prediction given the set of parameters?
3) Does adaptive control or tool condition interact with the other independent variables when investigating the relationship with energy used?

Proposed Null and Alternative Hypotheses

H_{01}: There will not be any significant mean score differences on energy used between levels of the independent variables.

$H_{A1:}$ The levels of the independent variables will be found to have significant energy used mean score differences, and therefore the independent variables will be significant influencers of energy used.

H_{02}: There is no statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.

H_{A2}: There is a statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.

H_{03}: There is no statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

H_{A3}: There is a statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

H_{04}: Independent variables will not be correlated significantly and will not produce statistically significant interaction effects in the energy regression models.

H_{A4}: Independent variables will be significantly inter-correlated, and there will be statistically significant interaction effects in the energy regression models.

Assumptions of the Study

It is assumed that the results obtained during this study, although conducted on a CNC lathe, are somewhat generalizable to other machine tools that adaptive control could be implemented on. It is also assumed that the results of the study will serve as a tool for specific targeting for future intervention in an attempt to reduce the amount of energy consumed throughout the entire manufacturing enterprise.

Assumptions regarding the statistical analysis

Alpha is the probability of committing a Type I error – that is rejecting the null hypothesis, H_0, when it is true. This error sometimes occurs in studies as it is not possible to study every item in the population. The alpha for this study was set to 0.05 – that is the 5 percent level. This level was chosen in order to obtain a 95 confidence which the researcher has determined to be the lowest acceptable confidence level for this type of research. A higher level of confidence was determined not to be needed and would have required more samples which would have cost additional money to collect.

Limitations

As indicated above, the environment for this study was a specific machine tool that was machining a specific material to a specific shape using a specific cutting tool insert. Accordingly, the results of this study may not be generalizable to all machine tools. However, this study should serve as a stepping stone for further research into other machine tools to determine if more generalizable patterns exist.

Significance of the Study

The results of this study should have significant practitioner interest. Since the literature has already shown that a high level of greenhouse gas emissions are attributable to manufacturing through the energy that is consumed by machine tools, reducing the amount of energy consumed will not only have a positive impact on the environment, but a positive impact on business performance through lower energy costs. The practitioner should take keen interest in the findings from this study to facilitate targeting specific machine tools for intervention so that the amount of energy consumed can be decreased.

Organization of the Study

This study consists of 5 chapters starting with this introductory chapter. Chapter 2 is a review of the relevant literature pertaining to sustainable manufacturing, machine tools, computer numerical control, and adaptive control. Chapter 3 explains the research methodology employed by the researcher. The findings and results of the study are discussed in Chapter 4 which in turn is followed by the fifth and final chapter where conclusions and directions for future research are discussed.

Definition of Terms

The following are definitions of terms that are utilized throughout this document:

Adaptive control - a method using automatic means to change the type and/or influence of control parameters to achieve near optimum processing performance (Drozda & Wick, 1983, p. 5-70).

Environmentally conscious manufacturing - an emerging discipline that is concerned with developing methods for manufacturing new products with as little negative impact on the environment as possible (Gupta & Lambert, 2008).

Green manufacturing - the continual optimization of material and energy resources during the design, manufacture, and end use of products in order to reduce production costs, eliminate negative environmental impacts, and increase business opportunities ("Develop green manufacturing skills," 2012).

Sustainable manufacturing - the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound ("How does Commerce define," n.d.).

Summary

This chapter has provided the background, purpose, justification, and rationale for the study that was conducted. The "problem" that the researcher investigated has been clearly stated. The environment, limitations, and assumptions of the study have also been discussed. Lastly, the significance of the study, as well as the organization of the study, has been detailed.

The following chapter will review the relevant literature pertaining to sustainable manufacturing, machine tools, computer numerical control, and adaptive control.

CHAPTER 2

Review of Literature

Chapter Overview

The previous chapter presented a brief introduction of the study, the background for the study, the problem statement, the need for the study, the purpose of the study, the proposed research questions, the proposed null and alternative hypotheses, the assumptions of the study, the limitations of the study, the organization of the study, and definitions of terms pertaining to the study. This chapter presents a summary of the literature reviewed for this study starting with a brief introduction to "Sustainable Manufacturing", the origin of machine tools, their subsequent evolution to "Computer Numerically Controlled" ("CNC") machine tools, an overview of "Adaptive Control" as it applies to machine tools and how it can be a key technology to further the advancement of "Sustainable Manufacturing".

Sustainable Manufacturing

As manufacturing converts raw materials into products, environmental wastes and emissions are simultaneously generated by the consumption of energy, water and excessive materials in the manufacturing system. Manufacturing wastes and emissions include various pollutants and material wastes such as air emissions, wastewater discharges, hazardous wastes and solid wastes ("The lean and the environment toolkit", 2011). The wastes generated from the manufacturing industry are very significant. According to the U.S. Environmental Protection Agency (EPA), about 12 billion tons of industrial wastes are generated annually in the United States and over one third of these wastes are hazardous wastes (Gungor & Gupta, 1999), (Fiksel, 1995).

Presently, the manufacturing industry is required to produce a higher-than-ever amount of goods and services to meet the needs of the growing population and people's increasing standard of living. As the earth has limited natural resources to supply for industrial productions, the increasing demands and consumption have led to a shortage of raw materials and a rapid deterioration in the global environment which affects all life on the earth for inhabitants and their prosperity.

In order to sustain the economic growth and social progress, sustainable development, defined as "development that meets the needs of the present without compromising the ability of future generations to meet their own needs", has been proposed in 1987 by the World Commission on Environment and Development of the United Nations (World Commission On Environment and Development, 1987, p.42). Sustainable development is a grand strategy for the whole global society. To achieve sustainable development, manufacturing is a fundamental enabler as it produces goods and services which are closely related to the economy, society, environment and technology (Jovane, et al., 2008).

Manufacturing is both material and energy-intensive. Environmental impacts of manufacturing result mainly from the materials and energy consumed in the manufacturing systems. Manufacturing is dominant in its environmental impacts in such categories as toxic chemicals, waste generation, energy consumption and carbon emissions (Gutowski, et al., 2001).

Toxic materials are widely and heavily used in manufacturing for both product development and process operations. There are grave concerns pertaining to their toxic effects and the significant impact on the environment and human health. There is a wide variety of toxic chemicals involved in various manufacturing operations for etching, forming, catalyzing, cleaning, etc. and such chemicals inevitably lead to waste emissions generation from the process operations.

Besides the toxic chemical releases, the manufacturing industry also generates a huge amount of waste, mainly in the form of solid waste and waste water, which also causes significant environmental problems and impacts. As reported, waste generated in the United States are more than any other single country in the world, in both absolute scale and per capita (Gutowski, et al., 2001), (Park & Labys, 1999).

According to the US Government's Energy Information Administration ("EIA"), manufacturing "accounts for about 80 percent of industrial energy consumption", and manufacturing "also accounts for about 80 percent of industrial energy-related carbon emissions" ("Energy-related carbon emissions in manufacturing," 2010). When you consider that industrial energy consumption represents approximately 40 percent of all energy consumed in the US according to the EIA ("What are greenhouse gases?, 2004") and, as stated above, manufacturing accounts for about 80% of that, it becomes abundantly clear how important it is for manufacturers to focus some of their efforts towards reducing their greenhouse gas emissions by reducing the amount of energy they consume in making their respective products.

Greenhouse gas emissions are another byproduct of manufacturing and are a serious concern of the global society. Industrial production consumes fossil fuels heavily through direct on-site combustion and indirect utilization of fossil-fuel-generated electricity, all of which contribute to the generation of significant amounts of greenhouse gases to the global environment. Greenhouse gases induce global warming problems and may cause dangerous anthropogenic interference with the climate system ("United nations framework convention on climate change," 1992). According to the Intergovernmental Panel on Climate Change (IPCC), based on current emission trends the average global temperature is expected to rise by 1.4 °C to 5.8 °C between 1990 and 2100 ("Climate change 2001: Synthesis report," 2001).

Sustainable Manufacturing Concept and Definitions

As the environmental impacts of manufacturing are so significant in the amount of emissions and wastes, sustainable manufacturing has received enormous attention in recent years as a comprehensive strategy for reducing the environmental impact and improving the economic performance of manufacturing. Sustainable manufacturing is an expanded concept of green manufacturing (also called environmentally conscious manufacturing). The sustainable manufacturing concept is developed through integrating the sustainability notion into the manufacturing system with an aim to achieve sustainable development of industrial production. Since sustainability is a broad three-dimensional concept involving environmental, economic and social concerns, a complete definition of sustainable manufacturing should also integrate environmental, economic and social aspects of manufacturing in that context. However, in current research and practice, sustainable manufacturing focuses much more on the environmental aspect of manufacturing. In addition, sustainable manufacturing is also defined as a means for manufacturers to add the most value to their products and services by making the most efficient use of the earth's limited resources, generating the least pollution to the environment, and targeting for environmentally clean production systems (Madu, 2001).

Motivations and Barriers to Sustainable Manufacturing

A manufacturing system involves a wide range of stakeholders including suppliers, manufacturers, retailers, consumers, policy-makers, etc. As the stakeholders are becoming more aware of the values of sustainable manufacturing in practice, the manufacturing industry is motivated to implement sustainable manufacturing strategies to reduce the environmental impact and moreover, to improve the economic performance of its manufacturing operations, as indicated by a number of research results (Ahmed, Montagno, & Firenze, 1998; Hart, 1995; Klassen & Whybark, 1999; Porter & van der Linde, 1995).

There are quite a number of drivers in effect motivating the manufacturing industry to sustainable manufacturing practices. The motivation factors are summarized in the following three categories: regulatory pressure, economic incentives, and competitive advantages.

Regulatory pressure

Aware of the significant environmental problems of industrial wastes and emissions, governmental agencies initiated efforts for environmental impact control and restoration by making a series of policies, regulations, and laws, which has achieved significant progress in advancing the environmental performance of industrial production activities. US environmental regulations have undergone three stages since 1970 (Frosch, 1995; Gungor & Gupta, 1999). The first stage focused on the "end-of-pipe" control of environmental wastes. Representative regulations include the Clean Air Act, the Clean Water Act, and the Resource Conservation and Recovery Act (RCRA). The second stage focused on reducing the environmental pollution of industrial activities, with the Pollution Prevention Act enacted in 1990. The third stage focuses on clean production by encouraging implementation of comprehensive environmental programs to reduce the overall impact of industrial production.

Economic incentives

Under regulatory pressure and governmental efforts, the manufacturing industry is driven towards sustainable manufacturing by the economic benefits which could result from the implementation of sustainability programs. Sustainable manufacturing, in general, includes such practices as pollution prevention, product stewardship, and emission control (Bansal, 2005;

Rusinko, 2007). The economic cost involved in emission control is tremendous for the manufacturing industry. It has been reported that the US manufacturers currently spend approximately $170 billion per year in waste treatment and disposal costs (Gutowski, et al., 2001). Appropriate sustainable manufacturing programs such as pollution prevention for minimizing waste generation in manufacturing could effectively cut the costs on both waste management and material consumption, and accordingly can improve the profit margin of the manufacturing industry. A recent survey on the U.S. commercial carpet manufacturers indicates that 84.6% of the manufacturers that adopt emission control strategies such as recycling water and diverting solid waste from landfills, and 100% of the manufacturers that adopt pollution prevention strategies like reducing raw materials usage and energy consumptions have successfully decreased their manufacturing cost (Rusinko, 2007).

Barriers to Sustainable Manufacturing

Although sustainable manufacturing is driven by a number of positive factors, the manufacturing industry still faces some barriers and challenges that hinder the application of sustainable manufacturing strategies in practice. Some early investigations have stated that environmental initiatives may induce a negative impact on company performance (Freeman, 1994; Judge & Krishnan, 1994). In general, the barriers for sustainable manufacturing could be summarized into the following three categories: economic barrier, technological barrier and managerial barrier.

Early sustainable manufacturing practices focused mainly on emission controls and waste management (Gutowski, et al., 2001). In the emission control and waste management process, the capital cost requirements are high and take a long time to be paid back. In some circumstances, the capital input of emission control may exceed the total amount of direct economic gains. This has greatly hindered the practical applications of sustainable manufacturing strategies in industry. But as sustainable manufacturing practices are switching from "end-of-pipe" emission control to pollution prevention, and the costs for waste disposal and environmental emissions are increasing, the economic barrier of sustainable manufacturing is gradually diminishing for the manufacturing industry (Gutowski, et al., 2001).

Another major barrier for sustainable manufacturing is that the manufacturing industry has to rely on certain processes, technologies or materials to make its products, which may be very polluting but cannot be avoided in the current stage due to the lack of appropriate technologies or processes. Using automotive manufacturing as an example, the painting operations generate a significant amount of volatile organic compound (VOC) emissions which cause air pollution by creating ozone and carcinogens. It has been reported that approximately 80% of Ford's toxic pollutants that were released into the environment were from the painting operations (Kim, Kalis, & Adams, 2001). Even with such an enormous impact identified, complete elimination of the painting emissions is not practical in this stage as the industry lacks appropriate technologies to replace the process.

The other major barrier for sustainable manufacturing is that the manufacturing industry lacks adequate and scientific decision support tools for effective implementation of sustainable manufacturing strategies. To achieve sustainable manufacturing, the industry needs appropriate analytical tools to characterize and benchmark the environmental impact of emissions and wastes from a specific manufacturing process/system to support decision-making. While manufacturing is such a complicated system that numerous types of processes, materials, and system patterns are employed, generic decision tools are difficult to use for the whole manufacturing industry as each manufacturing process/system has its own specificities. The manufacturing system is closely linked to many other industrial activities and the products from manufacturing impact almost everyone in society. As a result, the environmental impact of manufacturing must be assessed both comprehensively and specifically for robust decision support in the industrial applications. This needs further research efforts on environmental impact assessment methods and manufacturing process modeling and characterizations. For example, life cycle impact assessment, as a comprehensive system tool for environmental impact analysis, needs to be standardized, streamlined and further improved before wider application in industrial practice is seen (Hunkeler & Rebitzer, 2005).

System Management of Industrial Sustainability

Manufacturing is a comprehensive system which involves a wide range of partners including other manufacturers, suppliers, distributors, consumers, recyclers, policy-makers, etc. In real practice, a manufacturing system is interconnected with a large number of other systems and processes in the whole industrial, social and environmental context. The environmental impact of manufacturing partially comes from its upstream partners like materials acquisition, processing and supplying. At the same time some environmental consequences of manufacturing transfer with the manufactured products to its downstream partners like distributors, consumers, recyclers, etc. As a result, the implementation of sustainable manufacturing strategies needs to consider not only the impact and benefits of manufacturing itself, but also the interests of all the stakeholders associated with manufacturing during the industrial efforts towards an effective control and management of the environmental impact of manufacturing. As a result, sustainable manufacturing practices require a system level approach within and beyond the whole industry for sustainability management and improvement.

At the macro level, sustainable manufacturing practices are driven by governmental efforts through a series of "top-down" regulations, policies and incentives from the national level, followed by regional and industrial sector efforts for the establishment of appropriate environmental management programs and the development of specific roadmaps and strategic plans. However, the real implementations of sustainable manufacturing are at the bottom level of the industrial sector which involves individual or team efforts in technology innovations, process manipulations, product stewardship, and system improvements. In implementing sustainable manufacturing strategies, it is important to understand the different levels of the system required to make appropriate efforts at a specific level to support sustainability assessment and advancement.

The concept of sustainable manufacturing has only been raised in recent years and emphasized as a research focus due to the needs of manufacturing for a simultaneous improvement of the economic and environmental performance of industry (Chen, 2006) , (Seidel, Shahbazpour, & Seidel, 2007). In current sustainable manufacturing research, significant efforts are put on the development of metrics for environmental performance measurement of manufacturing and on the investigations of specific manufacturing processes or manufacturing systems for environmental performance improvement. However, few applications have been conducted on sustainability improvement of emerging technologies such as nano-scale manufacturing (Krishnan, et al., 2008).

Numerous environmental metrics have been developed for manufacturing and related industrial production activities. Young, Scharp, & Cabezas (2000) have developed a waste reduction algorithm for reducing the wastes from materials and energy consumptions in a chemical process. Life Cycle Assessment (LCA) as a comprehensive tool capable of performing a complete assessment of the environmental performance of a product system has been widely researched and applied on the manufactured products. Socolof, Overly, & Geibig (2005) performed an environmental life cycle impact study of CRT and LCD desktop computer displays. MacLean & Lave (1998) conducted a life-cycle assessment of an automobile by using economic input-output analysis. While implementing life-cycle assessment is very costly and time consuming and is beyond the capacity of many manufacturers, the manufacturing industry is in great need of a system approach which is economical, efficient and effective in facilitating decision making in the process of reducing its overall environmental impact.

Reducing the Environmental Impact of Manufacturing

Reducing the environmental impact of manufacturing is a complicated issue as it needs systematic investigations of the emission mechanisms, quantification of the environmental impact and identification of improvement opportunities for industry to implement sustainable manufacturing strategies. For reducing the environmental impact of manufacturing, the fundamental process and sequence of actions needs to be understood first and then followed in real practice. Generally the four steps below are followed in real practice for reducing the environmental impact of industrial production: first, understand the sources of the environmental impact; second, quantify the environmental impact of industrial emissions and wastes; third, identify improvement opportunities for reducing the environmental impact; finally, implement strategies to reduce the environmental impact and assess their effectiveness (Nazaroff & Alvarez-Cohen, 2001). Each is discussed below.

Understand the Sources of Environmental Impact

To reduce the environmental impact, the first step is to understand the sources of the impact. In manufacturing operations, the environmental impact results mainly from environmental emissions and waste generated from the materials and energy consumed in the manufacturing processes. A wide range of materials is used in manufacturing either as working materials (such as metals, polymers, etc.) to make products or as supplemental materials (such as chemicals, fluids, etc.) to assist the manufacturing operations. The residual working materials left over after manufacturing and the supplemental materials not completely consumed during manufacturing are all categorized as wastes after manufacturing operations. The energy consumed in manufacturing also generates a significant amount of emissions, both directly from on-site burning of fossil fuels and indirectly from the purchased electricity. The products manufactured also produce environmental impacts during their use phase and their end-of-life stage. Other closely linked processes such as product design, material production, supply chain, etc., all have environmental impacts associated with manufacturing (Nazaroff & Alvarez-Cohen, 2001).

Quantifying Environmental Impact

Quantifying environmental impact is necessary as it provides the information not only to improve people's understanding of the consequences of emissions and wastes on the environment, but also to assist decision-making during environmental impact reduction through quantitative evaluation and feedback. However, quantifying environmental impact of manufacturing is a complex issue since it needs to quantify the material and energy input into a manufacturing system, and measure the amount of emissions/waste output, as well as the effects of these emissions/wastes on both environment and human health (Nazaroff & Alvarez-Cohen, 2001).

Environmental Impact Control Opportunities

For industrial practice, the fundamental strategy for environmental impact reduction is environmental emission control and impact remediation. Manufacturing emissions are generated from a wide range of manufacturing activities and could be generally categorized into three groups: air emissions, water discharges and solid wastes. Controlling such emissions requires different strategies and techniques. Generally, there are three opportunities for environmental control of emissions and wastes: pollution prevention, “end-of-pipe” control, and environmental restoration, (Nazaroff & Alvarez-Cohen, 2001).

1. Pollution prevention: apply the emission control strategies before and during the emission generating process through such preventive measures as using less materials and energy, employing environmentally benign materials, etc.

2. “End-of-pipe” control: apply the control strategies after the emissions and waste are generated but before they are released into the environment through such techniques as recycling, collection, treatment, etc.

3. Environmental restoration: this is the environmental strategy typically employed to remediate environmental damage after the emissions/waste have been generated and released into the environment. Current environmental restoration strategies are mainly applied on land releases for hazardous waste management and site restoration, some on water treatment and just a few on airborne emission management. Environmental restoration is costly when compared with the other two strategies.

Environmental Impact Characterization Metrics

This approach covers the technology, energy and materials components of a manufacturing system and requires a number of metrics and models to characterize and quantify the environmental impact of manufacturing for pollution prevention practice. The metrics employed for the environmental performance characterization and analysis in this research are described in detail below.

Material Flow Analysis

"Material Flow Analysis" ("MFA") is a methodology developed for quantitative analysis of material flows into and out of a subject system. MFA is a material accounting procedure widely employed in the study of industrial ecology topics (Bouman, Heijungs, Van Der Voet, Jeroen Van Den Bergh, & Huppes, 2000). MFA generally employs a material balance approach for the analysis of material flows within a target system. The MFA target could be a selected substance, a material, a product, an industrial sector, or an economy (Cooper, n.d.). Material flow analysis can be conducted in various scales at international, national, or regional target systems.

Energy Flow Analysis

"Energy flow analysis" ("EFA") is a methodology developed for tracking and understanding the energy flows within a complex system, often for decision support in minimizing the energy consumption of the target system to reduce its environmental impact from fossil fuel energy use. EFA is very similar to MFA as described in the previous section in terms of modeling structure and data acquisition. In a manufacturing system, energy is universally needed to drive machines and operate manufacturing processes. The energy flows within a manufacturing system could be modeled by using an equipment centric approach as described in the literature (Krishnan, et al., 2008).

Risk Assessment

Toxic chemical substances used in product design and manufacturing have significant impact on the environment and human health. The potential impact of toxic chemicals on human health is typically assessed by using a risk assessment method (Ramaswami, Milford, & Small, 2005).

Cost of Ownership

In sustainable manufacturing practice, cost is an important factor to be considered in decision-making for all activities manipulating the components of a manufacturing system. A complete cost analysis needs to be performed frequently in sustainable manufacturing for decision-making since sustainable manufacturing related adjustments either lead to a cost-savings or require extra cost for operations. Decisions have to be made based on the cost and pay-back of the activities prior to the implementation of sustainability programs.

Background of Machine Tools

The faculty of manufacturing has always been based on a skill to produce a desired product and the ease with which such a skill can be manipulated. Traditionally these two aspects of manufacturing were independent entities with the former, i.e. the required skill, being the portfolio of the operator or workman while the later, i.e. available ease, implied a machine tool. The operator was the one responsible to produce the expected results from the machine and it was, as the saying goes, a workman with lesser skills who was at odds with his tools. The operator was therefore selling his skill in the form of a product that has utility for those who can afford it. This pattern of interaction between the manufacturer and end user changed dramatically with the societal conformance to industrialization and increased opportunities for an individual's economic growth. The demand for a product was created because of the ability of a larger part of the society to purchase that product. This meant that the manufacturing faculty was now required to produce not for the manifestation of a skill but for the consumption of a marketplace being governed by the concept of supply and demand. More precise requirements to accommodate more stringent engineering design criteria exposed the operator's skills to inherent limitations of human nature. Also, the awareness within the consumers to get one's money's worth being their right rather than a chance privilege made the industry compliant to the concept of quality that must be guaranteed to the customer.

These changing scenarios influenced not only the broader aspects of manufacturing, i.e. the dynamics of a shift from mere skill or a faculty to an industry that culminated into the concept of a complete system, but also concentrated on the man-machine interface at the shop floor level. It was understood that the process of producing precise profiles depends on the ability to define an accurate tool path around the work piece. The machine itself was more accommodating in providing a mean to this end and accuracy was incorporated into the machine by enhancing its ability to locate the cutting tool more precisely on and along the work piece. This created more sophisticated machine tools that gave more control to the operator to accurately define a profile and then reproduce that shape repeatedly with the same level of accuracy. However, to produce the given part in a greater quantity required better machine utilization and lesser human intervention. Machine utilization required better planning for the jobs which necessitated engineering management approaches that can ensure a smooth flow of inputs through the manufacturing system.

Making machines more independent of the operator's intervention in carrying out the desired operations required making the machine more capable to independently carry out a cut once a tool path has been defined by the operator. Turning operations carried out on lathes are a good example of such capability where once the feed rates have been selected, the tool post can be allowed to move along a defined cutting path (linear, or along a single axis) powered by the main spindle with the depth of cut reset by the operator after each single cut till the desired dimension is achieved (Chapman, 1972. p. 302).

This shift from manual to mechanical powering of the cutting tool path was followed by mechanical automation that allowed automatic tool change and location using a mechanism controlled through cams and follower links. This allowed for automating the manufacture of different commonly used high-volume items that had a compliant profile to the extent that dedication of equipment for a job became possible. An example of such a high-volume common use item is a screw that although comes in a number of different sizes, its manufacturing consists of a given number of well-defined steps; the most basic being turning, shouldering, thread-cutting and finally cutting-off. Screw cutting lathe machines, therefore, became one of the earliest machine tools for automatic profiling of a round stock or raw material (Arnold, 2001). This was an important step in the automation of the machine tools that was, however, subdued because of the limited scope and light nature of work that can be handled, with the major task of shaping complex profiles on difficult work pieces remaining the domain of highly skilled operators that can both set up the job and tooling as well as operate the machine for a given job (Chang, Wysk, & Wang, 2005).

The dawn of the electronic era, however, completely changed the set of possibilities available to the machine tool manufacturers for automating machine tools. The feedback capability of an electronic circuit gave this automation the necessary senses to not only carry out but also control the process of profile generation that was previously impossible using mechanical modes of automation. From hardwired, logically controlled circuits to the more sophisticated and centralized computer-controlled units, the visibility within the entire manufacturing organization was now clear from one end to the other. This was so because the computer on the machine tool can be easily connected to the one controlling other aspects of manufacturing such as planning, purchasing, maintenance, etc. thus making the information generated at any point available to those who are concerned with the process of decision making and operations. This facilitated integration, a concept that literally changed the organizational set up of the modern manufacturing industry.

Computer Numerical Control

Numerical control, the predecessor for CNC machines, is a method of achieving predefined mechanical motion in a machine by the use of a set of instructions in the form of an alphanumeric code (Groover, 2001). This code was digitally translated into electric signals that actuated required motions to perform the desired function, machining in this case, using an electronic processing unit. Thus the control required to position the tool as well as define and maintain the tool path was now fully within the capability of the machine tool itself with minimal, if any, intervention by the operator. A change of job implied changing the set of instructions being fed to the machine tool with the operator being more concerned with loading a punched tape rather than working out a new set up on the machine for a new job. The numerically controlled set up, therefore, consisted of three fundamental components that are briefly defined as follows (Groover & Zimmers, 1984, pp. 135-138):

a) Program of Instructions: The different steps required to carry out a machining operation were coded in the form of a set of alphanumeric instructions known as the program. These instructions were then transferred to a storage medium, generally a punch tape, from where the codes were digitally read into the control unit.

b) "Machine Control Unit" ("MCU"): The control unit consisted of electronics and hardware that step-by-step interpreted the program of instruction into actual operations of the machine tool. The program was read into the buffer memory instruction wise, processed, and the resulting output signals relayed to the servomotors for carrying out the desired motion.

Since the MCU was concerned with controlling the motion of the machine tool, NC systems were classified on the basis of the capability of the controller to position the tool and work piece for the purpose of machining. The two basic types of NC systems are (Hitomi, 1996, pp. 385):

• Point-to-Point or positioning system that was valid for such machining operations as drilling, punching etc. where the machining operation is carried out on a specific location. Thus the trajectory a tool takes to reach that location is of no importance and does not need to be controlled.

• Continuous Path or contouring system required a control on the trajectory of the cutting tool throughout the cutting operation and hence these systems were more sophisticated and expensive than the positioning systems. A series of points were identified on the work piece profile and the path between these points was interpolated either linearly or as a curve, thus defining the required tool trajectory for the cutting operation.

c) Machine Tool: This is the part of the NC system that actually performs the machining operation and contains the worktable, holding mechanism for tool and work piece as well as the driving mechanism. It can also contain a mechanism for automatic tool change to eliminate the necessity for machine stoppage and operator's intervention to change tooling for a given operation or a new job. A control panel was also included with the machine tool, as a built-on or an independent unit, to give necessary control to the operator for such inevitable functions as stopping or starting the machine etc.

NC machining was indeed a great leap forward from the concept of mechanical automation based on cams; however, it was based more on automating the motions of the machine rather than adjusting to the particular machining requirements of a job. This meant that how the instructions were to be converted into machine tool action, the mathematics and logic of the interpretation, came locked in with the particular controller being used – the so called hardwired electronics (Groover & Zimmers, 1984, pp. 204). Any alteration or upgrading of these units was generally not possible and the programs were therefore developed keeping in mind an "as is" scenario. Also the input mode for the NC machines, i.e. a punch-tape reader, was also highly inflexible to any changes that might be necessary to correct or improve the processing output of a machine (Groover & Zimmers, 1984, pp. 203).

Computers brought about a phenomenal change in how the machine control over the tool path could be obtained. The MCU was replaced by a computer in the CNC machines that provided great flexibility to develop, store and edit programs directly at the machine tool site and allowed inclusion of more sophisticated operations (McMahon & Browne, 1998, pp. 382-383). A number of different programs and routines can now be saved on a single computer and were readily available to be loaded as required into the machine tool. With the program of instructions and the controller now combined within the computer peripheral, the machine tool itself started to look for greater possibilities to facilitate automation of different auxiliary operations. These included a number of various features some of which are listed as follows (McMahon and Browne, 1998, pp. 384):

• Tool magazines were provided to hold a large number of tools on the machine. These tools were indexed to be recalled from within the program when required and loaded on the tool post for machining operation without the requirement of machine stoppage for tool change by the operator.

• Pallet loading system was devised to place the work piece along with the necessary fixtures on a pallet that can then be loaded directly on the machine tool table. Once the job was completed the pallet on board is replaced by another one in waiting decreasing the loading/unloading cycle time to a minimum. This also provided the flexibility to machine different parts one after the other by simply changing the program as the work piece gets loaded on the tool.

• Multiple machining spindles were provided on a single machine, known as a machining center, to carry out different natures of operations, such as turning and milling, without the necessity of loading/unloading for work piece movement between different machine tools. This is of great importance in a batch processing set up where requirement to load the job on different machines implies greater work-in-process inventory and hence a greater production planning effort.

Numerical Control: A Historical Perspective

Most of the manufacturing operations up until the middle of the last century were based on traditional machine tools powered generally by electrical supply and controlled mechanically through a system of gears and slides by the operator. Although these machines showed capability to define complex profiles on different types of work pieces, these machines required a highly skilled workforce to operate and a greater level of intervention to set them up for a particular job or machining operation. The machine itself, and also the operator, were becoming a concern for those who wanted to enhance productivity within the manufacturing environment (Kalpakjian & Schmid, 2007, p. 808). The concept of mechanization has been around for some time involving mechanical automation of repeated and simple operations on a machine but complete automation of a machine so that it is independently available to any sort of a machining job, with minimal human intervention and idle time, was still considered an impossible scenario on the shop floor.

Although automation as a concept has been quite awe inspiring in itself, enabling complex sets of operations to be completed on their own in order to provide some tangible output, the concept carried a predefined set of goals for those who were visualizing its possibility in the manufacturing industry; productivity, quality, integration and safety being some of the major ones (Kalpakjian & Schmid, 2007, p. 811). The actual machining time during which a machine tool is involved in processing a job is astonishingly small even if the loading/unloading time for the work piece is not considered. A simple turning operation on a conventional lathe implies that after the roughing cut the machine be stopped, inspection of the cut diameter, setting the tool for the next cut and then starting the machine for the cut. Whether the cut is of one inch in length or ten inches the procedural requirements remain the same. As the final or finishing cut is carried out greater intervention is required, from manual control to physical presence of the operator, to ensure the dimensional accuracy on the work piece. A job can be rendered completely useless because of even a single mistake at any step by the operator.

The nature of job complexity and the production quantity are two conflicting requirements that seldom can be separated for the convenience of the human operator. Jigs and fixtures can be developed for different jobs to facilitate tool location and path for the cutting operation but that added to the cost of the machining operation as well as an extra effort to design and manufacture the jig or fixture. Semi-automatic machine operations were incorporated in conventional machine tools that automated the motion of tool post or worktable for a given single cut. The control was mechanically shifted to the machine tool using gears and shafts once the feed rates and speed for the cut has been set by the operator. The machine itself was becoming more complex and demanding to learn for carrying out the machining process. The control mechanisms have been developed using mechanical engineering practices but the need was to somehow make the machine capable of understanding the processing requirements of a job and then carry out the job independently without the need of the operator to set feeds, locate tool and control the tool path for the cutting operation. Mechanical faculty was practically not equipped to impart such understanding to the machine tool through which the steps of machining can be communicated to the machine.

The answer was electronics. The ability to control the flow of current and voltage through a circuit using electronic devices to generate various output signals that can be electrically sensed and mechanically realized literally changed the perspectives of possibilities in every dimension. From vacuum tubes to transistors to integrated circuits, electronics became synonymous with the term microprocessor that works on the simple principle of data input, data processing, and output. The input can be an entire program of instructions at a computer terminal or a simple click of a button on a TV remote. Once the given input is processed by the electronic circuits the output can be obtained on peripheral screen right in front or as activation of an actuation device placed at a remote location. This was the sort of communication medium that was required to automate the controls of a machine tool so that the required steps of operation can be electronically conveyed to the machine which can generate electrical signals to actuate the control mechanisms on the machine. The beginning of electronically controlling the machine tools was, however, not that exciting as one might have expected after witnessing the present day state of the art technology.

Groover (2001) has provided a detailed account of the historical background that led to the evolution of Numerical Control systems for the purpose of machining operations. The detail has been summarized as follows to highlight the nature of initial efforts and the pioneers of a technology that brought about a revolution in the manufacturing industry (Groover, 2001, pp. 128-129). The pioneering work for the development of Numerical Control started in 1948 and is attributed mainly to John Parson and his association with the United States Air Force. He conceived the idea of using coordinate position data contained on punched cards to define and machine the surface contours of airfoil shapes. After the development work by Parson and his colleagues on their ‘cardamatic’ machine, so named because of the punch card, the idea was presented to the US Air Force in 1948 which signed a contract with Parson in 1949. In the same year Parson subcontracted with the Servomechanism Laboratories at the Massachusetts Institute of Technology (MIT) to carry out research and development work on his cardamatic machine. In order to accommodate required data transfer rates, punch cards were relinquished in favor of punch paper tape and the term ‘Numerical Control’ was adopted in 1951 for a retrofitted Cincinnati Milling Machine Company vertical Hydro-Tel milling machine. This prototype successfully performed simultaneous control of three-axis motion based on coordinate axis data punched binary tape. Although the reaction of machine tool companies to this prototype was not that keen, one company that showed its interest in the MIT work was Giddings and Lewis Machine Tool Company. This resulted in a second prototype which was a significant advancement over the first Servo Lab machine. Later, the US Air Force again came into the limelight by sponsoring development of NC machine tools at several different companies. These

NC machine tools were then used by different aircraft companies between 1958 and 1960. As the advantages of NC machines became apparent and aerospace industries started showing greater interest in their usage, production of NC machine tools gained momentum involving more machine tool manufacturers to join in the research and development work of a burgeoning industry. (Groover, 2001).

One cannot help but notice the role of the defense sector in the rapid growth of the manufacturing industry especially after the end of World War II. It was particularly so because of the advent of the aerospace industry that was at that time more or less confined to pursue the objectives of military defense. To be competitive they needed to work with high strength materials and required profiling with a higher degree of accuracy and reliability (Chang, Wysk, & Wang, 2005, p.452). According to Rachel Schmidt, there were two main reasons for the specific interest in numerical control; firstly, the Air Force was concerned with the lack of capability of the conventional equipment to provide the desirable flexibility and output for aircraft production, and, secondly was the rising cost of wages and shortage of skilled manpower (Schmidt, 1988, p. 5). Although, as mentioned in the quoted text, the initial reaction of machine tool manufacturers was far from eager acceptance, the people associated with the project and their sponsor, i.e. US Air Force, had anticipated the benefits of undertaking Numerical Control as a breakthrough technology. Production jobs that characteristically facilitated the application of NC machine tools as have been identified by Groover and Zimmers, and will be discussed in a later section, included geometric complexity, high metal removal requirements, multiple-operations processing, anticipated engineering design changes in the job, 100% inspection requirements and the frequent small-sized batches for production (Groover and Zimmers, 1984, p. 146).

It was mainly due to the research work carried out at the MIT and the commitment shown by the US Air Force for the pursuance of this project that awareness of the capabilities inherent to the Numerical Control for machine tools disseminated to the machine tool manufacturers. Commercial models of the NC machines were displayed at the National Machine Tool show in 1955, and by 1957 several of these machines were installed for use in industrial applications (Luggen, 1996, p. 21). According to Heinrich Arnold, the years between 1959 and 1965 saw a rapid expansion of the NC machines (Arnold, 2001, pp. 20-21). He emphasized this by stating that the first multifunction, multipurpose machining center appeared in 1958 and by 1960 ninety different models of NC machines were available. He also identified the historical events that led to the motivation of European machine tool industries to embrace the concept of Numerical Control and later in the 1960s, as the computer technology evolved, by the Japanese industries (Arnold, 2001, pp. 17-18). Great Britain (1957) and France (1958) were the first in Europe to produce NC machine tools but commercial production was not initialized till 1960 which took some further four years in taking off (Schmidt, 1988, p. 6).

In spite of the acknowledgement of possibilities associated with Numerical Control in machine tools, a number of challenges still existed for its general acceptance. The problems with conventional NC systems have been outlined by almost every author who has discussed the subject and were indeed important in understanding the events that made the computer a more widely accepted mode to achieve machine tool automation. Groover and Zimmers (1984) have discussed these problems at length and a brief account is listed below as a set of roadblocks in the application viability of this new technology (Groover and Zimmers, 1984, p. 203):

• Elimination of part programming errors in preparing a punch tape was quite cumbersome as well as achieving the best sequence of processing steps.

• Conventional NC machines did allow in-process changes in feed or speed with the programmer forced to go for worst case scenarios. This reduced the productivity level of the machining process.

• Handling and storage of the punch tape was itself a problem.

• The controller was a hard-wired unit whose control features were generally not accessible to a change or update.

• The conventional NC system was inherently stand alone in nature with little or no information regarding operational performance to assist managerial activities at the factory, or even on the shop floor, level.

Most of these problems were solved with the advancement in electronics particularly with the advent of the computer industry. Groover (2001) has again provided some interesting historical notes, which are the main crux of this sub-section, regarding the application of digital computers for Numerical Control (Groover, 2001, pp. 128-129). He reports that the first application of the digital computer for NC processing was to perform part programming. Again MIT coordinated with USAF for research on a computer-aided part programming system with the development of "Automatically Programmed Tools" ("APT") language in the early 1960s. This APT language demonstrated greater flexibility as a medium to develop NC machine tool programs being applicable to virtually every machine tool and meeting the Air Force's specification for up to five-axis control (Schmidt, 1988, pp. 5-6).

As the computers became capable of writing part programs the next logical step was to eliminate the necessity of using a punch tape medium to communicate with the NC system. The concept of Direct Numerical Control (DNC) was conceived in the mid 1960s, in which different NC machine tools were connected to a remote mainframe computer. The instructions were directly transmitted to the individual machine tool in real time from the computer. Two companies that pioneered the development of DNC were General Electric Company and Cincinnati Milling Machine Company. The problems that surfaced were the economic feasibility of a mainframe computer at a company level and the possibility of breakdown of the central computer that could render the entire NC system of a large number of machines completely redundant.

The start of the 1970s brought with it the opportunity of using a dedicated computer at the machine tool level. Use of integrated circuits increased the computational performance while decreasing size and cost associated with the computers. The result was the use of microcomputers as the machine control units for NC machine tools that surpassed the general acceptance of its predecessor DNC in the industrial application arena.

The Proliferation of CNC Machines

Computers are a very powerful tool to process, store and disseminate data. The hardwired electronics of the NC machine were practically no match for the extent of flexibility that was to be afforded by the computers to control the machine tools. The processing capability of the computers was increasing exponentially over time and the size as well as the cost of the circuitry was diminishing at almost a similar rate. However, it was the power of the computers to disseminate the data or information that has defined the nature of opportunities associated with the application of computers within the manufacturing industry. The interaction of computers with other computers and electronic devices for the interchange of relevant information evolved the concept of networking. This interconnectivity potential of the computers led to the possibility of integration of different disciplines, from managerial to actual processing, within the production unit. The entire manufacturing system got streamlined to the concept of automation under the influence of the power of the computers (Groover and Zimmers, 1984).

The hard-wired electronics of the machine control unit were replaced by a computer dedicated to the machine tool. This computer was used to perform the different functions of the numerical control using the software stored in its memory that can be accessed for change (Groover and Zimmers, 1984, p. 205). Tanner (1985) has especially concentrated on the enhanced interactive capability endowed to the CNC system at the man-machine interface for facilitating machine operations. He points out an essential provision of a multifunction screen to display the full operational or parametric data as a part was processed. An alphanumeric keyboard was also provided on many machines to facilitate manual data entry (Tanner, 1985). It is very interesting to note that whatever Tanner (1985) reported as anticipated features in the characteristic details for the future of CNC systems in the 1980s are a part of the current CNC Technology; this included a two or three-dimensional graphical display for viewing tool path and shop-level part programming facility to automatically convert part geometry into cutting tool path. Some of the other characteristic features that differentiated the new CNC technology from the previous units were the ability to store and edit more than one program at the machine tool, execution of high level interpolation schemes for defining tool path, cutter length and size compensation, acceleration/deceleration calculations to avoid sudden feed rate changes, communication interfaces and diagnostics (Groover, 2001, p. 130). The communication interfaces allowed the machine to be linked to other computers and computer driven devices in order to:

a) Download part programs from a central file as encountered in distributed numerical control.

b) Enable data collection related to machine operations such as work piece counts, cycle time and machine utilization.

c) Interface with peripheral equipment such as robots that load/unload parts.

As mentioned before, machine tool manufacturers also concentrated their efforts on the machine tool itself to increase the productivity of the system by making the machine capable of performing a wider range of machining operations with minimum set-up time and set-up changes (McMahon and Browne, 1998, pp. 383-384). Hitomi (1996) has contended that conventional NC/CNC included machines that were intended for a single type of machining operation such as lathe, drilling machine, milling machine etc. (Hitomi, 1996, p. 386). He further states that machining centers, originated by Kearney and Trecker Corporation in 1958, in contrast automatically performed multiple complicated operations on several faces of the work piece employing several axes of control and cutting tools. This allowed for centralizing of several production processes, simplifying process planning and scheduling requirements as well as yielding high utilization of the machine.

As outlined above the shift from the traditional hard-wired Numerical Control to the more flexible Computer Numerical Control resulted in a number of advantages for the operator at the machine level, however, to understand the scope of this technology in the manufacturing industry one needs to evaluate the influence of this technology from a broader perspective. The advantages and limitations of the CNC machine tools are therefore presented in the following paragraphs along with some major application characteristics for the technology that will need to be evaluated for the feasibility of the use of a CNC machine for a particular job.

Advantages and Limitations of CNC Machines

The advantages attributed to CNC machine tools in comparison with their NC counterparts or conventional rivals are listed below:

a) The shift to the software based CNC machines resulted in a reduction and simplification of the hardware circuits with an increased flexibility in controlling the machine operation. Also the availability of diagnostic software allowed for maintenance supervision of the machine (Narayan, Rao, & Sarcar, 2008, p. 273).

b) CNC offers complete control of all axes at all times, ensuring extremely good accuracy and repeatability, under optimum cutting conditions (Narayan, Rao, & Sarcar, 2008, p. 273).

c) The greater potential of the CNC systems to contour complex profiles make them a preferred choice particularly in aerospace, automotive and die/mold making industries. This is so because some form of computerized programming is essential for any three-dimensional tool path generation (Smid, 2003, p. 3).

d) A large number of different parts programs can be stored at the machine site and these programs are accessible at all times for editing, to debug errors or incorporate changes, and loading into the machine control unit. This makes a CNC machine more flexible to changes in engineering design and production schedules (i.e. a change in part).

e) The CNC machining systems allows the interconnectivity of machine peripheral computer with other computers in the factory network to facilitate computerized integration of different departments, i.e. design, production, distribution and management (Kalpakjian and Schmid, 2007, pp. 854).

f) Increased opportunities to accommodate newer manufacturing technologies and strategies that are inherently computer dependent as will be discussed in the next sections.

It must be pointed out that there are many other advantages that are also listed in literature which have not been included in this list, such as reduced skill requirement of the operator, lower scrap rates, lower machine idle time, simpler work and tool holding requirements, etc. This is so because this set of advantages is characteristic of the NC/CNC technology due the same principle of digital automation involved. That is why the disadvantages being discussed below are also somewhat similar to the two concepts. These disadvantages of NC/CNC systems have been discussed by Groover (2001) and are briefly outlined below (Groover, 2001, p. 145):

a) CNC machine tools are capital intensive investments due to specialized requirements of the machine tool, the electronics hardware and software requirements, and other auxiliary features and accessories that have not been associated with the conventional machine tools.

b) Higher maintenance costs and efforts due to the computers and electronics involved that also necessitates including personnel who are trained in maintaining and repairing this type of equipment.

c) Part programming is an added step for processing that is not present in the conventional machining setup.

d) Higher cost of the equipment required that higher machine utilization must be ensured including working in multiple shifts with the requirement for supervision and other support staff.

Applications

Groover (2001) has specified the following part or production characteristics for which the NC/CNC technology is most suitable. These characteristics that make this technology appropriate for low-to-medium production of medium-to-high variety parts are (Groover, 2001, p. 141):

a) Batch production: the production setup involves working in batches of small or medium lot sizes that will be uneconomical for dedicated automation because of the prohibitive cost and manual production will not be able to achieve high productivity levels, comparable to mass production systems, and will increase labor cost, lead time and scrap rate due to higher operator intervention.

b) Repeat orders: there is a tendency of producing same or similar parts in batches at random or periodic intervals requiring frequent job and set up changes. Such changes imply simply changing the part program in the machine control unit.

c) Complex part geometry: profiling of complex curved surfaces is generally not easy to achieve on conventional equipment especially where more than one axis is involved in controlling the tool trajectory.

d) High volume of metal removal: where the volume and weight of the final machined part is a relatively small fraction of the starting block.

e) Multiple machining operations on a single part: parts which require a number of different processing operations and hence different cutting tools and respective setups can benefit a lot from the use of this technology.

f) Expensive parts: when the part is expensive, whether due to a costly raw material or excessive machining requirements, mistakes in machining can render the part useless at the cost of time, effort and money.

NC/CNC technology has been applied to all types of machine tools for cutting operations as well as metal forming and non-machining operations (Groover, 2001, pp. 132-143). Not only the mainstream large scale industries that catered to the production of high-end engineering products, such as aerospace and automotive sectors, got involved in the application of CNC technology but also the auxiliary industrial sector, known as the vendor industry, was quick to join in for accommodating the requirements of their parent sectors. The accuracy and repeatability potential of CNC machine tools rendered them more suitable to facilitate technologically advanced trends in machining operations while maintaining high standards of product quality. The machine tool productivity for the machining processes was greatly increased due to minimal requirements for jigs or fixtures to facilitate work piece/tool holding or positioning and lesser requirements for setup changes needed to perform different types of machining operations. As machining centers, productivity and machine utilization got further enhanced, due to their ability to perform a number of different operations without a need to reposition the work piece, making the machine more accommodative to automatic loading/unloading of different parts and even jobs without the need for human intervention was made possible.

This meant that one of the main objectives of computerized automation of machine tools, i.e. to make the output productivity of batch-type production at par with that expected from a mass production system using dedicated machines and layout, was now a perceivable reality (Hitomi, 1996, p. 390). Economically feasible applications of CNC machine tools implied developing smart strategies to modernize the managerial agenda of a manufacturing organization. The recent time has been a witness to large scale organizational restructuring of manufacturing industries in order to maximize their benefits of shifting to CNC machine tools from their conventional or NC counterparts, a phenomenon that in its own self defined the strategic advantage and competitive survival of today's manufacturing industry.

Technology Trends Complementing CNC Proliferation

Krar and Gill, (2003) have given a detailed account of the different advanced manufacturing technologies that have developed in recent times. Although they have dealt with each of them as a separate entity most of these are associated with Computer Numerical Control in one way or the other and have paved numerous opportunities for the proliferation of CNC machine tools and systems. These technologies are briefly discussed in this section, mainly adopted from Krar and Gill (2003) to elaborate how Computer Numerical Control machining has become a common denominator in nearly all aspects of manufacturing operations at the very basic level of the machine tool itself.

a) "High Speed Machining" ("HSM"): according to Krar and Gill (2003) the speeds involved in high speed machining (HSM) can make CNC machine centers compete with a dedicated manufacturing system, such as mass production transfer lines, by delivering such benefits as:

   i. Producing more parts than are possible with conventional feed rates and spindle speeds.
   ii. Better surface finish can be achieved due to lighter cuts eliminating the need for a finishing operation like grinding.
   iii. Lighter depth of cut reduces the possibility of warping in large work pieces that present high-volume material removal requirements as is prevalent in the aerospace industry.
   iv. Production of a single complex part facilitates design integration.

Pasko, Przybylski, and Slodki (2005, pp. 2-3) have reported that there are three main categories of industrial sector using HSM due to their specific requirements; these categories are:

• Machining of non-ferrous parts, mainly aluminum, for use in automotive components, small computer parts or medical devices because of the need for high metal removal rates. High rate of material removal is a characteristic requirement for those jobs that require many machining operations.

• Aerospace industry that involve machining of long aluminum parts with thin cross-section. The requirement characteristics for this category are high volume of material removal and accuracy.

• Die mold industry where working with hard materials requiring high accuracy and finish from processing operations is a normal procedure.

b) Combination tools: in order to increase productivity at the machine level, CNC machining centers have a great potential to use special tools that can combine more than one operation and operational steps into a single tool thus reducing time required to prepare the machine tool for each individual operation. These tools are inherently CNC dependent by virtue of exploiting the CNC capabilities for helical interpolation.

c) Non-Cartesian machines: as the name indicates, non-Cartesian machines have a positioning system that is not based on three different axes for the machine worktable. Instead of the conventional design of three drives placed one on top of each other to achieve target position through individual motion of each slide in a Cartesian coordinate (X-, Y- and Z-axes) workspace that promotes cumulative error, these machines are developed on a hexapod design consisting of triangular linkages that provides a literally floating worktable similar to the concept of Stewart Platform employed in flight simulators (Bray, 2002).

CNC and Factory Automation

The use of NC and CNC techniques allows the introduction of sophisticated automation that has contributed in the implementation of a number of modern manufacturing strategies at the plant or factory level (Beddoes & Bibby, 1999, p. 223). These are briefly discussed as follows:

a) Cellular manufacturing: cellular manufacturing is related to the switch from the functional plant layout, characterized by similar machines grouped together, to layout based on group technology. In this layout parts can be divided into groups on the basis of similarity in features or processing requirements, and the equipment needed to carry out all those operations are grouped together to facilitate ease of part flow and process control (McMahon and Browne, 1998, p. 427). CNC technology allows full automation of part production as well as greater coordination with auxiliary equipment to minimize the supervisory requirements of a given cell. Thus manufacturing cells can be made flexible, to a greater product variety and smaller lot sizes, in a practically unmanned, highly automated environment (Kalpakjian and Schmid, 2007, p. 873).

b) “Flexible Manufacturing System” (“FMS”): FMS allows the integration of different activities related to manufacturing into a highly automated system (Kalpakjian and Schmid, 2007, p. 874). This is based on automated manufacturing cells consisting of CNC machine tools and equipment as well as an automated material handling system that can be interconnected to handle a large part variety irrespective of the order of production of the various parts. The control of the production process is concentrated on the production of a part rather than providing a route to an entire batch of a given part through the manufacturing system.

c) Computer Aided Design and Manufacture: the influence of computers in the manufacturing industry was not restricted to only the processing aspect but also was rapidly gaining acceptance in other activities related to the product development activities. Design of products was now not a cumbersome activity involving sheets and sheets of papers to convey the engineering and processing requirements to a large number of people with a varying level of understanding. Virtual models of the product can now be built on computers that communicated the design intent in a more accessible and understandable manner to all concerned and these models can be validated for design intent using simulation software. Once validated, these models can generate the engineering drawings that will be used by the process department to generate part program for the CNC machine tools.

d) "Computer Integrated Manufacturing" ("CIM"): since every aspect of manufacturing was now being automated through the use of computers, it was becoming more and more logical to integrate the different departments involved in the manufacturing activities, from design to production and ultimate marketing of the product (Kalpakjian and Schmid, 2007, p. 854). These departments have traditionally been islands of individual responsibilities and relevant information was used to travel in a sequential or "over-the-wall" manner between them. CIM is a methodology that provided a centralized information processing facility through the interconnection of a network of computers such that the entire status of each job or event can be updated and communicated on a real-time basis. Thus as a design engineer completes the formalities related to the design task, the material and processing requirements will be generated and communicated through the information system to the relevant departments.

CNC machine tools have greatly influenced the concept of automation not only at the shop floor level but throughout the entire manufacturing system. These machines have a great potential to incorporate different advanced machining technologies to increase their competitive advantage over conventional machining processes as well as making them suitable for a larger set of complicated machining applications. It can be confidently concluded that the potential of CNC machine tools will increase and develop in future, due to the powerful impact of computers on the automation and integration of manufacturing activities, as well as their accessibility for a wider set of application areas.

The final goal of manufacturing is to create products rapidly, economically, and with high quality. CNC machines are widely used in the metal cutting industry to achieve this goal while maintaining flexible production. Although the advent of CNC in the cutting industry has given many conveniences and benefits, CNC still has many limits. For example, contemporary CNC machines often cannot anticipate the problems caused by unexpected changes in the work piece. Consequently, much research has been done to develop techniques to respond to these changes.

While in the process of metal cutting operations, if a tool fails it may harm the tool holder, the work piece, or the machine elements. Also, as machining continues and the cutting tool begins to wear, the surface quality and the dimensional correctness of the product degrade. Furthermore, tool cracking may put the operator in danger from a safety perspective, or may cause a problem in the manufacturing system.

In turning operations especially, unexpected changes in the work piece material properties can have significant negative effects on the efficiency of the operation and quality of the product. Variations in work piece hardness and dimensions can cause variation in cutting forces, which can then lead to accelerated tool wear and even breakage. Such problems can be overcome during CNC operations by measuring the variation in hardness in the work piece and adjusting the cutting conditions to account for increased forces. However, there are limitations to in-process measurements of material hardness. Conventional hardness measurement devices require contact with the material being measured, which can be time-consuming and may damage the work piece. A method to detect variations in work piece hardness that does not rely on contact could preserve tool life without costing additional time or creating damage in the work piece. Theoretically, the spindle power required for turning operations in hard materials is higher than that required for soft materials. Therefore, a power sensor provides a novel means of detecting hardness changes in the work material without affecting the cutting process.

Adaptive Control of Machine Tools

The use of “Adaptive Control” (“AC”), to optimize production rate and product quality as well as to minimize cost, is a logical extension of the above described CNC systems (Arnone, 1998). According to Colwell, Frederick, and Quackenbush (1969), “throughout the nineteenth century and for more than half of the twentieth, adaptive control has been entirely dependent upon the skill of machine tool operators” (p. iii). The authors describe what followed as a “frantic "grasping for straws" in the search for automatic, instrumented, or mechanized adaptive control to solve the unpredictable problems which occur in manufacturing.” (p. iii).

AC allows the machine to automatically adapt the operating parameters to conform to newer circumstances (Kalpakjian and Schmid, 2007). Drozda & Wick define “adaptive control” as a “method using automatic means to change the type and/or influence of control parameters to achieve near optimum processing performance (1983, p. 5-70). Davim (2008, p. 330) describes AC this way:

An adaptively controlled machine is able to adapt to the dynamic changes of the system caused by the variability of machining process due to changes in the cutting conditions such as the hardness of the work material, tool wear, deflection of the tool and the work piece, and so on.

Davim (2008, pp. 330-331) goes on to explain the main objectives of an adaptive control system as:

1. to adjust the machining parameters such as cutting speeds and feed rates and/or the motion of the cutter to optimize the machining process by maximizing some performance criteria based on the cost or the production;
2. to satisfy various constraints against variations due to external factors and respond to such variations in the process in real time;
3. to automatically improve the performance of the machining process through its learning capability.

Chapman (2004, p. 236) describes AC as a "special feature that allows for the control to automatically override the programmed feed rate under certain conditions." Chapman goes on to say that "the programmer specifies the desired cutting parameters (speed, feed, etc.) and while the machine is executing the program the control monitors the cutting load on the tool and automatically reduces the feed rate if the load becomes too high." (p. 236).

Jain and de Silva (1999) note that AC has been "extensively used in several industries including chemical, aerospace, automotive, and pulp and paper." (p. 30). Youssef and El-Hofy (2008, p. 621) describe three types of AC as:

1. *Adaptive control with optimization (ACO),* in which an economic index of performance is used to optimize the process using online measurements. This strategy may involve maximizing material removal rate or improving surface quality.
2. *Adaptive control with constraints (ACC),* in which the process is controlled using online measurements to maintain a particular process constraint (force, power, temperature, and so on). If the cutting force and hence the torque increases excessively, the AC system changes the speed or the feed (cutter travel), to lower the cutting force to an acceptable level. Without AC or without direct intervention of the operator (in case of conventional machining), high cutting forces may cause the tools to chip or break, or the work piece to deflect or distort excessively. As a result the accuracy and surface finish would deteriorate.
3. *Geometric adaptive control (GAC),* in which the process is controlled using online measurements to maintain desired dimensional accuracy or surface finish.

Summary

This chapter has provided a thorough review of the literature pertaining to sustainable manufacturing, a rich background of machine tools, the history of computer numerical control as it pertains to machine tools, and lastly "adaptive control" as it pertains to machine tools. In the AC literature specifically, examples discussed to date suggest AC is useful in controlling work piece dimensions, the surface finish of the work piece, and the cycle time associated with machining the work piece. However, there is paucity in the literature related to how "adaptive control" might be employed to reduce the amount of energy consumed by machine tools in manufacturing. The next chapter will present the research methodology that the researcher used to carry out the study to explore the aforementioned paucity.

CHAPTER III

METHODOLOGY

Introduction

The previous chapter presented a review of the relevant literature pertaining to sustainable manufacturing, machine tools, computer numerical control, and adaptive control. The purpose of this chapter is to outline the study that was conducted to examine what factors might impact the energy efficiency of a machine in terms of reducing the amount of energy used when the machine is performing a programmed operation. It was envisioned that multiple factors may contribute to this measure of energy efficiency and they are addressed both individually and in combination or interaction with each other. The influencing independent variables studied were adaptive control, feed rate, spindle speed, depth of cut, coolant temperature, coolant flow volume, and tool condition. The research design and methodology that the researcher utilized in carrying out the study is outlined.

Data Collection

The researcher secured permission to collect the required data in an actual production environment at one of the factories that the researcher had management oversight of. The lathe chosen to be used in this research project was an Okuma LC40-2ST CNC (computer numeric control) turret lathe. A picture is provided below (Figure 1).

Figure 1. Okuma LC40-2ST CNC.

The lathe is programmed manually by a CNC programmer to generate the desired finished part geometry, while using the desired parameter values. Parameter values determine how quickly material is removed from the work piece. Feed rate is programmed in inches per revolution, and it describes the advancement of the tool in the direction of cutting; spindle speed is programmed in revolutions per minute, and describes the rate of rotation of the work piece; depth of cut is programmed in inches, and determines the amount of material removed from the surface of the work piece with each cutting pass. Additional parameters investigated as mentioned above were coolant flow volume, coolant temperature, tool condition, and adaptive control.

Each of the aforementioned parameters was set at two distinct levels during the study. “Adaptive Control” was programmed to be “on” 50% of the time and “off” the other 50% of the time. All of the other parameters listed above were programmed at a “high” level 50% of the time and a “low” level 50% of the time. Machining experts determined the exact ranges of "high" and low for each parameter taking into consideration the limits of the machine, tooling, and work piece. The ranges were sufficient to assure a distinctive difference as judged by the machining experts. It was hypothesized that adjusting the above parameters this way would impact the amount of energy required to complete the programmed operation. Tool wear and Adaptive Control were varied across two levels for all of the machine runs, but the other variables were varied on a level different than a standard machine level. Spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume were tested one variable at a time, and not within the same machine runs. A sample of "standard" runs using the typical program set-up to machine these specific parts in normal production, were collected, and then a sample of each of the following was collected: higher spindle speed runs, higher feed rate runs, smaller depth of cut runs, lower coolant temperature runs, and lower coolant flow volume runs. There were not any machine runs that mixed different levels of these variables at one time. The below figure pictorially displays the above described research model as framed:

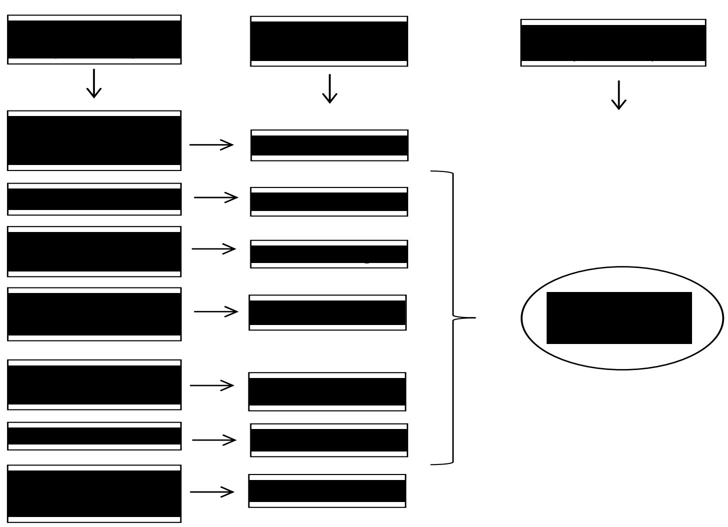

Figure 2. Planned research model.

Work pieces

The work pieces used for this research were forged steel (Grade 43400). The work pieces were heat treated to a Rockwell hardness range of RC 27 to 35. Their initial geometry is cylindrical, with outside diameter 6-7/8" and inside diameter 3". One end of the cylinder is open, while the other is closed. The diameter surface is roughly 16" long, the 'shoulder' is roughly 2-1/2" long, and the constant-diameter surface at the closed end of the work piece is roughly 2" long. A drawing of a typical work piece is shown below.

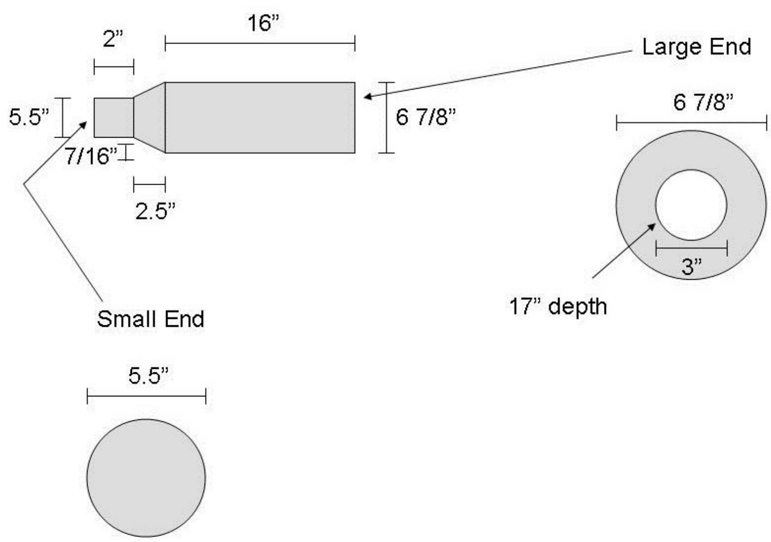

Figure 3. Work piece sketch.

Data Collection

The data collected for the study was done in a real production environment across 300 machine "runs" over a period of seven days. The data was collected over multiple shifts on multiple days. Machine operators never knew which variables were adjusted during any of the so called "runs" in order to prevent operator bias. The table below displays the frequencies for each level of the influencing variables.

Table 1

Base sizes of the sample population

Number of "runs"	N
Low Spindle Speed	50
High Spindle Speed	50
Low Feed Rate	50
High Feed Rate	50
Small Depth of Cut	50
Large Depth of Cut	50
Low Coolant Temperature	50
High Coolant Flow Volume	50
Adaptive Control On	150
Adaptive Control Off	150
Tool Condition New	150
Tool Condition Worn	150

Proposed Research Questions

The following questions were examined during this study:

1) Are there significant differences in energy used based on levels of the independent controlling variables in predicting energy used?
2) Do the independent variables described above have a relationship with energy used?
3) Can a predictive model using these variables be built that will explain a significant amount of the variability in energy used, and provide an accurate prediction given the set of parameters?

4) Does adaptive control or tool condition interact with the other independent variables when investigating the relationship with energy used?

Proposed Null and Alternative Hypotheses

The influencing variables of spindle speed, feed rate, depth of cut, coolant temperature, and flow volume were compared one level against a standard program one variable at a time. That is, spindle speed was adjusted to a higher level for some runs and a lower level for some runs while the other variables remained constant or standard. This produced a sub-sample of the total runs that were directly measuring spindle speed.

Since the main objective is to understand the influence that the independent variables had on energy used, a series of t-test mean comparisons were conducted first to compare the energy used averages for varying levels of spindle speed, feed rate, depth of cut, coolant temperature, flow volume, adaptive control and tool condition. Since adaptive control and tool condition was collected across all runs (on/off, new/worn), it is possible that the effects that they have on energy used may have been hindered by the fluctuations across the spindle speed, feed rate, depth of cut, coolant temperature, and flow volume levels. Adaptive control and tool condition effects on energy used were also studied within a subsample of standard runs when there were no other variables being manipulated. The following hypotheses were tested to learn what levels of the independent variables had the greatest average energy score differences:

H_{01}: There will not be any significant mean score differences on energy used between levels of the independent variables.

H_{A1}: The levels of the independent variables will be found to have significant energy used mean score differences, and therefore the independent variables will be significant influencers of energy used.

Beyond the mean comparisons, analysis was also conducted to investigate the relationships across the variables. Conducting a regression analysis model on the total sample of runs was not possible since several of the independent variables were tested only among a subset of runs so there is systematic missing data within each run. However, models were analyzed on each of the five sub-samples. Additionally, the interaction effects between spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume with adaptive control and tool condition were investigated. Regression analysis tables are reported that include correlation coefficients between the variables, the model ANOVA table, a summary of the regression model, and the regression coefficient tables with weights and significance levels of the variables.

Since it was believed that each of the independent variables would have an influence on energy used, all of the influencing variables were investigated in terms of their relationship with energy efficiency. The following hypotheses were tested through a correlation analysis to understand the relationship between the influencing variables and the measure of energy efficiency:

H_{02}: There is no statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.

H_{A2}: There is a statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.

In order to more fully understand the independent variables and their potential influence on energy efficiency, a predictive model was built using all the influencing variables as dichotomous variables predicting energy used. The regression output yielded significance levels and weights to formulate a prediction for energy used. The magnitude and significance of these weights aid in determining the potential influence each variable had in a combined model of energy used. The following hypotheses addressed the expectations of the influencing variables' predictive power:

H_{03}: There is no statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

H_{A3}: There is a statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

Additionally, the levels of interaction among the independent variables were investigated. Two-way independent variable combinations or interactions were investigated between adaptive control and spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume; and also between tool condition and spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume. The effects of the interactions were studied in terms of their ability to aid in the prediction of energy used.

It was hypothesized that the independent variables may interact in a meaningful way and contribute to explaining variation in energy used. The following hypotheses were tested.

H_{04}: Independent variables will not be correlated significantly and will not produce statistically significant interaction effects in the energy regression models.

H_{A4}: Independent variables will significantly inter-correlated, and there will be statistically significant interaction effects in the energy regression models.

Summary of Hypotheses Testing

The following table depicts the type of data analysis performed for each of the respective hypotheses presented in this chapter. The results of these tests are presented in the next chapter.

Table 2

Summary of hypotheses tests

Hypothesis	Description	Planned Test
1	Investigating the average energy used scores across the levels of the independent variables. Adaptive control and tool condition were investigated in total, on a sub-sample of standard runs, and within levels of spindle speed, feed rate, depth of cut, coolant temperature, and flow volume.	T-test
2	Investigating the relationship between 7 independent variables (adaptive control, feed rate, spindle speed, depth of cut, coolant temperature, coolant flow volume, and tool condition) with energy used during a machining cycle.	Correlation
3	Investigating the ability to build a significant predictive model of energy used from the independent variable sub-samples.	Regression
4	Investigating the relationship between the levels of the influencing variables to understand any potential interaction effect among adaptive control and tool condition with spindle speed, feed rate, depth of cut, coolant temperature, and flow volume.	Regression

Selection of Alpha

Alpha is the probability of committing a Type I error – that is rejecting the null hypothesis, H_0, when it is true. The alpha for this study is set to 0.05 – that is the 5 percent level. This level was chosen in order to obtain a 95% confidence which the researcher determined to be the appropriate confidence level for this study. A higher level of confidence was determined not to be needed and would have required more samples which would have cost additional money to collect. Had this study focused on product geometries and dimensional accuracy viewed as critical, a higher confidence level would have been chosen.

Statistical Assumptions

Assumptions regarding the sample population include:

1. Normality. The population of values for each combination of independent variables is normally distributed.
2. Equal Variances. The populations in Assumption 1 all have the same variance.
3. Independence. The dependent variables used in the analyses are independent. This typically means that each observed y value must be from a separate subject or entity.

Summary

This chapter began by presenting the framework for the proposed study designed to examine the influencing variables on energy efficiency, specifically the amount of energy used during machining. The null and alternative hypotheses that the researcher explored were presented. The next chapter will present the analysis of the data and the resultant findings from the tests conducted.

CHAPTER IV

ANALYSIS

Introduction

The previous chapter presented the framework for the research study as well as the research design and methodology that the researcher employed in carrying out the study. The respective research questions and hypotheses were outlined. The profile of the data was presented. This chapter will present the analysis results from the statistical tests conducted as it pertains to the hypotheses presented.

Data Description

As was described in the previous chapter, the data collected for the study was done in a real production environment across 300 machine "runs" over multiple shifts on multiple days. Machine operators never knew which variables were adjusted during any of the so called "runs" in order to prevent operator bias. Adaptive control and tool condition varied on two levels across all 300 machine runs. The other independent variables varied on one level versus a standard program. For data coding in SPSS, the following codes were used:

Adaptive Control: 1 = "on"; 2 = "off"

Tool Condition: 1 = new edge (first fifteen cuts); 2 = worn edge (all cuts after fifteen)

Spindle Speed: 1 = Low (800 revolutions per minute – "RPM"); 2 = High (1000 RPM);

Feed Rate: 1 = Low (381 mm per revolution); 2 = High (419 mm per revolution)

Depth of Cut: 1 = Low (2mm); 2 = High (4mm)

Coolant Temp: 1 = Low (ambient temperature less 10°); 2 = High (ambient temperature)

Coolant Volume: 1 = Low (one gallon per minute); 2 = High (four gallons per minute)

The tables below show the pairings of those levels with the standard program machine runs.

Table 3

Independent Variable Pairings

Adaptive Control	N
Adaptive Control On	150
Adaptive Control Off	150

Tool Condition	N
Tool Condition New	150
Tool Condition Worn	150

Spindle Speed	N
(A)Standard Program	50
(B)Higher Spindle Speed	50

Feed Rate	N
(A)Standard Program	50
(C)Higher Feed Rate	50

Depth of Cut	N
(A)Standard Program	50
(D)Smaller Depth of Cut	50

Coolant Temperature	N
(A)Standard Program	50
(E)Lower Coolant Temperature	50

Coolant Flow Volume	N
(A)Standard Program	50
(F)Lower Coolant Flow Volume	50

In terms of the dependent variable, power used, the table below displays the base, range, average and standard deviation.

Descriptive Statistics

Table 4

Dependent Variable Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness
Power Used	300	131.7	720.1	360.4	153.2	.564

The dependent variable, power used, median's value was 340.6, which is slightly lower than the mean indicating there is some positive skewness in the variable. The chart below illustrates that there is a large amount of runs that were in a 200-250 watt hours range and only a few runs over 700 watt hours.

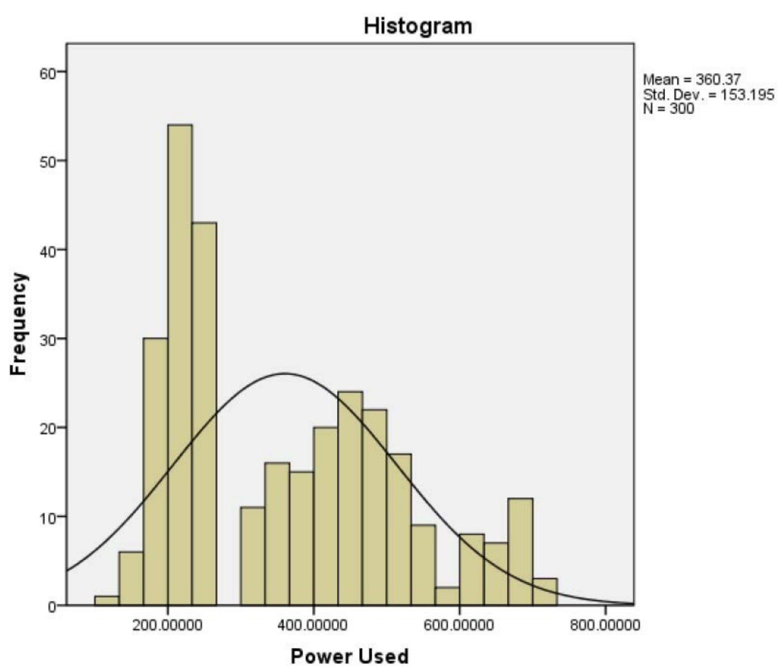

Figure 4. Histogram of Dependent Variable "Energy Used".

According to von Hippel, "since many statistical inferences assume that variables are symmetrically or even normally distributed, those inferences can be inaccurate if applied to a variable that is skewed" (as cited in Lovric, 2010, p. 1341). Von Hippel goes on to say that "inferences grow more accurate as the sample size grows, with the required sample size depending on the amount of skew and the desired level of accuracy" (as cited in Lovric, 2010, p. 1341). Since, as previously reported above, the alpha for this study was set to 0.05 in order to obtain a 95% confidence level. Von Hippel states that for a 95% confidence level, "a sample of fifty observations should be plenty even if the skew is as large as 2 or -2" (as cited in Lovric, 2010, p. 1342). As seen in Table 4 above, the skewness value for this sample was only 0.564 and the sample size was 300, therefore the inferences drawn from the analysis presented below can be viewed as accurate, despite the small amount of skewness.

Tests of the Hypotheses

As noted in the previous chapter, the first research question to be examined was whether or not there are statistically significant differences in energy used based on levels of the independent controlling variables in predicting energy used. It was hypothesized that energy used would be significantly different within levels of adaptive control, tool condition, spindle speed, feed rate, depth of cut, coolant temperature, and flow volume. The null hypothesis to be tested is:

H_{01}: $\mu 1 = \mu 2$ There will not be a statistically significant difference in mean scores on energy used between levels of the independent variables.

$H_{A1:}$ $\mu 1 \neq \mu 2$ There will be a statistically significant difference in mean scores on energy used between levels of the independent variables.

The tables below display the results of the t-tests of significance on these variables.

Table 5

Independent Variable T-test Statistics

	Adaptive Control	N	Mean	Std. Deviation	t-value	sig
Power Used	1.00 AC off	150	396.9	162.4	4.246	<.0001
	2.00 AC on	150	323.8	134.2		

	Tool Condition	N	Mean	Std. Deviation	t-value	sig
Power Used	1.00 Worn edge	150	368.4	156.8	0.906	0.366
	2.00 New Edge	150	352.4	149.6		

	Feed Rate	N	Mean	Std. Deviation	t-value	sig
Power Used	(A)Standard Program	50	453.0	91.1	-0.154	0.878
	(C)Higher Feed Rate	50	455.3	56.6		

	Spindle Speed	N	Mean	Std. Deviation	t-value	sig
Power Used	(A)Standard Program	50	453.0	91.1	-5.737	<.000
	(B)Higher Spindle Speed	50	563.3	113.1		

	Depth of Cut	N	Mean	Std. Deviation	t-value	sig
Power Used	(A)Standard Program	50	453.0	91.1	12.105	<.000
	(D)Smaller Depth of Cut	50	265.2	61.1		

	Coolant Temperature	N	Mean	Std. Deviation	t-value	sig
Power Used	(A)Standard Program	50	453.0	91.1	17.776	<.000
	(E)Lower Coolant Temperature	50	218.2	20.8		

	Coolant Flow	N	Mean	Std. Deviation	t-value	sig
Power Used	(A)Standard Program	50	453.0	91.1	18.118	<.000
	(F)Lower Coolant Flow Volume	50	207.1	30.2		

The results suggest that Adaptive Control achieved statistically significant mean differences on power use along independent variables of Spindle Speed, Depth of Cut, Coolant Temperature, and Coolant Flow while Tool Condition and Feed Rate did not. The table below summarizes whether or not the null hypothesis was rejected or failed to be rejected for each variable:

Table 6

Independent Variables Effect on Energy Used

Significantly less energy used:	**No significant difference on energy**
Adaptive Control On – rejected null *Lower Spindle Speed – rejected null* *Smaller Depth of Cut – rejected null* *Lower Coolant Temperature – rejected null* *Lower Coolant Volume – rejected null*	*Tool Condition - failed to reject the null* *Feed Rate - failed to reject the null*

Since many of the variables can fluctuate within levels of adaptive control and tool condition, adaptive control and tool condition can be analyzed within standard runs in order to more clearly measure their unique effects on energy. There were 50 standard runs within the sample. The following table displays and tests the energy scores within levels of adaptive control and tool condition on this sub-sample.

Table 7

Energy Used comparison within levels of Adaptive Control and Tool Condition

Adaptive Control		N	Mean	Std. Deviation
Power Used	1.00 AC off	25	434.1	93.2
	2.00 AC on	25	472.0	86.6

Difference *-37.9*

t=-1.489 *sig =.143*

Tool Condition		N	Mean	Std. Deviation
Power Used	1.00 Worn edge	25	468.6	96.0
	2.00 New edge	25	437.4	84.9

Difference *31.2*

t=-1.218 *sig =.229*

The above results reflect that there is no statistically significant energy difference among levels of tool condition and adaptive control, thus failure to reject the null hypothesis. There is a difference in energy averages when adaptive control is "on" versus "off" among the standard programs, but in a different direction than previously found across all runs when the other variables were allowed to fluctuate. In total, within the 150 runs where Adaptive Control was turned "on", the amount of power used was significantly lower than in the 150 runs when Adaptive Control was "off". In this case, the null hypothesis was rejected. Among the standard runs, when Adaptive Control is "on", the amount of power used is higher, although this difference is not statistically significant, thus failure to reject the null hypothesis. When the other independent variables were not allowed to fluctuate, as isolated in the standard runs, the results indicate that Adaptive Control would negatively impact the amount of energy. However, as the results above reflect, Adaptive Control's relationship with five of the independent variables indicates it can be an efficient controlling variable of power used.

The second hypothesis moves beyond the group mean differences to investigate the relationship between the influencing variables and energy used. Given the results of the t-test on differences by the levels of the independent variables, it was hypothesized that there would be a significantly linear relationship between the independent variables and the dependent variable of energy used. The null hypothesis from Chapter 3 states:

> H_{02}: $\beta_j = 0$ There is no statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.
>
> H_{A2}: $\beta_j \neq 0$ There is a statistically significant direct relationship between the influencing variables and the amounts of energy used during a machining cycle.

The relationship is measured through a Pearson Product Moment Coefficient, reflected in the below table displaying the resulting relationships (r-value), with corresponding significance levels (p-values). A full correlation matrix among the variables can be found in Appendix A.

Table 8

Correlations between independent variables and energy used

	Among Total Sample (n=300)		Isolated correlation between standard program and test program (n=100)		
Power Used	r	p-value	r	p-value	
Spindle Speed	.593	< .000	**.477**	< .000	*Higher Spindle Speed/More Energy Used*
Feed Rate	.278	< .000	.016	.878	
Depth of Cut	.278	< .000	**.774**	< .000	*Higher Depth of Cut/Higher Energy Used*
Coolant Temp	.416	< .000	**.874**	< .000	*Higher Coolant Temperature/Higher Energy Used*
Coolant Volume	.448	< .000	**.878**	< .000	*Higher Coolant Flow Volume/Higher Energy Used*
Adaptive Control	**-.239**	< .000			*Adaptive Control On/Lower Energy Used*
Tool Condition	-.052	.366			

The correlation between Adaptive Control and energy used is significant and negative, implying that when Adaptive Control is "on", the amount of energy being used is lower, thus the null hypothesis is rejected. If the correlation between Adaptive Control and energy used is calculated only among the 50 standard machine runs, it is an opposite direction, (r=.210/p=.143), implying that when Adaptive Control is "on", energy used is higher, although this relationship is not significantly different from no correlation and the null hypothesis could not be rejected, similar to what was found in the comparison of mean scores on power used by Adaptive Control levels.

The variables spindle speed, depth of cut, coolant temperature and coolant flow volume show positive correlation values with energy used, with coolant temperature and volume having the strongest relationship with power used. (r= .874, and r= .878, respectively), so the null hypothesis is rejected for each. The magnitude of these correlations suggests that lower coolant temperature and lower coolant flow volume have a strong relationship with lower amounts of energy used. Conversely, feed rate was not found to have a significant correlation thus the null could not be rejected for this variable.

In order to better understand the relationships between these variables and the effects on energy used, the next hypotheses measured the predictability of energy used among these variables in five separate data sub-sets. Since spindle speed, feed rate, depth of cut, coolant temperature, and flow volume were not varied within the same machine run, there is a valid set of runs for each of these variables. Since adaptive control and tool condition was collected across all machine runs, they can be included in each sub-set of data. Each of these subsets is defined below:

Table 9

Predictability of Energy Used Subsets

Sub-sample Definitions		Base
1 (Program A and B)	Spindle Speed/Adaptive control/Tool condition	100
2 (Program A and C)	Feed Rate/Adaptive control/Tool condition	100
3 (Program A and D)	Depth of Cut/Adaptive control/Tool condition	100
4 (Program A and E)	Coolant Temperature/Adaptive control/Tool condition	100
5 (Program A and F)	Coolant Volume/Adaptive control/Tool condition	100

Hypotheses 3 and 4 will be tested within each of these sub-samples. Hypothesis 3 will be testing the relationship of the independent variables in a regression model of energy used, and hypothesis 4 will test if there are significant interaction effects among the variables in the regression model. The results will be presented together by sub-sample, and full regression tables are displayed in Appendix B. Hypothesis 3 from Chapter 3 is restated here:

H_{03}: There is no statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

H_{A3}: There is a statistically significant predictive model that will show a direct linear relationship between influencing variables and energy used.

A mathematical equation representing hypothesis 3 would look like this:

$$\gamma_{(V1)} = \beta_0+\beta X_{AC}+\beta X_{V2}+\beta X_{V3}+\beta X_{V(2, 3)}+e$$

Rephrasing the third hypothesis by incorporating the specific variables would look like this:

H_{03}: Machine runs with or without Adaptive Control, Spindle Speed (V2), Tool Condition (V3), and AC Spindle Interaction ($V_{(2, 3)}$) will *not* significantly explain the variance in Energy Consumption (V1).

H_{A3}: Machine runs with or without Adaptive Control, Spindle Speed (V2), Tool Condition (V3), and AC Spindle Interaction ($V_{(2, 3)}$) will significantly explain the variance in Energy Consumption (V1).

The first sub-sample tested uses spindle speed, along with adaptive control and tool condition, and the interaction between adaptive control and spindle speed to predict energy used. The F-value of the regression model is significant (F=45.052/sig.<.000) thus the null hypothesis is rejected and the alternative hypothesis would be tenable, and the R-square value is fairly high (R-square=.655). Within this sample of 100 machine runs, about 66% of the variation in energy used can be explained by spindle speed, adaptive control, tool condition and the interactions among these variables. The table below displays the regression coefficients and their significance to the overall energy model.

Table 10

Regression Analysis of Spindle Speed/Adaptive control/Tool condition

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-36.667	74.121		-.495	.622
	Spindle Speed	472.200	44.215	2.042	**10.680**	**.000**
	Adaptive Control	278.140	44.176	1.203	**6.296**	**.000**
	Tool Condition	-25.229	13.998	-.109	-1.802	.075
	AC Spindle Interaction	-241.254	27.973	-2.273	**-8.625**	**.000**

The table shows that adaptive control, spindle speed, and the interaction of these 2 variables are significant predictors of energy used. The significant interaction implies that the combination of these 2 variables help predict the amount of energy used. The interaction is calculated by multiplying these variables together to form a new variable. The values of these variables are on a 1-2 scale, so the range of the interaction is 1-4. A value of 4 is a run with both adaptive control on, and a higher spindle speed. This situation can provide additional information beyond the singular influence of adaptive control and spindle speed. The regression equation for these results is: $\hat{y} = -36.667 + 472.2SS + 278.14AC – 25.229TC – 241.254ACS$ where “$\hat{y}$” is Energy Used, “SS” is Spindle Speed, “AC” is Adaptive Control, “TC” is Tool Condition and “ACS” is Adaptive Control Spindle interaction.

The next group analyzed used feed rate, along with adaptive control, and tool condition across 100 machine runs. Since feed rate was the lowest independent variable correlated with energy used, it was not expected that this model would be very strong. The results show a low, but significant F-value ($F=5.665$ / sig. $<.000$), thus the null hypothesis is rejected and the alternative hypothesis would be tenable. The R-square value for this model is relatively low, but still meaningful (R-square = .193), reflecting a correlation approximately 19.3% of the time. The table below displays the regression coefficients for the variables and their interactions.

Table 11

Regression Analysis of Feed Rate/Adaptive control/Tool condition

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	234.265	72.522		3.230	.002
	Feed Rate	183.419	43.782	1.221	4.189	.000
	Adaptive Control	158.069	43.786	1.053	3.610	.000
	Tool Condition	-13.787	13.856	-.092	-.995	.322
	AC Feed Rate interaction	-120.726	27.690	-1.752	-4.360	.000

The above table shows that adaptive control, feed rate, and the interaction of these two variables are statistically significant and may be predictors of energy used. The significant interaction implies that the combination of these two variables help predict the amount of energy used. The interaction is calculated by multiplying these variables together to form a new variable as was done with spindle speed. The values of these variables are on a 1-2 scale, so the range of the interaction is 1-4. A value of 4 is a run with both adaptive control on, and a higher feed rate. Again, this provides additional information beyond the singular influence of adaptive control and feed rate speed. The regression equation for these results is: $\hat{y} = 234.265 + 183.419FR + 158.069AC - 13.787TC - 120.726ACFR$ where "$\hat{y}$" is Energy Used, "FR" is Feed

Rate, "AC" is Adaptive Control, "TC" is Tool Condition and "ACFR" is Adaptive Control Feed Rate interaction.

The next sub-sample was based on 100 machine runs, and includes the depth of cut in the analysis. The F-value from the ANOVA table for this regression model is significant (F=52.534/sig. < .000), thus the null hypothesis is rejected and the alternative hypothesis would be tenable. The interaction term for this variable, as well as for coolant temperature and volume was calculated a bit differently. These variables are on a scale of 1-2 where 1=low, and 2=high. For depth of cut, coolant temperature and volume, high levels (2) are the standard program, and the variation or tested levels for these variables is a 'low' (1). To calculate the interaction term for this variable, if these variables are at a high level (2) and AC is off, the interaction term=1. If either the AC is on, or these variables are set to low, the interaction term equals 2. If these levels are set to low and AC is on, then the interaction term equals 4.

The coefficient table, which is displayed below, shows a significant interaction effect between adaptive control and depth of cut, although the individual significance for depth of cut is non-significant. This suggests that even though depth of cut has a good relationship with power used (r=.774) when used in a regression equation, its ability to predict power used becomes redundant when adaptive control and the interaction with adaptive control are taken into account. The summary table below shows that the significant predictors of this model are adaptive control and the interaction between adaptive control and depth of cut. The relationship formed between adaptive control and depth of cut is more significant than depth of cut isolated on its own. The regression equation for these results is: $\hat{y} = 431.325 - 8.592DC + 168.356AC - 11.516TC - 130.922ACDC$ where "$\hat{y}$" is Energy Used, "DC" is Depth of Cut, "AC" is Adaptive Control, "TC" is Tool Condition and "ACDC" is Adaptive Control Depth of Cut interaction.

Table 12

Regression Analysis of Depth of Cut/Adaptive control/Tool condition

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	431.325	71.821		6.006	.000
	Depth of Cut	-8.592	43.948	-.035	-.196	.845
	Adaptive Control	168.356	43.948	.694	3.831	.000
	Tool Condition	-11.516	13.899	-.047	-.829	.409
	AC Depth of Cut Interaction	-130.922	27.798	-1.176	-4.710	.000

As it was previously noted from the correlations with energy used, coolant temperature and coolant flow volume show strong correlation values with energy used. It is expected that the regression models for these variables with the addition of adaptive control, tool condition and interaction variables will yield strong predictive models of energy. Coolant temperature was calculated across 100 runs, and the results of the sub-sample regression for this group are displayed below. The F-values for these models are the highest of all of the sub-sample regressions.

Table 13

Regression Analysis of Coolant Temperature/Adaptive control/Tool condition

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	193.066	68.710		2.810	.006
	Coolant Temp	113.766	40.293	.423	2.823	.006
	Adaptive Control	117.989	40.205	.439	2.935	.004
	Tool Condition	-15.655	12.839	-.058	-1.219	.226
	AC Coolant Temp interaction	-80.720	25.492	-.654	-3.167	.002

For this regression model, adaptive control, coolant temperature, and the interaction of the two, carry significant weight in the prediction of energy used. The F-value for this model is very high, and significant (F=88.169.06/sig. < .000), thus the null hypothesis is rejected and the alternative hypothesis would be tenable, and the R-square value is also high (R-square = .788). The regression weights and correlations show that there is a direct pattern between the variables and energy used. When adaptive control is 'on', energy is lower. When coolant temperature is lower, energy used is lower; and in runs when adaptive control is on and coolant temperature is lower, energy used is lower. The regression equation for these results is: $\hat{y}$ = 193.066 + 113.766CT + 117.989AC – 15.655TC – 80.72ACCT where "$\hat{y}$" is Energy Used, "CT" is Coolant Temperature, "AC" is Adaptive Control, "TC" is Tool Condition and "ACCT" is Adaptive Control Coolant Temperature interaction.

Coolant flow volume shares a similar relationship with energy used. The last sub-sample is a group of 100 runs where coolant flow volume is adjusted (lower coolant flow volume vs.

higher coolant flow volume). The regression model includes coolant flow volume, adaptive control, tool condition and interaction variable. The F-value is very high (F=95.9565 / sig. < .000), thus the null hypothesis is rejected and the alternative hypothesis would be tenable, and the R-square value is .802. The results for this regression also show a significant interaction effect with adaptive control. The regression coefficient table is displayed below.

Table 14

Regression Analysis of Coolant Volume/Adaptive control/Tool condition

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	170.544	64.046		2.663	.009
	Coolant Volume	130.000	42.114	.464	3.087	.003
	Adaptive Control	114.272	41.328	.408	2.765	.007
	Tool Condition	-22.030	13.776	-.079	-1.599	.113
	AC Coolant Volume Interaction	-77.258	26.746	-.601	-2.889	.005

As seen in the coolant temperature analysis, there are significant regression weights for adaptive control, coolant flow volume and the interaction between the two variables. When both coolant flow volume is low, and adaptive control is on, energy used is lower. The regression equation for these results is: $\hat{y} = 170.544 + 130CV + 114.272AC – 22.03TC – 77.258ACCV$ where “$\hat{y}$” is Energy Used, “CV” is Coolant Volume, “AC” is Adaptive Control, “TC” is Tool Condition and “ACCV” is Adaptive Control Coolant Volume interaction.

The table below displays summary results on all the sub-sample regression models.

Table 15

Summary Results on all the Sub-sample Regression Models

Model	Definition	N	R-square	F-value	sig	Significant AC interaction
Among Program A and B	Spindle Speed, AC, Tool condition, AC interaction with Spindle speed	100	0.655	45.052	<.000	*
Among Program A and C	Feed Rate, AC, Tool condition, AC interaction with Feed rate	100	0.193	5.665	<.000	*
Among Program A and D	Depth of Cut, AC, Tool condition, AC interaction with Depth of cut	100	0.689	52.534	<.000	*
Among Program A and E	Coolant Temperature, AC, Tool condition, AC interaction with Coolant temperature	100	0.788	88.169	<.000	*
Among Program A and F	Coolant Volume, AC, Tool condition, AC interaction with Coolant volume	100	0.802	95.956	<.000	*

The regression results complement the initial t-tests and the correlational analysis by reinforcing that the following variables are significant and meaningful: spindle speed, depth of cut, coolant temperature, coolant flow volume, and adaptive control. The regression analysis further analyzes the interaction terms and shows that spindle speed, depth of cut, coolant temperature, and coolant flow volume all have a significant interaction effect with adaptive control. These interactions are investigated to understand the overall magnitude of the relationship between adaptive control and the other influencing variables. The table below displays the average amount of energy used for the levels of interaction.

Table 16

Interaction with Adaptive Control and the Effect on Energy Used

The Interaction with Adaptive Control and the Effect on Energy Used

		Power Used Average
Interaction between adaptive control and spindle speed (n=100)	Adaptive control off and lower spindle speed	434.1
	Either adaptive control on or higher spindle speed	569.5
	Adaptive control on and higher spindle speed	459.6
Interaction between adaptive control and feed rate (n=100)	Adaptive control off and lower feed rate	434.1
	Either adaptive control on or higher feed rate	484.4
	Adaptive control on and higher feed rate	413.9
Interaction between adaptive control and depth of cut (n=100)	Adaptive control off/larger depth of cut	434.1
	Either adaptive control on or smaller depth of cut	392.1
	Adaptive control on and smaller depth of cut	218.3
Interaction between adaptive control and coolant temperature (n=100)	Adaptive control off and higher coolant temperature	434.1
	Adaptive control on or lower coolant temperature	355.1
	Adaptive control on and lower coolant temperature	198.0
Interaction between adaptive control and coolant volume (n=100)	Adaptive control off and higher coolant flow volume	434.1
	Adaptive control on or lower coolant flow volume	352.5
	Adaptive control on and lower coolant flow volume	181.3

The mean scores above were analyzed using an ANOVA in order to understand if the changes in energy used by the levels of interaction are significant. The results of each analysis of variance test are presented in the tables below and full ANOVA tables and follow-up test results are displayed in Appendix C. This analysis was conducted to test hypothesis 4 from Chapter 3, which is stated again here:

H_{04}: Independent variables will not be correlated significantly and will not produce statistically significant interaction effects in the energy regression models.

H_{A4}: Independent variables will significantly inter-correlated, and there will be statistically significant interaction effects in the energy regression models.

A mathematical equation representing hypothesis 4 would look like this:

$$\gamma_{(V1)} = \beta_0+\beta X_{AC}+\beta X_{V2}+\beta X_{V3}+\beta X_{V(2,\,3)}+e$$

Table 17

Interaction with Adaptive Control and the Effect on Energy Used

Investigating the interaction with Adaptive Control

		Power Used		
		Mean	F	sig
Interaction between adaptive control and spindle speed	Adaptive control off and lower spindle speed	434.1	19.552	<.000
	Either adaptive control on or high spindle speed	569.5		
	Adaptive control on and high spindle speed	459.6		
Interaction between adaptive control and feed rate	Adaptive control off and lower feed rate	434.1	9.972	<.000
	Either adaptive control on or higher feed rate	484.4		
	Adaptive control on and higher feed rate	413.9		
Interaction between adaptive control and depth of cut	Adaptive control off/low depth of cut	434.1	42.933	.038
	Either adaptive control on or high depth of cut	392.1		
	Adaptive control on and high depth of cut	218.3		
Interaction between adaptive control and coolant temperature	Adaptive control off and low coolant temperature	434.1	33.255	<.000
	Adaptive control on or high coolant temperature	355.1		
	Adaptive control on and high coolant temperature	198.0		
Interaction between adaptive control and coolant volume	Adaptive control off and low coolant flow volume	434.1	36.967	<.000
	Adaptive control on or high coolant flow volume	352.5		
	Adaptive control on and high coolant flow volume	181.3		

For spindle speed, follow-up tests show that the amount of energy used is significantly higher in the machine runs where adaptive control is on or spindle speed is high, thus the null hypothesis is rejected and the alternative hypothesis would be tenable. For depth of cut, follow-up tests show that the amount of power used is significantly higher when adaptive control is on, and depth of cut is high, thus the null hypothesis is rejected and the alternative hypothesis would be tenable. For feed rate, follow-up tests show that the amount of power used is significantly higher when adaptive control is on, and feed rate is high, thus the null hypothesis is rejected and the alternative hypothesis would be tenable. Coolant temperature and volume share the same pattern and results. Power used is significantly higher when adaptive control is on, and coolant temperature or volume is high, thus the null hypotheses are rejected here as well. Having adaptive control on or a high amount of coolant temperature or volume uses significantly more power than runs with adaptive control off and a low coolant temperature or volume.

Summary of Results

The initial hypothesis focused on uncovering group differences among several independent variables. It was hypothesized that these independent variables would influence the amount of energy used in machine runs. The t-tests found that there were significantly different amounts of energy used across levels of adaptive control, spindle speed, depth of cut, coolant temperature, and coolant flow volume, thus the null hypotheses were rejected for these variables.

Given these results, correlational analysis was conducted to get a measurement of the linear relationship between these variables and energy used. It was again hypothesized that these independent variables would have a linear relationship with energy used, and as the levels of the independent variables were manipulated, energy levels would change. The results show that the same variables, adaptive control, spindle speed, depth of cut, coolant temperature, and coolant flow volume, all had a significant correlation with energy used, thus the null hypotheses were rejected for these variables.

Finally, to more fully understand the independent variables and their interactions with each other, regression analysis was conducted. Since five of the independent variables were gathered independently of each other, the regression analysis was run on five sub-samples of machine runs. Within each regression analysis, 3 independent variables were used to predict energy used. Adaptive control and tool condition were collected across all runs, so they are able to be analyzed in each regression analysis. Spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume were analyzed in separate regression models. The interaction effects between the variable and adaptive control was also included in the regression model to investigate possible interactive relationships that would impact energy use.

Each of the five regression models had significant F-values in the regression ANOVA table, thus the null hypotheses were rejected, and the significance of the independent variables mirrored the correlational analysis. Depth of cut was independently not as directly related with energy used, although its interaction with adaptive control was a strong predictor. The other variables: spindle speed, feed rate, coolant temperature and coolant flow volume were strong predictors of energy used.

Interestingly, adaptive control interacted significantly with all five of the independent variables when predicting energy used. The t-test results show that when adaptive control is on, energy used is significantly lower, although the other independent variables were allowed to fluctuate within the 2 groups. When isolated, keeping all other independent variables constant, having adaptive control on, increases energy used. The interaction between adaptive control and spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume further shows that the effects of adaptive control are heightened when combined with the levels of speed, cut, temperature, and volume.

The results of the analysis are in general agreement with the hypotheses – the independent variables influence energy used. There were little to no differences in energy used among varying levels of tool condition, but the other independent variables proved to be significant influencers of energy used. Coolant temperature and coolant flow volume are strongly linked to energy used. Adaptive control shows differences in energy when turned on vs. off, and also shows that it interacts significantly with other variables.

Summary

This chapter presented the analysis results from the statistical tests conducted as it pertains to the respective hypotheses presented. The next chapter will present the discussion of the above findings along with the managerial implications of them. Additionally, limitations of the study will be addressed as well as recommendations for future research. Finally, an overall conclusion will be made to summarize the project.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

Introduction

The previous chapter presented the analysis results from the statistical tests conducted as it pertains to the respective hypotheses presented. This chapter will revisit the originally stated purpose of the study and then present the discussion of the findings from the previous chapter. Implications for academic research as well as implications for practitioners will be addressed. Additionally, limitations of the study as well as recommendations for future research will be posited. Finally, an overall conclusion will be made to summarize the project.

Purpose of the Study Revisited

As previously mentioned, according to Richter (2009), "reducing the amount of energy the motors on a metal cutting machine tool use is one way for a manufacturer to increase its competitiveness…while "greening" its operations". Richter points out that the majority of energy consumed by manufacturers is in motor energy consumption on machines. Therefore targeting methods to reduce the amount of energy consumed by motors on machine tools, an effective approach to becoming a more sustainable or "greener" manufacturer, was the primary focus of this study.

Field research was conducted directed at reducing the amount of energy consumed by the motors on machine tools used in manufacturing through the employment of "adaptive control" technology. "Adaptive control" was the primary influencing independent variable researched. In addition to "adaptive control," other influencing independent variables explored included feed rate, spindle speed, depth of cut, coolant temperature, coolant flow volume, and tool condition. The dependent variable that was the focus of this research was the amount of energy used during a chosen machining cycle measured in kilowatt hours which is a common unit of measure for energy found in other research such as Ulmer and Ollison (2008).

Discussion of the Research Findings

Most of the variables speculated/hypothesized to have an influence on energy were shown to have significant findings. Multiple methods of analysis reinforced the significant independent variables influencing the dependent variable "energy used" were adaptive control, spindle speed, feed rate, depth of cut, coolant temperature, and coolant flow volume. T-tests found significant mean differences on "energy used" between levels of these variables. These variables also significantly correlated with energy used – meaning they move together (when one goes up/the other goes up), as reflected here:

Higher Spindle Speed/More Energy Used

Higher Feed Rate/More Energy Used

Higher Depth of Cut/Higher Energy Used

Higher Coolant Flow Volume/Higher Energy Used

Adaptive Control On/Lower Power Used

Higher Coolant Temperature/Higher Energy Used

Out of the above findings, they all made sense logically to the researcher, except the last one. One would expect a higher demand for energy if the spindle speed were to be increased. A higher feed rate puts more load on the machine's motors thus increasing energy, as would a higher (deeper) depth of cut. In order to increase coolant flow, the coolant pump motor has to run faster thus increasing the amount of energy required. And, since adaptive control is shown to reduce cycle time, here again it would seem reasonable that less energy would be required.

However, in order to have a higher coolant temperature, the machine's coolant chiller was turned off. Logically, a reduction in energy would be expected, thus this finding is counterintuitive.

Interestingly, when evaluating adaptive control in its purest form (among the standard runs only – all other variables held constant) the relationship is reversed from the overall findings. Overall, among all 300 runs, the average amount of energy used when adaptive control is on is 0.324 kwh, compared to 0.397 kwh when adaptive control is off. This was a significant difference and shows that when adaptive control is on, energy used is lower, which is exactly what the researcher expected to find. However, if adaptive control is looked at only within standard runs (so there is no fluctuation in depth of cut, spindle speed, etc.), then the results are opposite. The average amount of energy used in the standard runs when adaptive control is on is 0.472 kwh as compared to 0.434 kwh when adaptive control is off among the isolated 50 runs. The correlations support this as well. The correlation between adaptive control and energy used in total across all runs is $r = -.239$ (when adaptive control is on, there tends to be a lower amount of energy used). The correlations within the standard runs only is $r = .210$ (when adaptive control is on, there tends to be a higher amount of energy used). This is completely surprising given that the expectation of the use of adaptive control is that it would result in the machine requiring less energy. Apparently, without the influence of the other independent variables, along with their respective interaction with adaptive control, the extra energy consumed by the motors caused by adaptive control increasing feed rate outweighed the lesser amount of energy consumed due to the shortened cycle time. Fortunately, the interaction with the other key variables makes it an efficient energy reducing measure regardless.

What becomes important then is to understand how adaptive control combines with the other key variables that influence energy. This was done by adding an interaction component to the regression modeling and by evaluating average energy used scores by varying levels of these interaction terms. The results show that among all the other key variables (spindle speed, feed rate, depth of cut, coolant temperature, and flow volume) there was a statistically significant interaction with adaptive control. The significant interaction terms mean that the combination of the variables can be worked together to explain variation in energy used. The interaction term was calculated simply by multiplying the variables together. The interaction term for depth of cut, coolant temperature and coolant volume were calculated differently since the value is set to "high" for standard runs, and "low" for test runs of these variables. Since the interaction terms with the key variables were statistically significant, the average energy used scores were evaluated and tested across the three groups defined above and were all found to be significant.

Although all the key variables had significant differences, significant correlations, etc., when reviewing the results we can see which of the key variables show the largest differences /strongest correlation to energy. In the table below, results of the t-tests when each of the significant key variables was tested against its respective counterpart are shown.

Table 18

Strongest Correlation to "Energy Used" by Variable

Change in Power Used	*Changing Spindle Speed to High*	*Changing Feed Rate to High*	*Changing Depth of Cut to Low*	*Changing Coolant Temperature to Low*	*Changing Coolant Volume to Low*	*When AC On (across all runs)*	*When AC on (in isolated Program A runs)*
	110.3	2.3	-187.8	-234.8	-245.9	37.9	-73.0
t-value	-5.7	-0.2	12.1	17.8	18.1	1.5	4.2
sig	<.000	0.9	<.000	<.000	<.000	0.143	<.000
	significantly increases power used	*No change in power used*	*significantly decreases power used*	*significantly decreases power used*	*significantly decreases power used*	*Increases power used, but not significantly*	*significantly decreases power used*

It can be seen above that varying coolant temperature and coolant volume greatly impacts the amount of energy used (the "energy used" means were lower by 235 and 246 respectively suggesting these two variables most highly impact energy used. Additionally, their correlations are strongest to energy used, as shown below:

Table 19

Correlation of Coolant Temperature and Coolant Volume to "Energy Used"

Correlation with power used:	Isolated correlation between standard program and test program (n=100)
Coolant Temp	.874
Coolant Volume	.878

Implications for Practitioners

The above discussed research findings should result in keen interest by practitioners. As presented in Chapter 1 and Chapter 2, manufacturing is an extremely important economic sector to any country. Manufacturers in the US and many other countries are investigating ways to not only lower their manufacturing costs in order to be more competitive or to increase their profitability, but they are also beginning to investigate ways to lower their carbon footprint and become more "green". Reducing the amount of energy consumed by machine tools can be a significant enabler to accomplishing both. At the specific plant where this study was conducted, the approximate amount of energy consumed by machine tools during the year of the study was estimated to be 9,894,635 kwh at a cost of $688,331. Assuming the same 18.3% reduction of energy derived from using adaptive control that was found in the study could be achieved on all machine tools in the plant, the company could realize an annual savings on their energy bill of approximately $126,000. Using the "Greenhouse Gas Equivalencies Calculator" found on the

EPS's website, the same 18.3% reduction applied to the total amount of 9,894,635 kwh the plant used in 2012 would result in a reduction of 1,278 metric tons of carbon dioxide equivalent (Greenhouse Gas Equivalencies Calculator, 2013).

Unfortunately, the above described savings make it hard to justify the cost of installing requisite adaptive control modules on each machine. The cost of the unit used for the study was approximately $10,000. Based on projected machine usage provided by the plant, it would take approximately five years before the investment would pay for itself in energy savings. Such a "Return on Investment" ("ROI") time frame would be very difficult to justify. Market research would need to support the required investment through increased sales of product due to the "greener" moniker that could be offered.

Although not part of the research study as designed, it is worth mentioning that all of the 300 parts machined in this study passed 100% of the quality inspections performed on standard production parts and were utilized in subsequent downstream production. Practitioners should take note that the employment of adaptive control did not adversely affect the quality of the resulting machined part in any way.

Limitations of the Study

As mentioned in Chapter 1, the environment for this study was a specific machine tool that was machining a specific material to a specific shape using a specific cutting tool insert. Accordingly, the results of this study may not be generalizable to all machine tools. However, this study should serve as a stepping stone for further research into other machine tools to determine if more generalizable patterns exist.

Recommendations for Future Research

The findings of this research study, although significant on their own, need further validation. Replication studies should be undertaken. Additionally, in order to address the above mentioned limitations to the study, additional research should be undertaken varying the type of material, the type of machine tool, the type of cutting insert, etc., to determine if the results of this study are indeed potentially generalizable across varying environments.

Conclusions

This study provided a comprehensive and robust look at energy used by evaluating several potential measures in a structured and reliable manner. It focused on a number of variables, most of which had a significant impact on energy used. The effect on energy was evaluated by t-tests on group differences and correlations for pattern similarities. The analyses complemented each other by providing consistent results. Key variables to “energy used” were found to be adaptive control, spindle speed, depth of cut, coolant temperature, and coolant flow volume. The combination of key variables (adaptive control’s interaction with the other key variables) further increased the understanding and ability to capitalize on efficiency by providing a pathway to reducing energy used.

Although adaptive control is a technology that has been researched for many years, this study is the first time adaptive control has been investigated as a potential technology to be used to reduce the amount of energy consumed by machine tools used in manufacturing. Combined with the other influencing variables investigated in this study, adaptive control has been found to be a key technology that manufacturers who are interested in reducing costs and reducing energy, in order to reduce their carbon footprint and become more competitive, should seriously evaluate.

Summary

Chapter 1 provided the background, problem statement, need for the study, purpose of the study, and the proposed research questions that the study would address. Proposed hypotheses, assumptions of the study, limitations of the study, and the significance of the study were also discussed. Lastly, the organization of the study and the definition of key terms were detailed.

The second chapter reviewed the literature pertaining to sustainable manufacturing, the background of machine tools and computer numerical control, and the history of adaptive control technology relating to machine tools.

The third chapter presented the method of data collection, a description of the sample to be collected, proposed research questions and hypotheses, and lastly a summary describing the methodology of how the hypotheses would be tested.

Chapter 4 provided a description of the data collected, descriptive statistics, and the various analytical procedures followed to statistically investigate the hypotheses presented. It concluded with a presentation of the results of the analysis.

Lastly, this fifth and final chapter presented a brief review of the purpose of the study as well as a discussion of the findings from the previous chapter. Additionally, implications for practitioners were offered, limitations of the study were addressed, and recommendations for future research were posited. Finally, an overall conclusion was made to summarize the project.

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APPENDIXES

APPENDIX A

CORRELATION ANALYSIS

	Among Total Sample (n=300)		Isloated correlation between standard program and test program (n=100)	
Power Used	r	p-value	r	p-value
Spindle Speed	.593	< .000	**.477**	< .000
Feed Rate	.278	< .000	.016	.878
Depth of Cut	.278	< .000	**.774**	< .000
Coolant Temp	.416	< .000	**.874**	< .000
Coolant Volume	.448	< .000	**.878**	< .000
Adaptive Control	**-.239**	< .000		
Tool Condition	-.052	.366		

<u>Total</u>

Correlations

		Power Used	Adaptive Control	Tool Condition
Power Used	Pearson Correlation	1	-.239	-.052
	Sig. (2-tailed)		.000	.366
	N	300	300	300
Adaptive Control	Pearson Correlation	-.239	1	.067
	Sig. (2-tailed)	.000		.250
	N	300	300	300
Tool Condition	Pearson Correlation	-.052	.067	1
	Sig. (2-tailed)	.366	.250	
	N	300	300	300

Program A and Program B

Correlations

		Power Used	Adaptive Control	Tool Condition	Spindle Speed	AC Spindle Interaction
Power Used	Pearson Correlation	1	-.366	-.165	.477	-.046
	Sig. (2-tailed)		.000	.100	.000	.653
	N	100	100	100	100	100
Adaptive Control	Pearson Correlation	-.366	1	.040	.000	.688
	Sig. (2-tailed)	.000		.693	1.000	.000
	N	100	100	100	100	100
Tool Condition	Pearson Correlation	-.165	.040	1	.000	.046
	Sig. (2-tailed)	.100	.693		1.000	.650
	N	100	100	100	100	100
Spindle Speed	Pearson Correlation	.477	.000	.000	1	.688
	Sig. (2-tailed)	.000	1.000	1.000		.000
	N	100	100	100	100	100
AC Spindle Interaction	Pearson Correlation	-.046	.688	.046	.688	1
	Sig. (2-tailed)	.653	.000	.650	.000	
	N	100	100	100	100	100

Program A and Program C

Correlations

		Power Used	Adaptive Control	Tool Condition	Feed Rate	AC Feed Rate interaction
Power Used	Pearson Correlation	1	-.150	-.086	.016	-.184
	Sig. (2-tailed)		.137	.397	.878	.066
	N	100	100	100	100	100
Adaptive Control	Pearson Correlation	-.150	1	-.040	.000	.688
	Sig. (2-tailed)	.137		.693	1.000	.000
	N	100	100	100	100	100
Tool Condition	Pearson Correlation	-.086	-.040	1	.000	-.028
	Sig. (2-tailed)	.397	.693		1.000	.786
	N	100	100	100	100	100
Feed Rate	Pearson Correlation	.016	.000	.000	1	.688
	Sig. (2-tailed)	.878	1.000	1.000		.000
	N	100	100	100	100	100
AC Feed Rate interaction	Pearson Correlation	-.184	.688	-.028	.688	1
	Sig. (2-tailed)	.066	.000	.786	.000	
	N	100	100	100	100	100

Program A and Program D

Correlations

		Power Used	Adaptive Control	Tool Condition	Depth of Cut	AC Depth of Cut Interaction
Power Used	Pearson Correlation	1	-.116	-.058	.774	.516
	Sig. (2-tailed)		.252	.565	.000	.000
	N	100	100	100	100	100
Adaptive Control	Pearson Correlation	-.116	1	.000	.000	.688
	Sig. (2-tailed)	.252		1.000	1.000	.000
	N	100	100	100	100	100
Tool Condition	Pearson Correlation	-.058	.000	1	.000	-.009
	Sig. (2-tailed)	.565	1.000		1.000	.928
	N	100	100	100	100	100
Depth of Cut	Pearson Correlation	.774	.000	.000	1	.688
	Sig. (2-tailed)	.000	1.000	1.000		.000
	N	100	100	100	100	100
Depth of Cut Interaction	Pearson Correlation	.516	.688	-.009	.688	1
	Sig. (2-tailed)	.000	.000	.928	.000	
	N	100	100	100	100	100

Program A and Program E

Correlations

		Power Used	Adaptive Control	Tool Condition	Coolant Temp	AC Coolant Temp interaction
Power Used	Pearson Correlation	1	-.005	-.045	.874	.632
	Sig. (2-tailed)		.964	.658	.000	.000
	N	100	100	100	100	100
Adaptive Control	Pearson Correlation	-.005	1	-.120	.000	.688
	Sig. (2-tailed)	.964		.234	1.000	.000
	N	100	100	100	100	100
Tool Condition	Pearson Correlation	-.045	-.120	1	.000	-.064
	Sig. (2-tailed)	.658	.234		1.000	.525
	N	100	100	100	100	100
Coolant Temp	Pearson Correlation	.874	.000	.000	1	.688
	Sig. (2-tailed)	.000	1.000	1.000		.000
	N	100	100	100	100	100
AC Coolant Temp interaction	Pearson Correlation	.632	.688	-.064	.688	1
	Sig. (2-tailed)	.000	.000	.525	.000	
	N	100	100	100	100	100

Program A and Program F

Correlations

		Power Used	Adaptive Control	Tool Condition	Coolant Volume	AC Coolant Temp interaction
Power Used	Pearson Correlation	1	-.025	-.119	.878	-.025
	Sig. (2-tailed)		.808	.240	.000	.808
	N	100	100	100	100	100
Adaptive Control	Pearson Correlation	-.025	1	.240	.000	1.000
	Sig. (2-tailed)	.808		.016	1.000	.000
	N	100	100	100	100	100
Tool Condition	Pearson Correlation	-.119	.240	1	.000	.240
	Sig. (2-tailed)	.240	.016		1.000	.016
	N	100	100	100	100	100
Coolant Volume	Pearson Correlation	.878	.000	.000	1	.000
	Sig. (2-tailed)	.000	1.000	1.000		1.000
	N	100	100	100	100	100
AC Coolant Temp interaction	Pearson Correlation	-.025	1.000	.240	.000	1
	Sig. (2-tailed)	.808	.000	.016	1.000	
	N	100	100	100	100	100

APPENDIX B

REGRESSION ANALYSIS

Model 1 – Spindle Speed, Adaptive Control, Tool Condition

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.809	**.655**	**.640**	69.71	.655	45.052	4	95	.000

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	875657.1	4	218914.3	**45.052**	**.000**
	Residual	461618.6	95	4859.1		
	Total	1337275.7	99			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-36.667	74.121		-.495	.622
	Spindle Speed	472.200	44.215	2.042	**10.680**	**.000**
	Adaptive Control	278.140	44.176	1.203	**6.296**	**.000**
	Tool Condition	-25.229	13.998	-.109	-1.802	.075
	AC Spindle Interaction	-241.254	27.973	-2.273	**-8.625**	**.000**

Model 2 – Feed Rate, Adaptive Control, Tool Condition

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.439	**.193**	**.159**	69.23	.193	5.665	4	95	.000

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	108592.3	4	27148.1	**5.665**	**.000**
	Residual	455265.3	95	4792.3		
	Total	563857.7	99			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	234.265	72.522		3.230	.002
	Feed Rate	183.419	43.782	1.221	4.189	.000
	Adaptive Control	158.069	43.786	1.053	3.610	.000
	Tool Condition	-13.787	13.856	-.092	-.995	.322
	AC Feed Rate interaction	-120.726	27.690	-1.752	-4.360	.000

Model 3 – Depth of Cut, Adaptive Control, Tool Condition

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.830	**.689**	**.676**	69.44	.689	52.534	4	95	.000

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1013217.8	4	253304.4	**52.534**	**.000**
	Residual	458061.7	95	4821.7		
	Total	1471279.5	99			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	431.325	71.821		6.006	.000
	Depth of Cut	-8.592	43.948	-.035	-.196	.845
	Adaptive Control	168.356	43.948	.694	3.831	.000
	Tool Condition	-11.516	13.899	-.047	-.829	.409
	AC Depth of Cut Interaction	-130.922	27.798	-1.176	-4.710	.000

Model 4 – Coolant Temperature, Adaptive Control, Tool Condition

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.888	**.788**	**.779**	63.52	.788	88.169	4	95	.000

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1423090.6	4	355772.6	**88.169**	**.000**
	Residual	383335.4	95	4035.1		
	Total	1806426.0	99			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	193.066	68.710		2.810	.006
	Coolant Temp	113.766	40.293	.423	2.823	.006
	Adaptive Control	117.989	40.205	.439	2.935	.004
	Tool Condition	-15.655	12.839	-.058	-1.219	.226
	AC Coolant Temp interaction	-80.720	25.492	-.654	-3.167	.002

Model 5 – Coolant Flow Volume, Adaptive Control, Tool Condition

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.895	**.802**	**.793**	64.02	.802	95.956	4	95	.000

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1573348.9	4	393337.2	**95.956**	**.000**
	Residual	389416.7	95	4099.1		
	Total	1962765.6	99			

Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	170.544	64.046		2.663	.009
	Coolant Volume	130.000	42.114	.464	3.087	.003
	Adaptive Control	114.272	41.328	.408	2.765	.007
	Tool Condition	-22.030	13.776	-.079	-1.599	.113
	AC Coolant Volume Interaction	-77.258	26.746	-.601	-2.889	.005

APPENDIX C

ANOVA ANALYSIS

Interaction between Adaptive Control and Spindle Speed

ANOVA

Power Used

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	384218.2	2	192109.10	19.552	.000
Within Groups	953057.5	97	9825.34		
Total	1337275.7	99			

Multiple Comparisons

Dependent Variable:PowerUsed Power Used

	(I) acspindle AC Spindle Interaction	(J) acspindle AC Spindle Interaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
LSD	1.00	2.00	-135.4	24.3	.000	-183.62	-87.24
		4.00	-25.6	28.0	.364	-81.21	30.07
	2.00	1.00	135.4	24.3	.000	87.24	183.62
		4.00	109.9	24.3	.000	61.67	158.05
	4.00	1.00	25.6	28.0	.364	-30.07	81.21
		2.00	-109.9	24.3	.000	-158.05	-61.67

Interaction between Adaptive Control and Feed Rate

ANOVA

Power Used

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	96160.862	2	48080.431	9.972	.000
Within Groups	467696.814	97	4821.617		
Total	563857.676	99			

Multiple Comparisons

Dependent Variable:PowerUsed Power Used

	(I) acfeed AC Feed Rate interaction	(J) acfeed AC Feed Rate interaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
LSD	1.00	2.00	-50.3	17.0	.004	-84.05	-16.54
		4.00	20.1	19.6	.308	-18.84	59.12
	2.00	1.00	50.3	17.0	.004	16.54	84.05
		4.00	70.4	17.0	.000	36.67	104.19
	4.00	1.00	-20.1	19.6	.308	-59.12	18.84
		2.00	-70.4	17.0	.000	-104.19	-36.67

Interaction between Adaptive Control and Depth of Cut

ANOVA

Power Used

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	690851.1	2	345425.55	42.933	.000
Within Groups	780428.4	97	8045.65		
Total	1471279.5	99			

Multiple Comparisons

Dependent Variable:PowerUsed Power Used

	(I) acdepth AC Depth of Cut Interaction	(J) acdepth AC Depth of Cut Interaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
LSD	1.00	2.00	42.0	22.0	.059	-1.62	85.59
		4.00	215.8	25.4	.000	165.46	266.17
	2.00	1.00	-42.0	22.0	.059	-85.59	1.62
		4.00	173.8	22.0	.000	130.22	217.44
	4.00	1.00	-215.8	25.4	.000	-266.17	-165.46
		2.00	-173.8	22.0	.000	-217.44	-130.22

Interaction between Adaptive Control and Coolant Temperature

ANOVA

Power Used

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	734783.2	2	367391.60	33.255	.000
Within Groups	1071642.8	97	11047.86		
Total	1806426.0	99			

Multiple Comparisons

Dependent Variable:PowerUsed Power Used

	(I) accooltemp AC Coolant Temp interaction	(J) accooltemp AC Coolant Temp interaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
LSD	1.00	2.00	78.9	25.7	.003	27.82	130.02
		4.00	236.1	29.7	.000	177.05	295.06
	2.00	1.00	-78.9	25.7	.003	-130.02	-27.82
		4.00	157.1	25.7	.000	106.04	208.24
	4.00	1.00	-236.1	29.7	.000	-295.06	-177.05
		2.00	-157.1	25.7	.000	-208.24	-106.04

Interaction between Adaptive Control and Coolant Flow Volume

ANOVA

Power Used

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	848947.7	2	424473.85	36.967	.000
Within Groups	1113817.9	97	11482.66		
Total	1962765.6	99			

Multiple Comparisons

Dependent Variable:PowerUsed Power Used

	(I) accoolvol AC Coolant Volume Interaction	(J) accoolvol AC Coolant Volume Interaction	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
LSD	1.00	2.00	81.6	26.2	.002	29.50	133.69
		4.00	252.8	30.3	.000	192.63	312.94
	2.00	1.00	-81.6	26.2	.002	-133.69	-29.50
		4.00	171.2	26.2	.000	119.10	223.29
	4.00	1.00	-252.8	30.3	.000	-312.94	-192.63
		2.00	-171.2	26.2	.000	-223.29	-119.10

APPENDIX D

DATA

ID	Power Used	Adaptive Control	Tool Condition	Program	Spindle Speed	Feed Rate	Depth of Cut	Coolant Temp	Coolant Volume
A01	320.5	1	1	A	1	1	2	2	2
A02	354.7	1	1	A	1	1	2	2	2
A03	327.7	2	2	A	1	1	2	2	2
A04	363.4	1	2	A	1	1	2	2	2
A05	328.4	2	2	A	1	1	2	2	2
A06	368.8	1	2	A	1	1	2	2	2
A07	328.5	2	1	A	1	1	2	2	2
A08	381.7	1	1	A	1	1	2	2	2
A09	336.8	2	1	A	1	1	2	2	2
A10	399.6	1	1	A	1	1	2	2	2
A11	343.0	2	1	A	1	1	2	2	2
A12	428.9	1	2	A	1	1	2	2	2
A13	352.8	2	1	A	1	1	2	2	2
A14	433.8	1	2	A	1	1	2	2	2
A15	358.3	2	2	A	1	1	2	2	2
A16	438.4	1	2	A	1	1	2	2	2
A17	364.4	2	1	A	1	1	2	2	2
A18	451.0	1	1	A	1	1	2	2	2
A19	376.4	2	2	A	1	1	2	2	2
A20	458.2	1	2	A	1	1	2	2	2
A21	381.6	2	1	A	1	1	2	2	2
A22	464.7	1	2	A	1	1	2	2	2
A23	390.7	2	1	A	1	1	2	2	2
A24	472.9	1	2	A	1	1	2	2	2
A25	404.5	2	2	A	1	1	2	2	2
A26	474.7	1	1	A	1	1	2	2	2
A27	413.0	2	1	A	1	1	2	2	2
A28	476.2	1	2	A	1	1	2	2	2
A29	416.9	2	1	A	1	1	2	2	2
A30	482.5	1	1	A	1	1	2	2	2
A31	419.4	2	2	A	1	1	2	2	2
A32	483.9	1	1	A	1	1	2	2	2
A33	422.2	2	2	A	1	1	2	2	2
A34	494.5	1	1	A	1	1	2	2	2
A35	476.8	2	1	A	1	1	2	2	2
A36	502.8	1	1	A	1	1	2	2	2
A37	495.2	2	1	A	1	1	2	2	2
A38	507.1	1	2	A	1	1	2	2	2
A39	496.6	2	2	A	1	1	2	2	2
A40	561.0	1	1	A	1	1	2	2	2
A41	513.7	2	1	A	1	1	2	2	2
A42	567.3	1	2	A	1	1	2	2	2
A43	534.2	2	2	A	1	1	2	2	2
A44	631.8	1	1	A	1	1	2	2	2
A45	549.6	2	2	A	1	1	2	2	2
A46	634.6	1	2	A	1	1	2	2	2
A47	583.2	2	1	A	1	1	2	2	2
A48	646.1	1	2	A	1	1	2	2	2
A49	607.0	2	2	A	1	1	2	2	2
A50	630.9	2	2	A	1	1	2	2	2

ID	Power Used	Adaptive Control	Tool Condition	Program	Spindle Speed	Feed Rate	Depth of Cut	Coolant Temp	Coolant Volume
B01	334.0	1	1	B	2	1	2	2	2
B02	610.4	2	2	B	2	1	2	2	2
B03	355.2	1	2	B	2	1	2	2	2
B04	617.3	2	2	B	2	1	2	2	2
B05	394.5	1	1	B	2	1	2	2	2
B06	617.9	2	1	B	2	1	2	2	2
B07	410.9	1	2	B	2	1	2	2	2
B08	621.5	2	2	B	2	1	2	2	2
B09	420.9	1	1	B	2	1	2	2	2
B10	623.0	2	1	B	2	1	2	2	2
B11	424.0	1	1	B	2	1	2	2	2
B12	639.3	2	1	B	2	1	2	2	2
B13	427.0	1	1	B	2	1	2	2	2
B14	640.8	2	1	B	2	1	2	2	2
B15	430.2	1	1	B	2	1	2	2	2
B16	644.8	2	2	B	2	1	2	2	2
B17	430.8	1	2	B	2	1	2	2	2
B18	662.2	2	1	B	2	1	2	2	2
B19	452.2	1	1	B	2	1	2	2	2
B20	662.6	2	2	B	2	1	2	2	2
B21	459.5	1	1	B	2	1	2	2	2
B22	667.2	2	1	B	2	1	2	2	2
B23	469.9	1	1	B	2	1	2	2	2
B24	670.9	2	1	B	2	1	2	2	2
B25	470.0	1	2	B	2	1	2	2	2
B26	671.8	2	1	B	2	1	2	2	2
B27	475.5	1	1	B	2	1	2	2	2
B28	675.1	2	1	B	2	1	2	2	2
B29	480.5	1	2	B	2	1	2	2	2
B30	677.8	2	2	B	2	1	2	2	2
B31	481.3	1	1	B	2	1	2	2	2
B32	678.0	2	1	B	2	1	2	2	2
B33	481.5	1	2	B	2	1	2	2	2
B34	679.3	2	1	B	2	1	2	2	2
B35	486.6	1	1	B	2	1	2	2	2
B36	686.8	2	2	B	2	1	2	2	2
B37	503.1	1	2	B	2	1	2	2	2
B38	691.4	2	2	B	2	1	2	2	2
B39	507.6	1	2	B	2	1	2	2	2
B40	693.8	2	2	B	2	1	2	2	2
B41	516.8	1	2	B	2	1	2	2	2
B42	699.1	2	2	B	2	1	2	2	2
B43	518.1	1	1	B	2	1	2	2	2
B44	699.5	2	2	B	2	1	2	2	2
B45	519.3	1	1	B	2	1	2	2	2
B46	707.1	2	2	B	2	1	2	2	2
B47	519.6	1	2	B	2	1	2	2	2
B48	718.3	2	2	B	2	1	2	2	2
B49	522.4	1	2	B	2	1	2	2	2
B50	720.1	2	2	B	2	1	2	2	2

ID	Power Used	Adaptive Control	Tool Condition	Program	Spindle Speed	Feed Rate	Depth of Cut	Coolant Temp	Coolant Volume
C01	327.5	1	1	C	1	2	2	2	2
C02	428.8	2	1	C	1	2	2	2	2
C03	336.9	1	1	C	1	2	2	2	2
C04	434.7	2	1	C	1	2	2	2	2
C05	359.1	1	2	C	1	2	2	2	2
C06	434.7	2	1	C	1	2	2	2	2
C07	367.0	1	2	C	1	2	2	2	2
C08	434.8	2	2	C	1	2	2	2	2
C09	373.1	1	2	C	1	2	2	2	2
C10	444.6	2	2	C	1	2	2	2	2
C11	377.4	1	1	C	1	2	2	2	2
C12	466.1	2	2	C	1	2	2	2	2
C13	388.0	1	2	C	1	2	2	2	2
C14	478.5	2	1	C	1	2	2	2	2
C15	404.2	1	1	C	1	2	2	2	2
C16	482.8	2	2	C	1	2	2	2	2
C17	404.4	1	1	C	1	2	2	2	2
C18	487.0	2	2	C	1	2	2	2	2
C19	407.6	1	1	C	1	2	2	2	2
C20	487.1	2	2	C	1	2	2	2	2
C21	415.6	1	2	C	1	2	2	2	2
C22	487.4	2	1	C	1	2	2	2	2
C23	423.1	1	2	C	1	2	2	2	2
C24	492.1	2	2	C	1	2	2	2	2
C25	433.1	1	2	C	1	2	2	2	2
C26	503.1	2	2	C	1	2	2	2	2
C27	434.8	1	2	C	1	2	2	2	2
C28	505.5	2	1	C	1	2	2	2	2
C29	434.8	1	1	C	1	2	2	2	2
C30	507.2	2	2	C	1	2	2	2	2
C31	437.0	1	2	C	1	2	2	2	2
C32	518.2	2	1	C	1	2	2	2	2
C33	437.5	1	2	C	1	2	2	2	2
C34	518.3	2	1	C	1	2	2	2	2
C35	438.1	1	2	C	1	2	2	2	2
C36	518.4	2	1	C	1	2	2	2	2
C37	442.9	1	1	C	1	2	2	2	2
C38	521.5	2	2	C	1	2	2	2	2
C39	445.7	1	2	C	1	2	2	2	2
C40	538.2	2	1	C	1	2	2	2	2
C41	446.4	1	1	C	1	2	2	2	2
C42	540.8	2	2	C	1	2	2	2	2
C43	450.7	1	1	C	1	2	2	2	2
C44	541.2	2	2	C	1	2	2	2	2
C45	451.5	1	1	C	1	2	2	2	2
C46	548.2	2	1	C	1	2	2	2	2
C47	454.6	1	2	C	1	2	2	2	2
C48	548.5	2	1	C	1	2	2	2	2
C49	457.4	1	1	C	1	2	2	2	2
C50	551.2	2	1	C	1	2	2	2	2

ID	Power Used	Adaptive Control	Tool Condition	Program	Spindle Speed	Feed Rate	Depth of Cut	Coolant Temp	Coolant Volume
D01	208.5	1	1	D	1	1	1	2	2
D02	243.9	2	1	D	1	1	1	2	2
D03	210.1	1	2	D	1	1	1	2	2
D04	245.6	2	2	D	1	1	1	2	2
D05	210.5	1	1	D	1	1	1	2	2
D06	246.4	2	1	D	1	1	1	2	2
D07	211.6	1	1	D	1	1	1	2	2
D08	246.7	2	1	D	1	1	1	2	2
D09	212.4	1	1	D	1	1	1	2	2
D10	247.3	2	1	D	1	1	1	2	2
D11	212.5	1	1	D	1	1	1	2	2
D12	247.9	2	2	D	1	1	1	2	2
D13	212.9	1	1	D	1	1	1	2	2
D14	249.3	2	2	D	1	1	1	2	2
D15	214.9	1	2	D	1	1	1	2	2
D16	251.2	2	2	D	1	1	1	2	2
D17	215.1	1	1	D	1	1	1	2	2
D18	260.0	2	2	D	1	1	1	2	2
D19	215.4	1	2	D	1	1	1	2	2
D20	312.1	2	1	D	1	1	1	2	2
D21	218.0	1	2	D	1	1	1	2	2
D22	313.9	2	1	D	1	1	1	2	2
D23	218.2	1	1	D	1	1	1	2	2
D24	317.0	2	2	D	1	1	1	2	2
D25	219.8	1	2	D	1	1	1	2	2
D26	318.2	2	2	D	1	1	1	2	2
D27	220.0	1	2	D	1	1	1	2	2
D28	319.7	2	2	D	1	1	1	2	2
D29	220.9	1	2	D	1	1	1	2	2
D30	328.8	2	2	D	1	1	1	2	2
D31	221.8	1	1	D	1	1	1	2	2
D32	333.7	2	1	D	1	1	1	2	2
D33	222.6	1	1	D	1	1	1	2	2
D34	339.4	2	2	D	1	1	1	2	2
D35	222.9	1	1	D	1	1	1	2	2
D36	341.9	2	1	D	1	1	1	2	2
D37	223.1	1	2	D	1	1	1	2	2
D38	346.3	2	2	D	1	1	1	2	2
D39	223.1	1	2	D	1	1	1	2	2
D40	353.5	2	2	D	1	1	1	2	2
D41	223.2	1	2	D	1	1	1	2	2
D42	371.1	2	1	D	1	1	1	2	2
D43	224.4	1	1	D	1	1	1	2	2
D44	379.3	2	2	D	1	1	1	2	2
D45	224.4	1	2	D	1	1	1	2	2
D46	385.0	2	1	D	1	1	1	2	2
D47	224.5	1	2	D	1	1	1	2	2
D48	389.2	2	1	D	1	1	1	2	2
D49	225.2	1	1	D	1	1	1	2	2
D50	417.9	2	1	D	1	1	1	2	2

ID	Power Used	Adaptive Control	Tool Condition	Program	Spindle Speed	Feed Rate	Depth of Cut	Coolant Temp	Coolant Volume
E01	187.1	1	1	E	1	1	2	1	2
E02	234.2	2	1	E	1	1	2	1	2
E03	188.8	1	1	E	1	1	2	1	2
E04	234.5	2	1	E	1	1	2	1	2
E05	192.2	1	1	E	1	1	2	1	2
E06	235.3	2	1	E	1	1	2	1	2
E07	193.4	1	1	E	1	1	2	1	2
E08	235.4	2	1	E	1	1	2	1	2
E09	193.7	1	2	E	1	1	2	1	2
E10	235.4	2	1	E	1	1	2	1	2
E11	194.4	1	1	E	1	1	2	1	2
E12	235.4	2	2	E	1	1	2	1	2
E13	195.4	1	1	E	1	1	2	1	2
E14	235.6	2	2	E	1	1	2	1	2
E15	196.9	1	2	E	1	1	2	1	2
E16	235.9	2	2	E	1	1	2	1	2
E17	197.8	1	2	E	1	1	2	1	2
E18	235.9	2	1	E	1	1	2	1	2
E19	198.0	1	2	E	1	1	2	1	2
E20	235.9	2	2	E	1	1	2	1	2
E21	198.2	1	2	E	1	1	2	1	2
E22	236.2	2	2	E	1	1	2	1	2
E23	199.2	1	1	E	1	1	2	1	2
E24	236.4	2	2	E	1	1	2	1	2
E25	200.2	1	1	E	1	1	2	1	2
E26	236.4	2	1	E	1	1	2	1	2
E27	200.3	1	2	E	1	1	2	1	2
E28	237.5	2	2	E	1	1	2	1	2
E29	200.3	1	2	E	1	1	2	1	2
E30	238.2	2	2	E	1	1	2	1	2
E31	200.7	1	1	E	1	1	2	1	2
E32	238.6	2	2	E	1	1	2	1	2
E33	200.9	1	2	E	1	1	2	1	2
E34	239.0	2	2	E	1	1	2	1	2
E35	200.9	1	2	E	1	1	2	1	2
E36	239.2	2	1	E	1	1	2	1	2
E37	200.9	1	2	E	1	1	2	1	2
E38	239.6	2	1	E	1	1	2	1	2
E39	201.1	1	2	E	1	1	2	1	2
E40	239.9	2	1	E	1	1	2	1	2
E41	201.2	1	2	E	1	1	2	1	2
E42	240.6	2	1	E	1	1	2	1	2
E43	201.3	1	2	E	1	1	2	1	2
E44	241.5	2	1	E	1	1	2	1	2
E45	202.3	1	1	E	1	1	2	1	2
E46	244.6	2	1	E	1	1	2	1	2
E47	202.3	1	2	E	1	1	2	1	2
E48	246.9	2	1	E	1	1	2	1	2
E49	202.7	1	2	E	1	1	2	1	2
E50	250.1	2	1	E	1	1	2	1	2