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Modeling Energy Consumption in Automotive Manufacturing

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By

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ABSTRACT

Developing a dynamic model of energy consumption for CNC machines in automotive industries helps to reduce the energy consumption in these machines. Over the last decade, a significant rise in energy usage has occurred due to the growth in the developing world. According to (IEO2013), this trend will continue over the next three decades.

In CNC machines, there are various parameters in milling and turning operations which have significant roles in reducing energy consumption. In the first case study presented, parameters of machine tools are changed and the energy consumption is calculated to identify the parameters that have the greatest impact on saving energy. An energy consumption model is developed by using system dynamics in order to comprehend the behavior of complex system. Then, data from the first case study is used in order to demonstrate how buffer inventories can help manufacturers to save more energy during high electricity demand.

DEDICATION

This thesis is dedicated to my mother, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my husband, who taught me that even the largest task can be accomplished if it is done one step at a time.

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ATCE	ATC Energy Consumption [kWh]
BPT	Best Practice Technology
CES	Carbon Energy Management
CNC	Computer numerical control
CPE	Coolant pump Energy [kWh]
DFE	Design for Environment
DM	Demand Management
DR	Demand Response
DSM	Demand Side Management
EEM	Energy Efficiency Management
EMS	Energy Management System
GHG	Green House Gas
LCA	Life Cycle Assessment
MRR	Material Removal Rate
NC	Numerical Control
NIP	Nonlinear Integer Programming
OECD	Organization for Economy Corporation Development
SD	System Dynamics
SE	Specific Energy
SEC	Specific Energy Consumption
SME	Servo Motors Energy [kWh]
SPCE	Specific Energy Consumption
SPE	Specific Process Energy
TSE	Total Specific Energy
WEA	World Energy Assessment

NOMENCLATURE

a_i	Accumulation rate for peak buffer inventory
A	Non-symmetry of milling (mm)
a_e	Radial depth of cut (mm)
a_p	Axial depth of cut (mm)
A_t	Constant
b	Steady-state specific energy
B	Contact length of milling tool (mm)
B_i	Inventory level
C_{pd}	Total on-peak demand and energy use charges
C_D	On-peak demand charge rate
c_i	Consumption rate of the buffer inventory
C_p	On-peak energy consumption charge rate
C_R	Off-peak energy consumption charge rate
CCS	Capturing and storing carbon
CME	Energy consumption of compressor [kWh]
d_p	Depth of cut (mm)
E_1	Machine setup energy (energy consumed by idle machine), kWh
E_2	Cutting energy (energy consume during material removal), kWh
E_3	Energy consumed during tool change, kWh
E_4	Energy to produce cutting tool per cutting edge , kWh
E_c	Consumed energy (kWh)
E_{cool}	Energy consumption of coolant
E_{cs}	Specific consumed energy (kWh/cm^3)
E_e	The electricity consumption of machine tools
E_{feed}	Energy consumption of feed
E_{fix}	Energy consumption of spindle
$E_{spindle}$	Energy consumption of spindle
E_{tool}	Energy consumption of machine tool
E_{total}	Total direct energy requirements
Ecs	Specific Energy Consumption
f	Feed rate (mm/min)
F	Feed force (da N)
F_c	Cutting force (N m)
F_t	Tangential component of cutting force (da N)
F_x	Feed force (N m)
f_y	Radial force (N m)
F_z	Thrust force (N m)
h	Uncut chip thickness (mm)
h_i	Holding cost for Just-for-Peak buffer inventory
H_i	Average holding cost
J_i	Peak buffer inventory
K_c	Specific cutting force in the shear zone

$k_{c1.1}$	Shear stress of the work piece material
K_i	A set of binary variables
L	Length of cut(mm)
L	Ball screw lead(mm)
M	Moving part weight (N)
m_c	Cutting constant
M_t	cutting torque (N m)
N	Spindle speed (rpm)
P_0	Power consumed by machine modules without the machine cutting(kw)
P_1	Basic power
P_2	Idle power
P_3	Cutting power
P_{air}	Air cutting power
P_{avg}	Power demand
P_c	Constant power (W)
P_{cool}	Power of the coolant pump motors
P_{cut}	Cutting power
P_{fan}	Power of fan motors
P_m	Power for enabling the operating state
P_{m1}	Power loss in machine tool and electric motor (kW)
P_{mc}	Consumed power (kW)
p_0	Idle power due to auxiliary components (kW)
P_{servo}	Power of the servos system
Pt	Cutting power (kW)
P_{tool}	Power of the tool change motor
P_{total}	Total machine power (W)
P_v	Variable power (W)
S_z	Feed per tooth (mm/tooth)
SCE	Energy consumption of cooling system of spindle [kWh]
t	Machine time(s)
t_b	Transmissibility of ball screw system
t_p	Scheduled peak
t_1	Set up time (s)
t_2	Actual cutting time (s)
t_3	Tool change time(s)
T_C (K_i)	Total cost per production time
t_{ce}	Ending time for cutting
T_{ce}	Spindle running end time(s)
t_{cos} -t_{coe}	Running time of the coolant pump motor
t_{cs}	Starting time for cutting
T_{cs}	Spindle running start time (s)
T_e	The electricity consumption of Cutting tools
t_{fei}	Starting time of the ith-axis feed
t_{fsi}	Ending time of the ith-axis feed motor
T_l	Torque load (Nm)
T_m	Application torque of ball screw (Nm)
t_{me}	Ending time for spindle

t_{ms}	Starting time for spindle
t_{tool}	Turret rotation time
T_{total}	Total machine time
T_u	Axis friction torque (Nm)
T_{CE1}	EC of lift up chip conveyor [kWh]
T_{CE2}	EC of chip conveyor in machine tool [kWh]
V_f	Feed speed
V_c	Cutting speed
X	Machine cost rate
X	Machine cost rate
X_{ij}	production rate per hour
Y	total volume of material removed (cm^3)
Y_c	tooling cost per cutting edge
Y_e	Energy footprint per tool cutting edge, kWh
y_E	Energy per cutting edge
z	Number of teeth of milling(teeth)
α	Setting angle or approach angle (rad)
β_a	The friction between the tool and the chip
γ_o, α_r	Cutting rake angle (rad)
Δt	Processing time
Θ	Gradient angle from horizontal plane (rad)
μ	Friction coefficient of slide way
τ_s	Shear stress of work piece
$1/\beta$	Feed exponent
η_m	Machine tool efficiency
φ_i	Rated power of machine i
$\emptyset c$	Shear angle (rad)
$1/\alpha$	Cutting velocity exponent in tool life equation

1 INTRODUCTION and BACKGROUND

1.1 Introduction

According to the *Oxford English Dictionary*, manufacturing is the "action or process of manufacturing something" through production or fabrication and also refers to "the sector of the economy engaged in industrial production" (Anon, 2015).

Automotive manufacturing plays an important role in the economy because it requires a large labor force and makes products requested by consumers. It accounts for a substantial share of the industrial sector in developed countries, which is almost 66% (Angelo Young 2013; EconomyWatch, 2010). Because the automotive industry relies heavily on energy in its processes, manufacturers with access to the most current energy-efficient technologies are able to decrease productions costs. This in turn frees their capital to be invested in other technologies that increase productivity and improve quality, giving them distinct competitive advantage in the global market. However, CO_2 emissions and other adverse effects linked to these activities are controversial as many critics believe they have a negative impact on the environment. Likewise, statistics show that excluding food and recyclable materials, almost 70% of the 12 billion tons of waste created was ascribable to industrial activities (Sheng, et al., 1995).

Manufacturing industries are responsible for more than one third of worldwide primary energy use. This fraction of energy consumption includes energy related to carbon dioxide discharges (Price, et al.,2006). In developing countries, the tension between target of economic advancement and limited energy sources can result from consumption of a large portion of energy supply. The manufacturing sector plays an important role in producing motor vehicle parts and it incorporates different firms that make finished components and subsystems such as powertrain parts, electrical equipment and steering and brake systems (Incorporated, 2009). In addition, some processes in manufacturing require significantly more energy, such as engine and transmission assembly, which encompasses a vehicle's power train and are made from aluminum or cast iron. These processes require a lot of machining, which consume an excessive amount of energy. As a result, some researchers have been focused on developing energy efficient methods.

One of the most important and useful processes in manufacturing is metal cutting. A detailed research is performed by considering input work material, setting of machine parameters and the output. Advancement in the process efficiency can be achieved by experimenting with different cutting parameters, such as cutting velocity or depth of cut, and finding the most effective limits for each factors and thereby securing the desired output. There are machine tools which use enormous amounts of power but working with little efficiency, mostly productivity lower than 0.2 (Draganescu, et al., 2003). Thus, it is necessary to study more about the machine tool efficiency, the relationship between cutting parameters and specific consumed energy since the available information is not enough and the machine tool's efficiency has not been investigated by many researchers.

Given the controversy surrounding the environmental impact, reducing costs is not the only reason to improve energy efficiency; it is also important to reduce energy consumption to decrease the environmental burden of manufacturing and the disposal processes based on the Life Cycle Assessment (LCA) policy. These policies are defined for future manufacturing systems according to the Design for Environment (DfE) (Narita, et al., 2006). Currently, the largest share of emissions comes from industrial energy consumption in Asia. In this region, because of high rate of usage in industrial sector and heavy use of coal, power sectors produce more than a third of total CO_2 emissions in the world (Mckane, et al., 2007).

Finally, the electricity consumption during peak periods is known as a major contributor to the electricity load management systems. The electricity demand in the USA is expected to increase by 30%, from 3873 billion kWh in 2008, to 5021 billion kWh in 2035. Moreover, because of the growth in the cost of fossil fuels and new grid capacity investment, the price of the electricity prices will increase from 8.6 cents per kWh in 2011, to 10.9 cents per kWh in 2035 (U.S. Energy Information Agency, 2013). To reduce the financial pressure and lower electricity production cost and more responsible for the environmental burden, the unregulated market model has been suggested among suppliers and marketers. Under the unregulated electricity market model, the end customers can decide to face stochastic pricing, which is based on the variable wholesale price or deterministic pricing (2015 Electric Power Supply Association, 2013). In addition, DSM programs are useful methods in reducing economic and environmental impacts of growth in electricity use (Fernandez, et al., 2013). Therefore, peak buffer inventory is introduced as a methodology to reduce the energy consumption while it is can reduce the system's throughput during high electricity demand (Fernandez, et al., 2013).

1.2 Background

Industrial sector requires more energy supply than any kind of end-use sectors: it consumes almost one- half of the world's total energy delivered (Outlook, 2012). There are different sectors of manufacturing industries, such as chemical, food, iron and steel, nonferrous metals, and paper. Likewise, there are nonmanufacturing processes, such as construction, mining, and agriculture. However, different industries in various countries or regions require different amounts of fuels that are dependent on the combination of technological advancement and economic circumstances.

1.2.1 Global energy consumption in manufacturing industry

Global energy consumption in the industrial sector is reported to be as 200 quadrillion Btu in 2010 and 307 quadrillion Btu in 2040, which indicates an average annual growth of 1.4 percent. Nevertheless, the industrial sector was responsible for the decrease in energy use throughout the global economic recession, which started 2008 and ended in 2010. One of the reasons can be decline in production in manufacturing (Schwartz 2009). Energy demand is addressed as an issue in countries with faster economic growth. Therefore, this problem needs to be addressed due to economic competiveness. Moreover, the rate of energy consumption is predicted to rise by 33% from 1980 to 2030 (EconomyWatch, 2010).

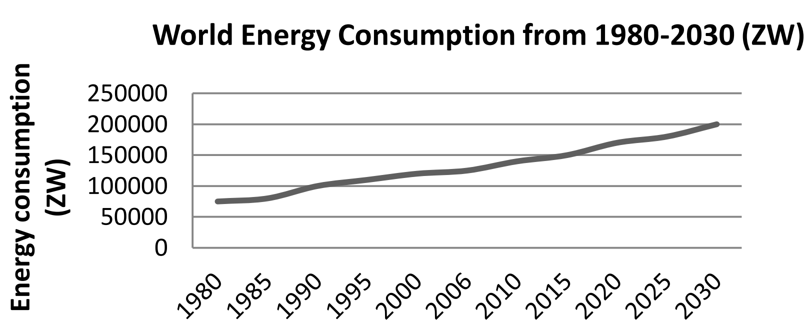

Figure 1-1 Energy consumption of world market from 1980 to 2030 (EconomyWatch 2010)

Countries outside of the Organization for Economic Cooperation and Development (non-OECD) have the highest rates of energy consumption. The Central African Republic, Chad, Chile, China, Colombia, Ukraine, Iran, Turkey, India and Mexico are examples of non-OECD countries (Rica & ITU-D 2009). The OECD countries include the United States, the United Kingdom, Belgium and the Netherlands, among others. From 2010 to 2040, the annual growth rate of energy use in non-OECD countries has been 2.3% while the annual growth rate for OECD countries is much less at 0.4% (Schwartz 2009). One of the reasons being OECD countries shift from manufacturing economies to service economies. In addition, increases in productivity, slow growth in demand for manufacturing products, and a loss of markets to imports have influenced this trend. OECD economies have encountered a drop in their share of global manufacturing employment simultaneous to a rise in their share of the service sector. However, the decline in manufacturing employment in non-OECD countries was not associated with the growth trend in manufacturing employment in OECD countries (Pilat, et al., 2006).

Figure 1-2 indicates that the non-OECD countries have used 62% of the total energy consumption in manufacturing industries since 2006. However, so far China is recognized as the biggest energy user with a share of 21% in 2013, followed by the American industries that consumed 19.3% of the total energy produced worldwide (Schwartz 2009).

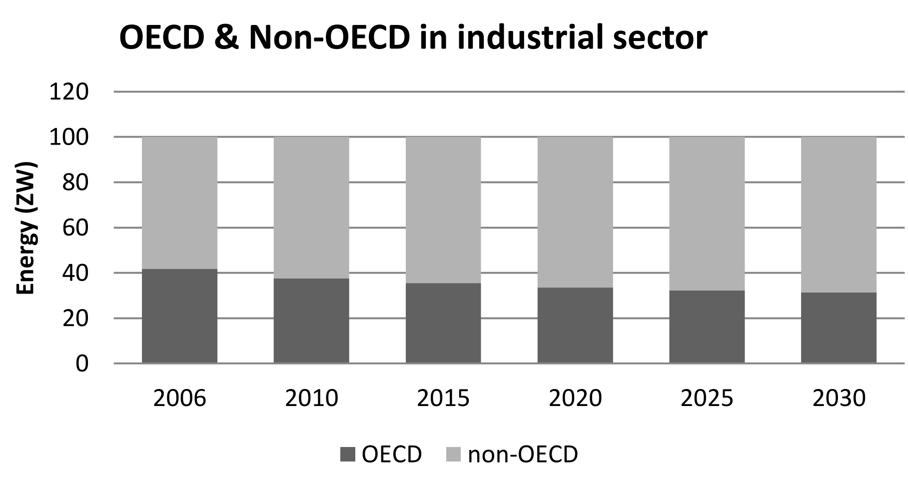

Figure 1-2 Energy consumption (ZW) for OECD and non-OECD (U.S. Energy Information Agency 2013)

China's energy consumption has increased by 5.5% annually – the most among non-OECD countries. The energy consumption in the Chinese manufacturing industry is 37% of the world’s total delivered energy, which is the highest in the world (EconomyWatch, 2010; Sheng, et al., 1995).

Different resources can be used to generate energy. For example, liquids fuels, which include both oil-based products and natural gas liquids used for both feed stocks and fuel in the industrial manufacturing industries, are expected to grow in use by 1.2% from 2010 to 2040. Likewise, the rate of electricity usage for producing energy in the manufacturing industries is expected to grow by a rate of 1.8 percent yearly during the same period and its portion in total energy consumption is forecasted increase from 14.6 in 2010 to 16.3 percent in 2040. Alternately, the liquids portion of total delivered energy produced in manufacturing industries is expected to drop during the same period. The natural gas and coal consumption rates in manufacturing industries are also expected to rise by 1.5 percent and 1.4 percent respectively (U.S. Energy Information Agency, 2013).

The OECD countries consumed almost 70 (Quadrillion Btu) in 2010, the highest portion of which came from liquids, almost 26 (Quadrillion Btu), followed by natural gases, which comprised almost 22 (Quadrillion Btu; U.S. Energy Information Agency, 2013).

One of the reasons that explains why OECD countries are trying to transition to service industries is because they are trying to decrease the portion of energy sources by outstanding their production lines and manufacturing industries to non-OECD countries. Moreover, this trend has a significant effect on the environmental problem. OECD countries plan to decrease the amount of resources needed in producing energy in manufacturing and environmental burden of machine tools. Another reason is that investors do not want to invest in physical assets, eventually lose value over time. Such investments tie up the investment capital, which is not recoverable and leads to losing profit.

However, according to the U.S. Energy Information Agency (2013) in non-OECD countries, the total portion of energy consumption was almost 125 (Quadrillion Btu) in 2010 and is predicted to be almost 220 (Quadrillion Btu) in 2040. It can also be observed that the highest portion of energy is generated by coal, almost 46 (Quadrillion Btu), and it is forecasted that almost 65 (Quadrillion Btu) of coal will be consumed to produce energy in 2040. Then, liquids and natural gases are the next energy producers that are 25 (Quadrillion Btu) and 23 (Quadrillion Btu) respectively.

The U.S. Energy Information Agency (2013) provided the energy consumption comparison (Quadrillion Btu) between OECD and non-OECD countries in 2010 Figure 1-3. As it can be readily understood the OECD countries are using less coal than non-OECD countries.

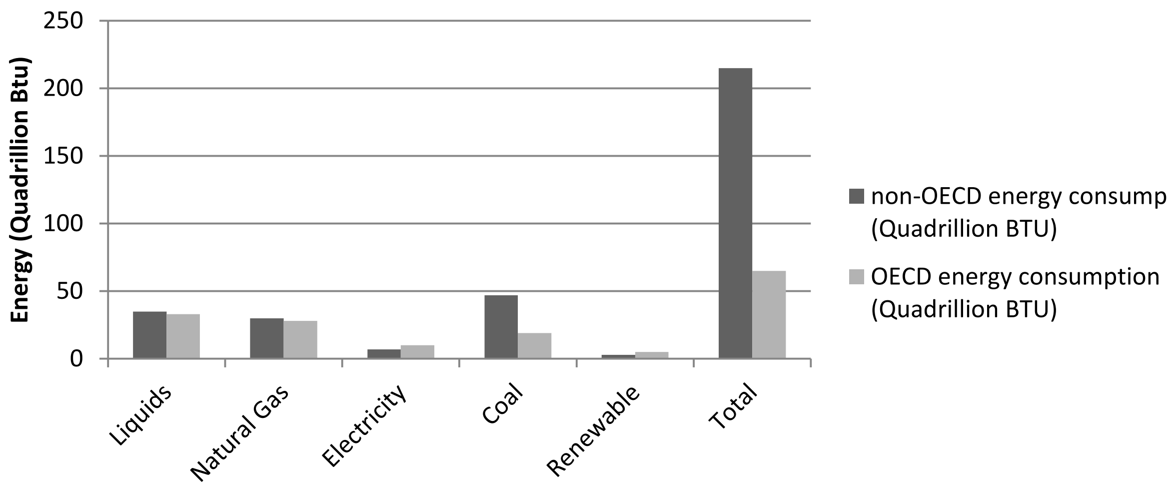

Figure 1-3 Comparison between non-OECD and OECD countries (U.S. Energy Information Agency 2013)

Production of nonferrous metals such as aluminum, zinc, lead and copper made up 2% of the industrial sector energy use in 2010. Aluminum production is the most energy intensive among nonferrous metals, but, it can be easily recycled (Iai 2009). Likewise, energy cost of the aluminum manufacturing is almost 30% of the total energy cost of the initial aluminum manufacturing and is second most expensive after raw material alumina. Because of the worldwide recession in 2008 to 2010 and its adverse effects on the global economy in different manufacturing industries such as automotive, the demand for aluminum dropped. This effect was not critical in non-OECD countries, and these countries got aluminum transferred from OECD manufacturing sectors. It is predicted that non-OECD industries will grow in their aluminum production sector (IHS Global Insight, n.d.).

Aluminum production in the United States uses two different methods; each requires its different amounts of energy for production. The primary method produces (manufacturing) aluminum parts from raw material or ingots, and has intense energy demands, specifically electricity. The second form of production includes recycling aluminum scrap to make new products. This process requires less energy. For instance, aircrafts use primary aluminum because of the attribute and persistency limitations, whereas the beverage cans and automotive casting usually use secondary aluminum. Rate of energy consumption in manufacturing with aluminum, noting that the total amount of energy consumption in the aluminum sector is over 300 (trillion Btu) in 2006 (U.S. Energy Information Agency, 2013).

Aluminum is an incomparable metal in improving fuel economy and battery power because it has high strength and light weight. It can also be a good replacement for steel, which can be highly effective in decreasing fuel consumption and environmental burdens. This is because the less a car weighs, the less fuel is needed to move it. Thus, the advantages of aluminum use in automotive applications are:

1) By using aluminum instead of steel, it is possible to reduce fuel consumption by 5 to 7 percent for every 10 percent weight reduction.
2) Weight reduction in automotive industry is considered as the most important strategy in reducing cost in achieving a 50+MPG fuel economy target.
3) Aluminum benefits electric vehicles by offering a more efficient, lower weight solution to combat heavier battery weight, potentially yielding up to a $3,000 savings per vehicle.
4) Using aluminum in electric vehicles can increase the vehicle's driving range by roughly the same proportion as it decreases weight. For example, reducing the weight by 20 percent will allow the vehicle to travel 20 percent farther.
5) Aluminum-structured hybrids achieve 13.5 percent better fuel economy than steel-bodied hybrids (DRIVEALUMINUM, 2015).

1.2.2 Economy and energy

Another important fact that has a substantial effect on the global energy use is the rapid growth in the world population, which has reached at 7.2 billion in 2015 and is forecasted to have a steady growth up to 2050 (Worldmeters, 2015). The rise in the world gross domestic product (GDP) also has an influence on the global economy. Table 1-1 indicates that although there was a drop in world GDP through 2007 and 2009 because of the global recession, the world GDP data showed a growth in the universal financial resources in 2010 (International Monetary Fund, 2010).

The growth rate in GDP is explained by the rise in the rate of production ,and it is related to the increase in the energy required to supply raw materials, production processes, and transporting products (Rajemi, 2010).

Table 1-1 Gross Domestic Product (International Monetary Fund, 2010)

	2007	2008	2009	2010	2011	2012	2013	2014	2015
World GDP (US Billion Dollars)	55,392	61,220	57,937	61,781	65,003	68,701	72,740	77,132	81,789
European Union GDP (US Billion Dollars)	16,942	18,387	16,447	16,543	16,925	17,507	18,139	18,806	19,482

1.2.3 Process different material

The production and processing of aluminum and steel accounted for the highest amount of energy use compared to the other materials in the transmission system (Figure 1-4). Almost 49% of the energy consumption during the production of the transmission system was for the production and processing of virgin steel parts. Production and processing of virgin aluminum parts consumed a further 38%, followed by iron parts at 4%.

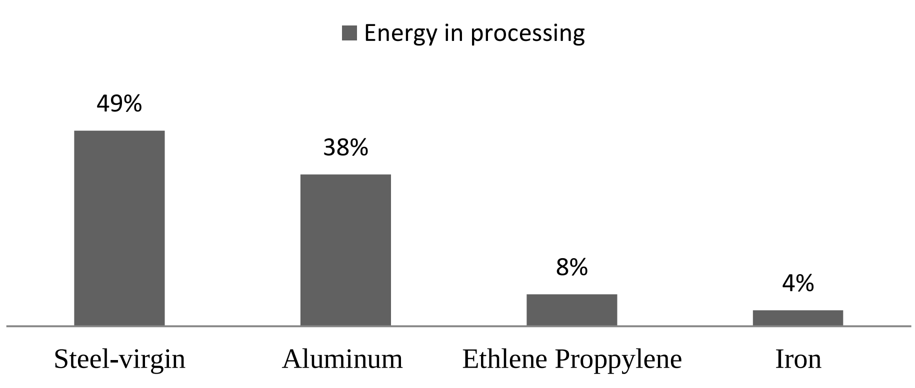

Figure 1-4 Material energy consumption, data adopted from (Incorporated 2009)

Aluminum alloy and steel take significantly more energy to be processed than any other materials. According to (Incorporated, 2009) the majority of the energy (96%) in producing and processing the aluminum is assigned to the material production part. Material production energy is the energy associated with raw material acquisition and processing. For instance, the material production energy associated with aluminum includes the energy required for bauxite mining, bauxite refining, alumina reduction, and Al melting and initial casting.

1.2.4 Energy consumption in automotive industry

The overall energy needed to make a car is divided among four types of activities: raw material processing, car manufacturing, car use and recycling (figure 1-5). The amount of energy used in different stages of car production (press, body, paint and assembly) is almost 700 kWh/ vehicle and the energy cost is almost 9-12% of the total cost. Thus, reducing the energy cost by 20% results in almost 2-2.4% saving of the whole manufacturing costs (Paralikas et al. 2011; Fysikopoulos, et al., 2012).

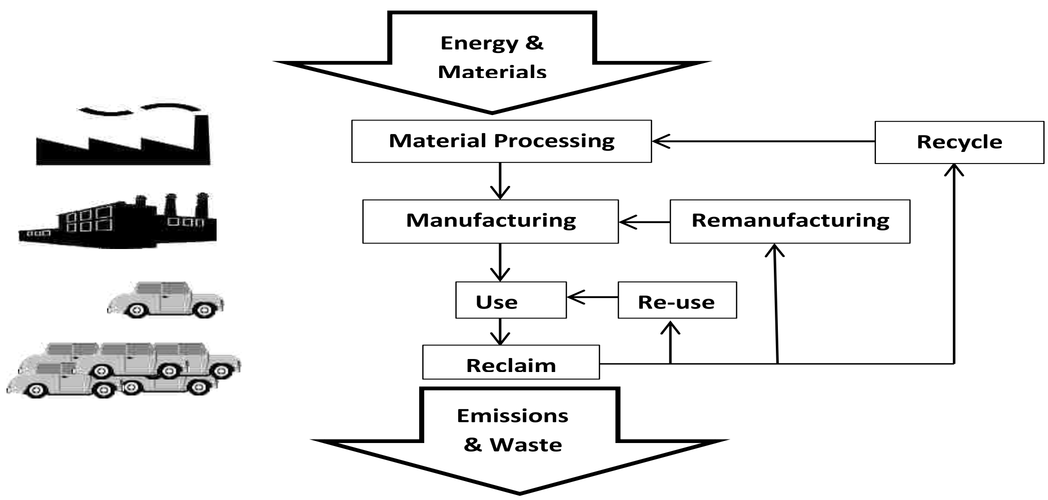

Figure 1-5 Total car life cycle, adopted from (Fysikopoulos, et al., 2012)

(Fysikopoulos, et al., 2012) indicates that the energy consumption depends on the demand rate or the amount of input. Moreover, the energy of the busy state is more than the energy in idle times. Therefore, one of the recommendations made by the authors was that accurate line balancing and planning the idle times can save more energy and money for the manufacturers.

Fysikopoulos, et al. (2012) have proposed a detailed information and simulation for the energy efficiency of a production plant. They have considered the assembly line of car's under-body since it is a vital part of the body, which connects to the major components of a car such as transmission and motor. It can also have an important role in the cars' rigidity and defines the cars' length.

As for the assembly line structure, it can produce three types of underbody in order to fulfill the need for multi-variant vehicles. The final products are the underbody variant 1 (UV1), the variant 2 (UV2) and the variant 3 (UV3; Paralikas, et al., 2011). The whole production line is based on four sub-assembly lines in which the first three sub-assembly lines (front end module, floor module, and rear end module) are functioning in parallel, and the fourth part, which is the main underbody assembly, builds the final assembly (Fysikopoulos, et al., 2012).

Improvements in automotive manufacturing can be suggested as greater productivity; fewer rejected parts and wastes, reduced emissions to the environment, and lower energy expenditures. These developments made in automotive manufacturing could also be used in industries with similar processes or equipment, for instance, the manufacture of farm equipment, industrial machinery, fabricated metals, heavy trucks, rail cars, ships, and aircraft (US Department of Energy, 2008).

1.3 Machining processes

Machining is a material removal process that shows the use of different cutting tools for cutting metals. What is important to notice is that these processes are precise in dimension, flexible in different operations and productive in relation to cost when limited production volume is considered. The machining processes are diverse since they can be involved in the pre-production process and anywhere else up to and including the final stages of production. However, because removal processes that involve material removal, they can leave waste in energy and materials (Dahmus and Gutowski, 2004). The area of focus in this study is only saving specific energy consumption in machining processes by changing specific machining parameters. As for the machining operations, both turning and milling processes are investigated.

1.4 Energy performance benchmarking in automotive industry

Benchmarking data is a useful resource in energy efficiency since there is a necessity of initiating the policies for decreasing the CO_2 emission. The benchmark curve can be a useful tool in comparing the performance of different plants in industry sectors. Furthermore, it includes information about best-practice technologies (BPT), such as energy efficient technologies (Saygin, et al., 2010).

Energy benchmark data can provide information on:

— The most energy efficient plant. This is referred to as the Best Available Technology (BAT)

— The international benchmark (i.e., the plant at the 1st decile, as described above)

— The last decile plant (i.e., the most efficient plant in the last decile); and the least energy efficient plant in the entire dataset (Saygin, et al., 2010).

1.4.1 The environmental and economic burden of fuel in automotive manufacturing

In the manufacturing industry there are different fuel prices depending on the different kinds of energy resources. For instance, liquid fuels are more costly than other types of fuel. Liquid fuels growth rate is only 0.68% yearly with an estimated drop in the rate of usage in the manufacturing industry by the year 2030. As a result, liquid fuels usage is being replaced by electricity, which is estimated to increase by 3.5% from 2006 to 2030 (Pilat, et al., 2006).

Gutowski (2006) argues that the major source of energy in the manufacturing industries is electricity and notes that almost 66% of the electricity is produced by fossil fuels, which leads to CO_2 emissions and cause negative effects on the environment (Gutowski, et al., 2006). In 2004, the total amount of CO_2 emissions related to the energy consumption of manufacturing industry was almost 10 GT, which was 37% of the total CO_2 emissions in the world.

Price, et al. (2006) predicts that the CO_2 emissions would rise in all regions of the world until 2010 when CO_2 emissions from developed countries of the North America, Western Europe and Pacific OECD regions are predicted to peak and then should begin to decline.

Furthermore, the emissions were expected to increase in developing countries, though with a slower rate. It is predicted that the developing countries will surpass the CO_2 emissions from developed countries in industrial subdivision by 2020 and that they will become the main sources of CO_2 emissions in manufacturing industry (Price, et al.,2006).

Jeswiet, et al. (2008) likewise proposes a method that shows the connection between electricity consumption in manufacturing and carbon emissions. They developed the carbon energy signature (CES) concept that can be utilized in any industry using energy sourced from fossil fuels. Another important metric useful in the carbon emissions and manufacturing is Green House Gas (GHG) label, which is a method of showing how much carbon has been released in production and manufacturing. A GHG label can provide information to the customers about carbon emissions of a product (Jeswiet and Kara, 2008).

1.4.2 Energy efficiency in manufacturing

To be successful in the business, manufacturers have to participate in a competitive market environment and this can be achieved, in part, by producing more products while consuming less energy. Since energy prices fluctuate in the market, they can have an adverse effect on the production rate (US Department of Energy, 2008). (Price and Ross 1989; Dag 2000) observe that significant amounts of energy are wasted during shut downs or idle times, thus introducing energy management systems can decrease the non-productive energy consumption by inspecting the lighting and heating, ventilation and air-conditioning (HVAC) equipment (Dag 2000; Price, and Ross, 1989). In their study, energy efficiency measures were characterized either by the utility systems, such as motors, compressed air, heat and material handling, or by process painting, welding and stamping.

In brief, OECD countries have shifted from manufacturing economies to service economies and this has a significant effect on both economy situation and environmental burden of non-OECD countries. Non-OECD manufacturers are using more energy to increase production for OECD countries and boost their economy by creating more jobs and increasing the production rate. However, this has a harmful effect on the environment due to the fact that non-OECD manufacturers have consumed large amount of natural resources in order to supply energy for production. Among these resources, fossil sources are used significantly more in producing power and energy for manufacturing industries. It is predicted that there will be a shortage in the fossil resources. Likewise, because of growth in the energy demand in machine tools, the cost of expanding electrical energy is increasing. As a result, the extra costs on the environment are rising.

As previously mentioned, chemicals iron and steel making are the largest energy consumers in manufacturing industry. Among non-ferrous metals, aluminum is of the most significance metal as it is frequently used in the automotive industry. Although it takes a lot more energy in machining processes, it helps in reducing the cost of fuel and battery power since it is light weight. It can also reduce the environmental burden by reducing the amount of energy consumption.

1.5 Problem statement

Electricity (energy) demand has been increasing substantially in the manufacturing industries since the beginning of modern manufacturing era. This trend calls for capacity expansion of the power grids. There is a need for analyzing the machining system and energy flow to find the best opportunity in saving energy. Energy flow was presented before in a three-level structure, namely enterprise level, shop floor level and process level. To reduce energy in the enterprise level, the energy monitoring methods are suggested by (Kara, et al., 2011). Also, as real time online energy management systems (Arinez 2010; Diego 2009) are utilized in this level.

As for the second or shop floor level, energy consumption can be analyzed in the production department. Likewise, methods in production planning and process scheduling developed by (Pechmann 2011; Mouzon and Yildirim 2007) to reduce energy in shop floor level. Another approach recommended here is the line balancing in the production line in order to save more energy. “Just for Peak” buffer inventory is used in this study to reduce electricity demand in peak time.

The bottom level is a process level in which it is shown that energy is distributed among four parts: machine tools, auxiliary equipment, tools and material supply. Further detailed analysis may be needed due to diverse capabilities of machine tools, functionalities of auxiliary equipment, tools and variety of materials. They all have different effect on the energy consumption at this level (Peng and Xu, 2014).

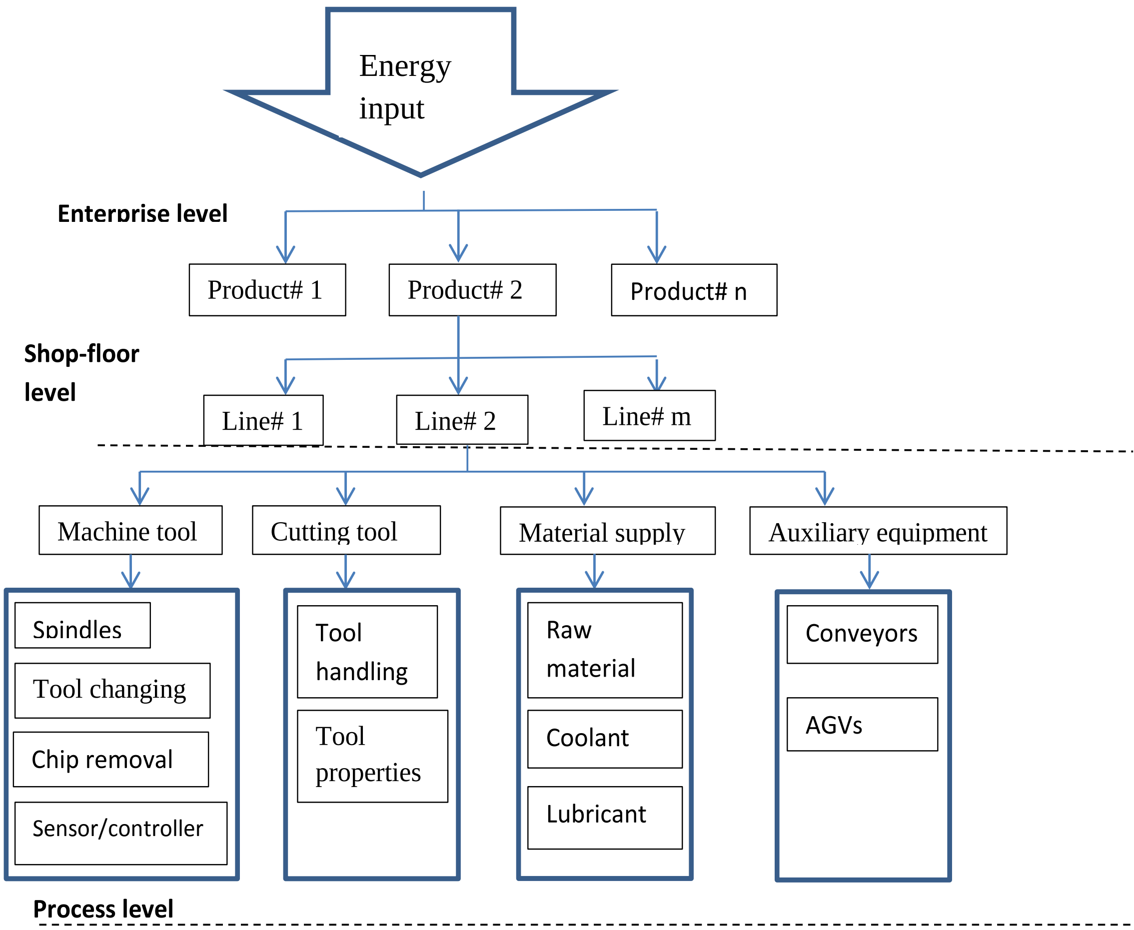

Figure 1-6 Overview of energy flow in a three-level structure (Peng and Xu, 2011)

In this study, two critical aspects of energy savings are being considered, both applicable at shop floor and process level. The process-level method is the energy efficiency assesment in cutting processes which is explored while evaluating the relevance in cutting parameters and the output in milling and turning operations. The goal here is to develop a dynamic model based on the static cutting formulas introduced in past research. This model can analyze the overall milling/turning processes for Aluminum Alloy during the cutting time in order to identify the best set of cutting parameters that have the most significant impact on energy consumption. It is necessary to know that each material has a specific cutting data range. Therefore, acquiring these data for each material and process and applying them to this model can provide a great understanding of each cutting process and help to save more energy.

Next savings opportunity can be thought-out at the enterprise level and it is about energy saving during peak times of electricity demand in cutting, milling and turning processes. A nonlinear integer programming (NIP) is used in this study to minimize the cost of electricity while maintaining system throughput. Furthermore, buffer inventories during high electricity and applying load management policies can help to manage the electricity demand and lower the holding cost. The objective function considered for this problem is minimizing the total cost, which is calculated by sum of the holding cost of buffer inventory and energy consumption cost during off peak and on peak period (Fernandez, et al., 2013).

1.6 Proposed approach

To begin with, some past research identified the relationships between cutting parameters, power consumption and surface roughness in various machine operations. The majority of these have considered power consumption rate, cutting velocity, and depth of cut. However, there are some other parameters, such as rake angle, whose effects on reducing energy have not been considered in comparison with other cutting parameters. Thus, the evaluation between the effect of rake angle on saving energy and other milling parameters is added in this study. In addition, system dynamics methodology is used in order to investigate the relationship between the new selection of cutting parameters and energy consumption. Next, in this section the effect of peripheral devices of a machine tool, such as spindle motor and servo motor, has been illustrated. Then, by varying the cutting parameters and applying analysis methods, such as response surface method and sensitivity analysis, allows identifying parameter settings for energy-conserving process.

Furthermore, one of the main problems that have to be addressed is that the cost of electricity rate is much higher during peak usage time (e.g., daytime), which leads to financial pressure in manufacturing industries. Therefore, the electricity demand reduction should be considered both during off peak and peak periods, while increasing the system throughput. A suggested method relies on load management system and buffer inventory solutions in the period of high electricity consumption. The balanced distribution of electricity during various periods is essential in process planning. Besides, this method allows decreasing the cost of holding the buffer inventory and production cost in off-peak electricity demand. The next important point, which has not yet been considered in any other studies, is how to save more energy consumption with the changes in the market demand. The linear equation formulated in this study indicates how the electricity demand is changing according to the specific market demand.

2 LITERATURE REVIEW

2.1 Introduction

In this chapter, the study of energy consumption is divided into four categories. Firstly, energy in manufacturing processes. In this section, the general idea of manufacturing and energy is given. Likewise, assessing machinability in manufacturing process and reason of monitoring the energy consumption is introduced. Secondly, energy and force model in manufacturing process proposed. Furthermore, mechanics of milling and turning processes is presented from different research. Aluminum alloy is the material considered in this study. Specific energy consumption and material removal rate of this material is illustrated. Next, energy and sustainability is illustrated and a prediction system for environmental burden of machining operations based on the Life Cycle Assessment (LCA) strategies is discussed in this section. Finally, in the energy and cost section, the need for optimization in manufacturing processes is given as a result of the growth rate in the cost of energy consumption and energy demand in manufacturing processes.

Summary of important research regarding energy consumption in milling and turning processes:

1) Energy consumption in the milling operation

In a study performed by Shao et al. (2004) various cutting conditions were examined. Average tool flank wear was considered in developing the cutting power model in face milling process.

Diaz et al. (2011) provided strategy for energy and power reduction in milling operations and considered the specific energy as a function of material removal rate and demonstrated the specific energy model, which helped a product designer to evaluate the manufacturing energy consumption of their part’s production without needing to measure power demand directly at the machine tool during their part’s production.

Armarego et al., (1991) developed a model to show the relationship between specific power and cutting parameters, such as feed per tooth, depth of cut, and cutting speed in face milling process.

The effects of cutting conditions on cutting force and cutting energy was illustrated (researched) by Polini and Turchetta (2004). The authors explained that the cutting energy and force are related to the shape of the idealized chip thickness. The effect of changing feed speed and depth of cut were used in predicting the cutting force and energy in milling operation.

Performance assessment of milling process is defined according to the performance specifications, such as material removal rate, tool life, tool wear, surface roughness and energy consumption. There are many studies about performance modeling of milling that are focused more on tool wear, surface roughness, and cutting force. However, less research has been performed so far about the effect of energy consumption specifically in milling and turning operations. Draganescu, et al., (2003) proposed a statistical model of machine tool efficiency and specific energy consumption. The authors used the experimental data and response surface methodology in order to show the relationship between cutting parameters (depth of cut, feed rate, cutting speed and contact length of milling) with specific energy consumption. However, the effects of shear angle and rake angle were not included in the specific energy consumption model.

2) Energy consumption in the turning operation

Camposeco-Negrete, (2013) developed strategies to reduce energy consumption by optimizing cutting parameters in turning of AISI 1018 steel under constant material removal. The mathematical model presented by Soni, et al., (2014) in order to predict the surface roughness and material removal rate in turning process by considering cutting speed, feed rate, and depth of cut as process parameter. Malagi and Rajesh, (2012) Developed software to estimate cutting forces in turning process while including depth of cut and feed rate in their evaluation. The work presented by Cica, et al., (2013) predicts the cutting parameters (feed rate and depth of cut) in turning while researchers applied several methods of cooling and lubricating of the cutting zone. Furthermore, artificial neural network and adaptive networks-based fuzzy inference systems were used in order to predict the cutting forces. Guo, et al., (2012) provided a methodology that incorporated both energy consumption and surface roughness for optimizing the cutting parameters in finish turning. Cutting parameters, namely depth of cut, cutting speed and feed rate, were optimized to achieve an accurate surface finish with minimum energy consumption. However, the effect of material removal rate was not defined completely in this study. The work of Rajemi, et al., (2010) clearly identified the effect of flank wear in reducing energy use and reduced the energy cost and environmental footprint. The optimum cutting speed was presented to determine the optimum tool life for minimum energy. The effect of cutting parameters, such as depth of cut, material removal, and feed rate, added in this study to find which parameter has the most effect on the energy consumption.

2.2 Energy in manufacturing processes

2.2.1 Machinability in manufacturing industry

(Malakooti, et al., 1990) Machinability is a general concept that includes all phases of manufacturing, specifically the process planning, product design, machining operations and quality control. The main purpose of machinability is to reduce energy required in machining process and minimizing cost. Originally, machinability was defined as a property or characteristic of a material measured by its physical attributes (properties) namely, metal (material) hardness.

There is no general measurement for machinability yet. This assessment usually depends on manufacturers' demand and other factors. For example, some manufacturers assume that tool life is one of the major standards in assessing machinability, whereas others think the surface cut quality is the best factor in evaluating machinability (Malakooti, et al., 1990).

Due to the fact that there is no universal strategy in assessing machinability in manufacturing processes, and there is a huge selection of raw material in every market, many manufacturers are facing problems in choosing suitable material for their products. Also, machinability has the main influence on material selection, machinability study. This is the basis for evaluating the cutting fluid performance and optimizing the machining parameter.

There have been various studies performed on machinability. For instance, the first mathematical formula introduced by Taylor (1907) shows the relationship between tool life and cutting velocity in machining operations. Another work presented by Herbert (1928) describes the relationship between tool life and cutting velocity in machinability; however, other aspects influencing machinability were not considered by the author.

There are two important types of material attributes in machinability namely, inherent and behavioral attributes. An inherent property is about innate characteristics such as microstructure and chemical composition. However, these attributes cannot always accurately describe machinability. Inherent attributes include physical, chemical and mechanical properties, which can be evaluated by non-machining tests. The behavioral attribute is related to material's performance during the machining processes in terms of economic and technical outcomes, such as tool life, surface finish, cutting power, and energy consumption (Malakooti, et al., 1990).

The fishbone diagram (figure 2-1) illustrates parameters which cause the energy inefficiency in manufacturing processes. There are four possible categories explaining the causes of this problem in manufacturing processes. The first category is environmental effect. This problem is resulted from waste, recycle, CO2 emission, and natural resources. Then, machine tool condition and parameters, namely friction, cutting parameters, and temperature result in energy efficiency in manufacturing processes.

The next energy efficiency category is work piece material which is very important in manufacturing processes since it can vary the energy output significantly. For instance, the hardness of the work piece material is highly important because it determines the energy demand and causes tool breakage. Finally, process planning, production scheduling and selection of cutting parameters are the examples of methods that affect the energy inefficiency in manufacturing process.

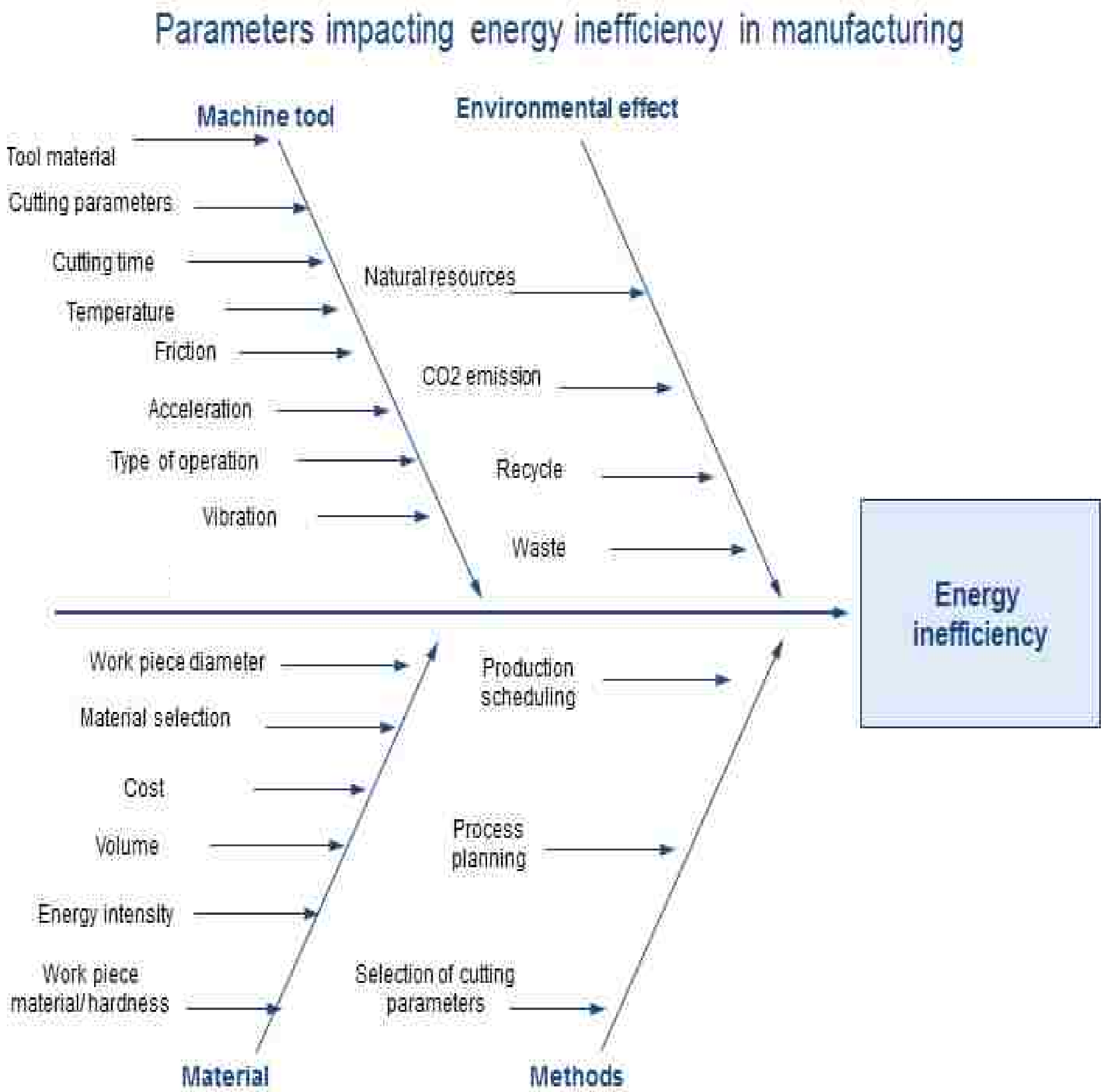

Figure 2-1 Fishbone diagram for energy inefficiency sources in machining processes

2.2.2 Manufacturing and energy

Many studies have been performed to explain the machining processes in manufacturing. However, the environmental effects of the machining operations have not been yet fully noticed, with the exception of a research carried out by Dornfeld and Gutowski's group at the Massachusetts Institute of Technology (MIT; Vijayaraghavan & Dornfeld 2010; Dahmus and Gutowski, 2004). This study developed a flow diagram of environmental burden of machining operations presented in Figure 2-2. Moreover, this figure indicates the significant factors involve in machining processes.

The major contributor to the environmental burden and energy budget is the energy consumed in the machining process and the energy of the material being, which is processed by machine tools. The energy in the industrial sector is generated by the electrical grid and is important to know that the highest percentage of electricity is produced by coal (Rajemi, 2010).

Various kinds of material need different methods of extracting and refining, which all have different effects on CO_2 emissions. Therefore, it is important for the manufacturing industries to know the information regarding the CO_2 emissions of processing raw material. The carbon footprint comprises the direct energy footprint of manufacturing processes and the indirect footprint included in the inputs of each process (Rajemi, 2010).

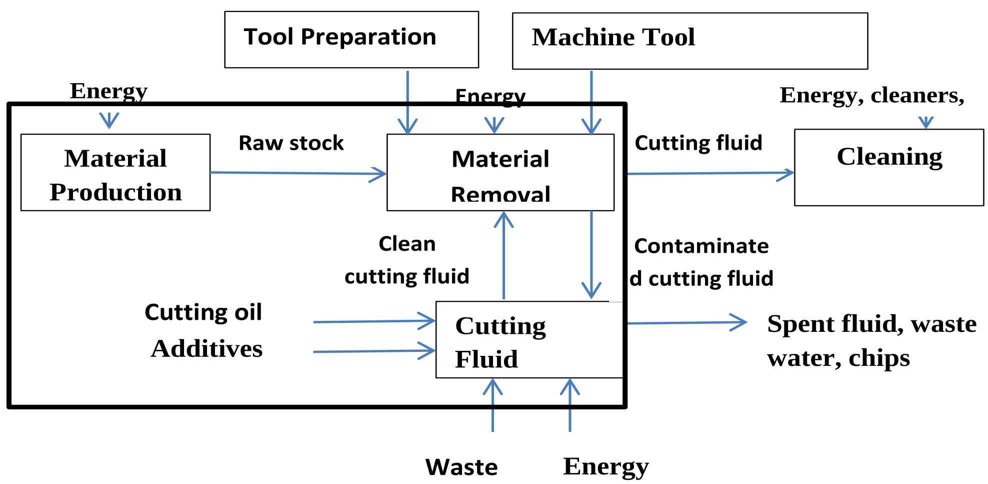

Figure 2-2 Energy in manufacturing processes (Dahmus & Gutowski, 2004)

2.2.3 Need for monitoring energy in manufacturing industries

Manufacturing processes are becoming more complex and related data resources are increasing significantly. In spite of the complexity, there are many improvements that have been made in the past on the process level than the system level. Thus, there is need to investigate the best systematic method to find the complexity in the system flows, specifically the energy consumption of machine tools. Energy consumption of machining operations presented by Dahmus and Gutowski (2004) shows an example of environmental burden of machine tools and its effect on the Life Cycle Assessment (LCA; Dahmus and

Gutowski, 2004). This approach shows the difference between the energy needed for chip formation and manufacturing tools operation (Dahmus and Gutowski, 2004).

A method of macro planning based on machining processes was introduced by (Srinivasan and Sheng, 1999). This method was used to analyze the process parameters, tooling, and cutting fluid based on energy consumption in machining processes, process quality and machine time. However, their work can only explain the process planning and energy consumption in the chip removal (Srinivasan and Sheng, 1999).

A study of power consumption of a machine tools in various operations was performed by Toenissen (2009). In this research, power usage of machine tool components was estimated by applying empirical analysis. Another study, performed by Devoldere, et al., (2007), investigates the power needed in the machine processes in discrete part production and categorizes productive and non-productive periods.

These approaches are theoretical and can only be used to estimate the energy needed in different machining operations and operations in manufacturing a part (component). For example, the method applied by Devoldere, et al., (2007) cannot help in making decision for different machining processes. Thus, these methods are not efficient enough in complex manufacturing systems (Vijayaraghavan and Dornfeld, 2010).

A research performed by Vijayaraghavan and Dornfeld, (2010) defined a framework using event stream processing in order to analyze the relationship between energy consumption and machine tools performance. Software-based framework was used in their research according to the complexity of manufacturing. The event stream processing technology can help to understand the large data streams in the events that occur in the streams as well as complex abstracted events (Anon, 2009).

In brief, the method introduced by Vijayaraghavan and Dornfeld, (2010) is comprehensive since it can analyze the energy consumption and the environmental performance of machine tools. The events stream processing technology enables reasoning of vast data streams in different event streams.

2.3 Energy and cost in manufacturing industry

2.3.1 Energy and cost issues in automotive industry

Nowadays many manufacturers are increasing environmentally aware and try to remanufacture products with the aim of reducing environmental impact while reducing the cost. One of the reasons that oblige manufacturers to decrease the energy consumption in manufacturing processes is the growth in the cost of energy required in their processes. As it is discussed before, as a result of massive use of natural resources, specially coal for providing energy for different industries, most of the resources are depleting. Therefore, the cost of having these resources is increasing to force the manufacturers to switch to some other types of sources for generating energy.

2.3.2 Energy and cost in CNC machines

In the research performed by Anderberg and Kara, (2009) the total energy consumption rate was measured and a flank wear of 0.8 was utilized for assessing the tool life. The tool's wear was measured after five times machining and five different approaches by changing feed rate and depth of cut applied. The result from this case study indicates that the direct machining energy cost has a main effect on total cost whereas; the indirect cost, such as the cost of electricity is small in relation to other machining cost. This confines a substantial saving opportunity for manufacturers if they utilize energy efficient machining. Moreover, this efficiency can be achieved with the minimum energy consumption that is resulted from high material removal rate (Beno, et al., 2009; Dietmair and Verl, 2009; Shaw, 2005).

One of the most important factors affecting the energy cost is the level of automation. In other words, automation drives the energy costs up (Anderberg and Kara, 2009).

In order to reduce the environmental effect, every sector of a society should come up with a specific goal and solution (measurements) (Anderberg and Kara, 2009). The manufacturing industries are the greatest energy consumers including CNC machines which are the basic manufacturing technologies (Dahmus and Gutowski, 2004). Energy constitutes 4-20% of the life cycle cost of machine tools (Dervisopoulos, et al., 2008).

The cost model was introduced by Anderberg, et al., (2010) to estimate the machines operation costs, machine tool and labor cost, set up cost, idle cost, direct and indirect tool cost. This model became more comprehensive by adding costs components namely, direct and indirect energy costs and extra costs related to environment burden of machine tools (Anderberg, et al., 2010).

2.4 Mechanics of orthogonal cutting

Altintas (2000) presented that the most common cutting process are three dimensional, which are geometrically complex but two dimensional orthogonal cutting can be used to explain the general mechanics of material removal. In the orthogonal cutting, the material is removed by a cutting edge that is perpendicular to the direction of relative tool-work piece motion.

The mechanics of more complex three-dimensional oblique cutting operations are usually evaluated by geometrical and kinematic transformation models used to the orthogonal cutting process. Orthogonal cutting model was developed by Merchant (1945), the model assuming that the shear zone to be a thin plane. Similarly, (Lee and Shaffer 1949; Palmer and Oxley 1959) have their assessment on a thick shear deformation zone. There are studies comparing the orthogonal cutting with oblique cutting. There are many studies explaining non-orthogonal cutting however, because of the complexity of this process, there is a need of more detailed analysis of this model.

In this study, orthogonal cutting model is used since it is more simple and easier to implement (evaluate).

2.5 Turning and Milling energy and cutting force models

2.5.1 Mechanics of turning (Turning process)

Turning process is one of the most important operations useful in manufacturing industries such as automotive, aerospace and shipping. In this process, a single point cutting tool removes material from a surface of cylindrical work piece while it is rotating. The cutting tool is fed linearly in the same direction of axis' rotation. Turning is performed on a lathe which provides the power to run and turn the work piece at a rotating speed and feed to the cutting tool at particular rate and depth of cut. As a result, there are three major cutting parameters namely; cutting speed, depth of cut and feed rate need to be optimized in turning operation (Abhang and Hameedullah, 2010).

Three cutting force components can be identified in turning process:

1- Thrust force (F_z), which acts in the cutting speed direction

2- Feed force (F_x), which acts in the feed rate direction. This force tends to push the tool away from the chuck.

3- Radial force (F_y), which acts in radial direction and tends to push the tool away from the work piece (Trent, 1984; Kalpakjian, 2001; Nagpal, 1982).

The actual cutting force model is formulated in equation 2-1(Altintas, 2012):

$$F = \sqrt{F_x{}^2 + F_y{}^2 + F_z{}^2} \qquad \textbf{2-1}$$

The energy model describes the amount of energy required to remove a unit of material under various process conditions. In general, the required power for a machine tool is composed of a constant and a variable component (Dahmus and Gutowski, 2004). The constant component is the power which is independent from the machining parameter settings and can be apportioned to machine tool accessories namely, the pumps, computer, fans and lighting. The variable power con depends on the process parameters. It is mostly related to the changes in the spindle and the axis drives (X, Y, Z). The total machine power is depicted in equation 2-6.

To estimate energy consumption of machining, the specific energy (J/mm^3) can be used; it is defined as the ratio of the power (W) consumed and the material removal rate (mm^3/s). Specific energies can be calculated for P_t, P_v and P_c as presented in equations 2-2, 2-3, 2-4 and 2-5. The total specific energy (TSE) is calculated as the ratio of the total machine power over the material removal rate, the specific process energy (SPE) is obtained through dividing the variable power by the material removal rate and the specific constant energy (SCE) is calculated from the ratio of constant power over the material removal rate. The equation 2-5 shows that the total specific energy is the sum of the specific process energy and the specific constant energy (Guo, et al., 2012).

$$TSE = \frac{P_t}{MRR} \qquad \textbf{2-2}$$

$$SPE = \frac{P_v}{MRR} \quad \textbf{2-3}$$

$$SCE = \frac{P_c}{MRR} = \frac{P_c}{f.d_p.V_c} \quad \textbf{2-4}$$

$$TSE = SPE + SCE \quad \textbf{2-5}$$

$$P_{total} = P_v + P_c \quad \textbf{2-6}$$

2.5.2 Mechanics of milling (milling process)

Milling is the operation of machining flat, irregular or curved surfaces by feeding the work piece against a rotating cutter with multiple cutting edges. The milling machine comprises of a motor driven spindle which mounts and rotates the milling cutter and reciprocating flexible work table, which is used in order to mount and feed the work piece. Milling machines fall into two categories, horizontal and vertical machines. There are six load categories for milling operation which can be mentioned as a knee-type, ram-type, manufacturing or bed type, and planer-type. Milling processes can be used in different industrial applications and creating a complex shaping, removing large amounts of material accurately. Milling process is required in making planner surface, cutouts, slots and holes (Engineers Edge, 2009).

The cost of milling machines can be reasonable (low) if general tooling and equipment is used. Milling can accommodate a set of standard blocks, work clamps and other work piece holding equipment. Thus, milling processes can work with minimum number of equipment. Milling is the main part in prototyping, die work, and other low volume manufacturing processes (Engineers Edge, 2009).

The key parameter which determines the energy consumption in milling processes is force. According to Li and Kara (2011) there are two methods for cutting force estimation. The first method applied in orthogonal machine processes developed by (Oxley, 1998; 2-8), whereas, the second method was initiated to use in empirical modeling. An example of this method is the force calculation model by (Armarego, et al., 2000). Originally, the cutting forces in machine tools introduced by Kara (2009) was the theoretical minimum cutting power; it is assessed based on cutting force projection and the physical relationship between power and force showed in equation 2-7 (Kara, 2009).

As it can be seen from equations 2-7 and 2-9, these models include distinctive force and power equations illustrating cutting forces. Also, it is challenging to find coefficients for each material in each case, and the relationship between different equations. In most cases, the prediction of minimum cutting power based on force prediction is mostly applied when evaluating the capability of machine tools by comparing the machine torque output. Therefore, this method considers only tool tip and no any other cutting parameters (Li and Kara, 2011).

The manufacturers of cutting tools, such as Seco tools, have introduced particular information for cutting power required in machine processes. Moreover, the power consumption is related to cutting parameters, tool geometries, work piece material, and efficiency. This is illustrated in equation 2-9 (Seco Tools, 2009). In this equation, the efficiency is an important factor since it shows the relationship between the energy consumption of the tool tip and energy consumption of the machine tool. More supplemental studies (information) are needed to find the power consumption and the cutting parameters otherwise the power formula is not useful (practical) (Li and Kara 2011).

$$P_t = F_c \times v \tag{2-7}$$

$$F_c = K_c \times f \times d = \frac{1 - 0.01\,\gamma_o}{(f \sin\alpha)^{m_c}} \times \tau s \times f \times d \tag{2-8}$$

$$Pc = \frac{v \times f \times d \times K_c}{60000\,\eta_m} \tag{2-9}$$

Draganescu, et al., (2003) have provided more comprehensive estimation method describing the relationship between cutting parameters and energy efficiency in vertical milling tools. This work included the spindle speed, feed rate, and cutting torque. Similarly, a study proposed by (Gutowski, et al., 2007; Gutowski, et al., 2006) performed a series of environmental analysis of manufacturing processes includes based on thermodynamic equilibrium approach, which the authors called the “Exergy Framework”. It is necessary to show the relationship between the energy consumption and process rate MRR (material removal rate) which is cited as a key factor in machine process. In equation 2-10, p_0 is the idle power because of auxiliary components and k is the specific cutting energy. Though, the factors, k (specific cutting energy) and p_0 (idle power) were not stated very clearly, therefore, the output (energy consumption) formula was not practicable (feasible).

$$p = p_0 + K.\mathrm{MRR} \qquad \textbf{2-10}$$

As a result of evaluating of all these equations explained before, the equation 2-7 defined by Kara (2009) includes the necessary parameters (cutting force and speed) since cutting force is the major key in defining energy and power consumption.

2.5.3 Modeling of energy demand in CNC machines

In order to meet the eco design instructions and CO_2 emissions objectives, some targets regarding the reduction in energy usage in machining was introduced by (Kyoto Protocol,1997; Gielen, 2007). More studies needed to be done to understand the design of machine tools from that perspective.

The research done so far does not specify a common method that can be applied in calculating the energy needed in machining of a particular material. The majority of papers considered specific machine tool as a black box, thus it is essential to create the connection between energy requirements and machining numerical control (NC) commands to provide the minimum energy approaches in machining. There has been some improvement in the models of energy in machine tools which includes the models of machine states, work piece machinability and the effects of various cutting parameters, while the authors emphasized the integrity of energy forecasting model which is important in creating a process planning with its effect on environmental burden (Tanaka, 2010).

Another approach by (Ostaeyen, 2010; Kellens, et al., 2012) categorized the machine tool state into two states based on operational characteristics of the manufacturing processes, namely ”Basic State” and “Cutting State”. “Basic State” is the energy required in making the machineries to start operation while the “Cutting State” is about the energy needed at the tool tip for material removal.

Past research namely (Beno, et al., 2009; Fysikopoulos, et al., 2012; Shaw, 2005; Dietmair and Verl, 2009; Dervisopoulos,et al. 2008; Anderberg, et al., 2009; Anderberg, et al., 2010) performed regarded the electricity use of machine tools. However, there is a need for a precise model that indicates exactly how the energy demand is distributed in a machine. A basic mathematical model of energy analysis in machines founded in Gutowski et al. (2006), where E (J or Ws) is the necessary energy for machining processes, P_0 (W) is the power required by the machines before cutting, k (Ws/mm_3) is the specific energy requirement for particular material, MRR (mm_3/s) is the material removal rate and t (s) is machine time:

$$E = (P_0 + k*MRR)\, t \qquad \textbf{2-11}$$

A summary of the mathematical models of energy in machines was presented by the MIT group Balogun and Mativenga, (2013) as shown in Table 2-1.

Balogun and Mativenga (2013) have compared the models in Table 2-1 with other machine tool energy models. Firstly, the model defined by Mori, et al. (2011) is similar to (Gutowski et al. 2006) and idle power is defined as a “ready State”. Then, the model presented by Diaz et al. (2011) is about the total machine time or cycle time not equal to the time for material removal and there is time spent on the machine tools engage and disengage.

Table 2-1 Energy Model of Machine Tools (Balogun and Mativenga, 2013)

Energy model in machine tools	Authors	
$E = P_1(T_1 + T_2) + P_2(T_2) + P_3(T_3)$	(Mori, et al. 2011)	**2-12**
$e_{cut} = k \times 1/MRR + b$	(Diaz, et al., 2011)	**2-13**
$E_{total} = E_{spindle} + E_{feed} + E_{tool} + E_{cool} + E_{fix}$	(Diaz, et al., 2011)	**2-14**
$E_{total} = \int_{tme}^{tms} Pm\, dt + \int_{tce}^{tcs} Pc\, dt + \sum_{i=1}^{m} Pi\, dt + Ptool\, Ttool + Pcool\, (T_{coe} - t_{cos}) + (Pservo + Pfan)(t_e - t_s)$	(He et al. 2012)	**2-15**
$E_{cs} = P_c/60\eta z$	(Draganescu, et al., 2003)	**2-16**
$SEC = C_0 + C_1/MRR$	(Li and Kara, 2011)	**2-17**

Contrasting with Gutowski, et al. (2006) model, and He, et al. (2012) model proposed a different approach for energy consumption of the chip formation process as the authors included the cutting forces instead of specific energy to formulate the energy and it consists of different parameters which have different effects on the energy consumption and this model was improved by He et al. (2012). The fixed energy only considering the servo power does not represent the effects of other parameters such as cutting velocity, feed rate and depth of cut in machine operations. The model proposed by He et al (2012) describes that the machine tools' energy in unload state needs to be determined in the energy consumption model. A new model recommended by Blogun and Mativenga (2013) incorporates the air cutting time because it can decrease over valuation of energy consumption. So the new model defined in equation 2-18 by (Balogun and Mativenga, 2013):

$$E_t = P_b t_b + (P_b + P_r) t_r + P_{air} t_{air} + (P_b + P_r + P_{cool} + K_v) t_c \tag{2-18}$$

In brief, by comparing different cutting energy models presented before, it can be concluded that the cutting energy developed do not characterize all parameters such as shear angle and cutting velocity which have major effects on the energy consumption. None of the research has presented the effects of all these parameters on energy consumption; therefore, there is a need to provide a complete model and simulation which includes most of the mathematical formulas for specifically cutting energy.

2.5.4 Specific cutting energy

Bayoumi, et al. (1994) have explained machinability of materials, which is usually estimated by the amount of energy required to remove a unit of material, it is also known as specific cutting energy (SPCE) in machining operations.

According to Grieve (2004) machinability includes various factors, namely tool life, power required for cutting, surface finish obtained, and cost of removing material. Among these factors tool life is the most important factor and machinability rate can be determined based on it. This factor is not considered since it is not the main focus of the study; however, the energy power needed for cutting work piece was studied in detail. Other factors influencing machinability can be mentioned as flexibility and rigidity. Increasing rigidity (hardness) makes cutting by the tool more challenging, and it reduces the machinability. Another important factor that affects the machinability is the cutting tool wear which can be affected by the tool temperature. Likewise, tool temperature changes due to the low work piece: thermal conductivity, thickness and particular heat (Grieve, 2004).

SPCE is the amount of energy which is needed to remove a unit volume of material. This cutting energy is defined as energy needed in primary and secondary deformation zones, energy necessary for the production of new surfaces and interfacial friction activities at the tool and work piece interfaces (Bayoumi, et al., 1994).

Specific energy (SE) is considered by Ucun and Aslantas (2012) as one of the most important factor in defining the energy efficiency in cutting processes. Moreover, specific energy can be acquired by applying a critical method of using different cutting parameters throughout the cutting processes. Specific energy depends on the cutting forces and power consumption in the cutting process. SE goes down when the cutting velocity increases in cutting turning, whereas SE can rise slightly in end milling process when the cutting speed increases. Likewise, SE declines as the depth of cut increases. Maximum specific energy rates can be reached at minimum depth of cut, minimum cutting speed, and minimum feed rate. Also, SE rate depends on the portion of material (Aluminum Alloy) which is removed as the time is increasing.

The research performed by Diaz, et al. (2009) explained the effect of cutting parameters on the energy consumption per unit produced for the end milling process. According to the authors, the energy per unit manufactured is defined as power demand of machine tools in machining processes and time to finish a process (Berkeley, et al., 2009).

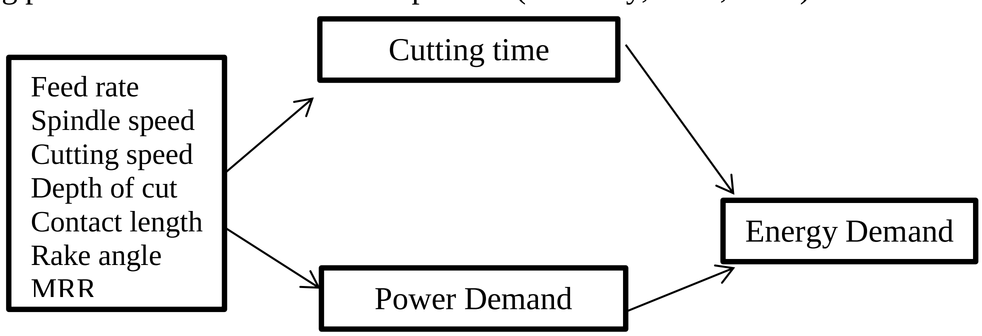

Figure 2-3 Effect of different process parameters on the energy consumption (Berkeley, et al., 2009)

The power required in machining operation can be categorized (divided) to a constant and variable factor (Dahmus and Gutowski, 2004). The total power required in machining operations is independent of process parameter selection. However, the variable power demand is dependent on different process parameters. Process time per unit produced is determined by the feed rate (Berkeley, et al., 2009).

Three regions of machining process are presented in Figure 2-4. In region 1, the decline because of shorter process time dominates the growth in the power demand variable while the feed rate is set at highest rate (highest speed). In the region 2, the energy demand in machining processes is fairly constant though the rise in the power demand predominates. Moreover, in the region 3, if the feed rate is low, it leads to less energy demand in producing one unit product (Berkeley, et al., 2009).

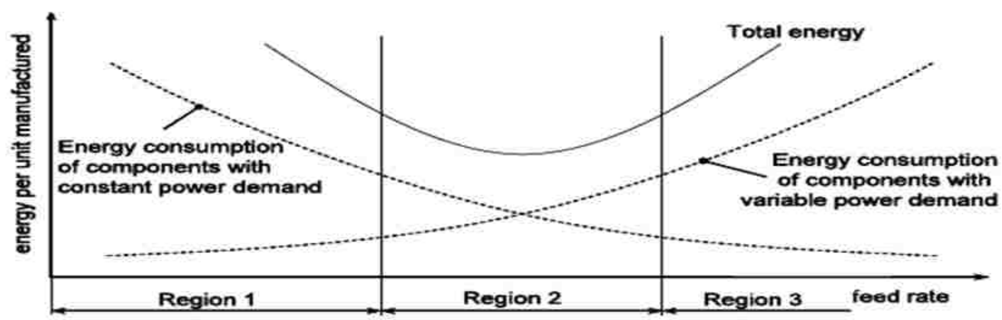

Figure 2-4 Regions of machining process (Berkeley et al. 2009)

It is also discussed by authors Diaz, et al. (2009) that there are two different conditions (factors) which can affect the energy per unit produced. In the first condition, while the power demand is constant, the feed rate is increasing and the processing time is dropping. As a result, the contribution of the constant power rate (consumption) to the energy in producing one unit of product is reduced. In the second condition, the growth in the feed rate requires more power from the machine while the cutting speed can stay constant.

It is concluded by authors that higher cutting speed leads to less energy consumption per unit produced. Because of the decline in the processing time had a stronger effect on the energy needed per unit produced than the increase in power demanded (Berkeley, et al., 2009).

2.5.5 The effect of different parameters on specific energy consumption

Cutting parameters are very important in machining processes since they are key factors in achieving the highest level of efficiency and output with lower cost (Montgomery, 1990).

One of the examples of cutting parameters in milling operation is cutting speed, which can have an important effect on energy and power consumption of machine tools and it varies depending on the type of mill. If the cutting speed passes a certain limit, the balls will be pinned to the walls of the milling chamber and stop applying force on the powder. If the cutting velocity is below a certain limit, the growth in the cutting speed can increase the milling intensity. Moreover, increase in the speed causes higher temperature of the milling chamber (Suryanarayana, 2001).

Per Sureh, et al. (2002), cutting parameters should be set according to the cutting process. In some cases of economic machining and optimization of energy consumption in machining operations, cutting parameters such as depth of cut, shear angle, feed rate and cutting speed are selected in order to optimize the objective function. In addition, based on the report produced by Kumar, ET al. (2006) there is some constraints required in selecting the cutting parameters depending on particular machining operation, machine tools and the work piece material. These constraints include tool life constraint, cutting power constraint, cutting force constraint, cutting energy constraint etc.

Diaz, et al. (2009) performed an experiment in which spindle speed, feed rate, depth of cut and cutter type were varied in order to assess the effects of these cutting parameters on energy consumption while milling a low carbon steel, AISI 1018 steel. Inamasu, et al., (2010) compared the effect of increase in the cutting speed on energy consumption, machine costs and tool wear in end milling, face milling and drilling processes. Moreover, the authors concluded that increase in tool wear and cutting tool cost can happen because of significant deviations in the value of cutting parameters. In other words, there is a limit for each machine parameter and different work piece material. If an experiment is conducted below this limit, the results will be acceptable and can help in finding the optimum value of process parameters and save energy consumption.

Diaz, et al. (2009) analyzed the material removal rate’s effect on cutting power and energy consumption. The material removal rate variations were demonstrated through the width of cut and depth of cut experiments. It was presented by authors that an increase in the width of cut can cause a hike in the power demand of machine operations. The same result can be observed in which the increase in the material removal rate can raise the power demand in machine processes while it decreases the energy consumption in machine process.

Equations 2-19 and 2-20 show the material removal rate in cutting milling and turning processes (Sheikh-Ahmad 2009; Diaz et al. 2009):

$$MRR \approx Acv = f\times a_p \times v = \pi f \times a_p \times n \times D_i \quad \textbf{2-19}$$

$$MRR = a_e \times a_p \times v_f \quad \textbf{2-20}$$

The effect of depth of cut on power and energy demand in machining processes was verified by (Diaz et al., 2009), through analyzing the changes in depth of cut while the feed rate and spindle speed rate varied. Although these parameters account for higher loads on the machine tools and power demand increase with the load, the effect of material removal on saving energy and power demand is more significant. Another study by Draganescu, et al. (2003) analyzed the effect of depth of cut on the specific energy consumption in face milling of aluminum alloy, which indicated that the growth in depth of cut increased power demand and reduced the specific cutting energy (E_{cs}) required in machining processes equation 2-21 . Specific cutting energy shows how the consumed energy absorbed from the power network and utilized in cutting processes. Moreover, specific consumed energy indicates the relationship between energy, power and material removal rate.

$$E_{cs} = \frac{P_c}{60\eta MRR} \quad \textbf{2-21}$$

$$E = K * \frac{1}{MRR} + b \quad \textbf{2-22}$$

According to equation 2-21 (Draganescu, et al., 2003) P_c is the cutting power at main spindle (KW) and MRR is the material removal rate (cm^3/min) and Ecs is specific cutting energy. In equation 2-22, k (specific energy requirement for particular material (Ws/mm^3) is a constant and basically it has units of power and b symbolizes the steady-state specific energy.

Specific cutting energy explains how the power is related to the efficiency and material removal rate. If the machine tool efficiency or material removal rate is higher for the same amount of cutting power, less amount of energy is required (Draganescu, et al. 2003).

It is discussed by many researchers that the milling time is the most important milling parameter. Though, the contamination level can rise with milling time and some undesirable phases may form if a powder is milled for too long. Substantial reduction in particle size usually occurs with milling time and typically takes the form of exponential decay (Phenomena 2008). Energy consumption of machine operations is based on the power required (P_{avg}) and process time (Δt; equation 2-23; Diaz et al. 2011).

$$E = P_{avg} * \Delta t = (P_{cut} + P_{air}) * \Delta t \quad \textbf{2-23}$$

Power required in machining processes alters because of internal cooling of machine tools. The average power needed in the operation (P_{avg}) can be defined as power required in cutting (P_{cut}) and air cutting power (P_{air}) which is considered constant. However, the air cutting power used in machine operations should not stay constant to develop the applicability of the power consumption. Thus, more work should be conducted in which the air cutting power required in machine operations is varied in order to develop the applicability of the trade-off between power demand and process time.

According to Draganesc, et al., (2002), it is essential to perform more research on machine tools efficiency since there is a large number of machining operations and growth in machine tools nominal power.

Machine tool efficiency model (equation 2-24) is explained by (Anon, 1975). This model describes energy efficiency as a ratio between cutting power (P_c) and consumed power (P_{mc}) resulted from power network by electric motor.

$$\eta = \frac{P_c}{P_{mc}} = \frac{1}{1 + (\frac{P_{m1}}{P_c})} \quad \textbf{2-24}$$

(P_{m1}) was the power loss in machine tool and electric motor. Because cutting power is formulated as a function of machine parameters, namely spindle speed (n), the torque at main spindle (M_t), feed rate (f) and feed force (F) the tool efficiency can be considered as a function of these parameters. Machine tool efficiency is a function of parameters based on the kinematic chains of machine tools as shown in equation 2-25.

$$\eta = f\,(n, M_t, f, F) \quad \textbf{2-25}$$

$$\eta = f\,(n, M_t)$$

$\eta = f(f, F)$

In this study the objective function is to minimize the energy consumption in milling and turning operation.

A study performed by Mori, et al. (2011) presented how power consumption can be decreased by considering these methods:

1- Power consumption in face/ end milling can be decreased by setting the cutting conditions high yet within a value range which does not compromise tool life, surface finish, thus reducing of machining time.

2- Power consumption for deep-hole machining can be reduced with an adaptive pecking cycle, which performs pecking as required by sensing cutting load.

3- Power consumption can be reduced further by synchronizing the spindle speed with the feed rate at rapid traverse phase.

2.5.6 Specific energy consumption and material removal rate of Aluminum

Aluminum alloy has been considered as the work piece material in this study in milling and turning processes because it has the advantage of exceptional machinability and finish degree with higher tool life, higher cutting velocity and lower cutting force (Kishawy, et al., 2005; Gatto, et al., 2010) In addition, lower weight and higher thermal exchange rate are other advantages of using aluminum alloy in automotive industry comparing to steel (Amorim and Weingaertner, 2002; Ozcelik, et al., 2010). The thermal conductivity of Aluminum moulds is 5 times higher than the steel moulds. Also, high thermal exchange helps to have more accurate work piece with lower risk of warpage and sink marks, lower mould-in stress (Erstling, 1998). The authors also concluded that use of aluminum alloy in high speed machining can save more time and cost with best surface finish, accurate dimension, and lower tool wear (Rajemi, 2010).

Table 2-2 shows cutting specifications for different materials. Rajemi (2010) concluded that aluminum alloy had the highest cutting speed but this did not cause consuming more energy in removing material, comparing to other metals.

Table 2-2 Specific Power Requirements, Adopted from (Rajemi, 2010)

Work piece material	Specific cutting energy (kW/h)
Aluminum	0.7
Cast Iron	1.2
Steel	4.3
Brass	2.2
Titanium alloy	2.9

(Rajemi, 2010) compared the power required in material removal of aluminum alloy with other metals such as Cast iron, Steel, Brass and Titanium. The author found that aluminum needs the least power in material removal in machine process (milling, turning) compared to other materials.

2.6 Energy and sustainability in manufacturing

2.6.1 Environmental burden of machine tools and the approached methods

The research by Hirohisa et al (2006, 2008) developed a prediction system for environmental burden of machining operations based on the Life Cycle Assessment (LCA) strategies. The authors provided a system which can show detailed information about emissions resulting from different manufacturing activities. In addition, this system can calculate the environmental burden (CO_2 emission) of machine tool components, cutting tool status, coolant quantity, lubricant oil quantity and metal chip quantity.

According to Jeswiet and Kara (2008), reducing the energy consumption in machining processes is one of the most important methods in reducing the CO_2 emissions. Also, the method suggested in the study by VanLoon and Duffy, (2000) connects the electrical energy consumption in manufacturing processes to the carbon emissions (CE) by applying carbon emissions signature (CES) in systems. Carbon Emission Signature (CES) (kg CO_2 / Gj) is a function of a power grid. The carbon emitted (CE) is formulated by multiplying energy consumption (EC) by the Carbon Emission Signature (CES).

$$CE = EC\ (GJ) \times CES(\frac{kgCO2}{GJ}) \qquad \textbf{2-26}$$

Energy consumption in manufacturing industries should be decreased in order to drop CO_2 emissions resulted from energy use. This concept has been explained further by (Dahmus

& Gutowski 2004; Rajemi, et al., 2008), moreover, these studies defined that energy consumed by non-cutting operations make up the largest share of the total energy consumption. The importance of machine tool selection to decrease the energy consumption in machining operations is illustrated by (Liow, 2009). Moreover, this study clarified energy consumption of conventional Mazak VTC-41 machine and compared the energy consumption of this machine with that of a micro milling tool in machining process of a micro device. It is explained by Liow (2009) that the conventional machine required 800 times more energy than the micro milling device whereas replacing with more energy efficient machines can be very costly for manufacturer. Thus, strategies which can develop energy efficiency in machines should be applied to the current machines.

2.6.2 Sustainable manufacturing and energy

Decreasing energy required in machining operations can help a lot in reaching a better level of manufacturing sustainability. As shown in the research by Alting and Jøgensen (1993) sustainable manufacturing production has an important role in managing the product life cycle, namely, designing, production and distribution to the disposal phase (Alting, et al., 1993).

Energy consumption in manufacturing processes is a main contributor to CO_2 emissions and environmental issues such as climate changes. Thus, decreasing the energy consumption of manufacturing industries is important fact in sustainable manufacturing (Rajemi, et al. 2010).

Pusavec, et al. (2009) recommended methods of improving production sustainability on the machining technology level. One of these methods is about using different machining technologies, such as cryogenic and high pressure jet-supported machining which help to reduce resource consumption and create less waste. As a result, this method can be beneficial by reducing costs and increasing competitiveness among manufacturers. Moreover, the production technology methods develop the sustainability performance that includes energy consumption reduction of machining tools, generating less waste and trying to increase waste recycling, use resources efficiently, use recyclable materials or reuse machine tool components (Pusavec et al. 2009) .

Three major steps were introduced by Steeneveldt, et al., (2006) in order to decrease CO_2 emissions. These steps are "improving the energy efficiency, switching the fuel source from coal to gas, and capturing and storing carbon" (CCS; Steeneveldt & Berger, 2006). The CCS strategy initiated the idea of keeping the CO_2 emission from fossil fuels in a geological storage. So by applying this method, lower percentage of CO_2 will be released into the environment (Gibbins and Chalmers, 2008). However, capturing and storing carbon needs extra energy to complete the process of burning and separating. One of the recommendations made by Hamilton and Turton, (2002) was to reduce the CO_2 emission by altering the fuel source.

In a few words, CCS is a comprehensive method in the sustainable manufacturing helping to reduce CO_2 emissions in the environment. However, this method takes a lot of time to be implemented and natural resources are becoming short in quantity. (Viebahn, et al., 2007) commented about the CCS technology which should be improved faster because in the next few years the fossil power plants might need to be substituted while the CCS technology cannot be fully implemented yet.

2.7 The need of optimization in manufacturing processes

Because of huge changes in different aspects of manufacturing industries, the developments of optimization methods in metal cutting operations is necessary for manufacturing industries in order to react efficiently to the fluctuations in the global market and compete successfully while meeting the rising demand of quality market. Therefore, optimization methods in metal cutting operations are absolutely essential for improving quality.

The significant growth in the manufacturing technology (metal cutting in this case) can be as a result of common goal for different manufacturing sectors in reaching higher level of productivity in machining operations. Tan and Creese, (1995) discussed that selection of optimal machining conditions is a key factor in reaching machining process efficiency.

Optimization of machine processes is stated based on minimum cost criterion. An example of single pass turning is given in the study carried out by (Rajemi, et al., 2010). The total cost is defined by adding the nonproductive cost, actual cutting cost, tool change cost and the cost of tooling, however, in this equation, the material cost is not included as it is not dependent on cutting velocity (Rajemi, et al., 2010).

$$C = x\left(t_1 + \frac{\pi D_{avg}\, l}{f V_c} + t_3\ \frac{\pi D_{avg}\, l}{At}\ V_c^{\left(\frac{1}{\alpha}-1\right)}\ f^{\left(\frac{1}{\beta}-1\right)}\right) + \ \frac{Y_c\, \pi\, D_{avg}\, l}{A_t}\ V_c^{\left(\frac{1}{\alpha}-1\right)}\ f^{\left(\frac{1}{\beta}-1\right)} \qquad \textbf{2-27}$$

Another optimization technique was introduced by (Peklenik and Jerele, 1992). This study illustrated that the optimum tool life which reaches the minimum cost criteria can be considered as an optimization philosophy. Moreover, in order to get the optimum tool life (T_{opt-c}), the total machine cost can be calculated while changing the cutting speed each time. The optimum tool life (T_{opt-c}) for minimum cost in single pass turning operations is shown in equation 2-28.

$$\mathrm{T}_{\mathrm{opt-c}} = \left(\frac{1}{\alpha} - 1\right)\left(\frac{x t_3 + y_c}{x}\right) \qquad \textbf{2-28}$$

Optimization refers to improving the performance of a system, a process or a product to achieve the maximum advantage (benefit) from it. The term optimization was used in the chemistry field to find conditions that could be used in a procedure leading to best response (Pedro 1996). Originally, optimization was applied by monitoring the effect of one factor at a time on an experimental response. Moreover, when only one parameter is changing, the other parameters are staying constant. This method is called one-variable-at-a-time, however, this method does not consider simultaneous effects of all parameters on the output (Bezerra, et al., 2008). To find the best solution for this problem, the analytical optimization procedures were performed by applying multivariate statistical methods. An example of this approach is response surface methodology (RSM). Response surface methodology is a set of mathematical and statistical methods based on the fit of a polynomial equation to the experimental data, which defines the behavior of a data set with the objective of making statistical previsions. Though, if response functions of the experimental data cannot be fit by linear function, quadratic response surface should be applied, namely Box- Behnken, three level factorial and Doehlert design (Montgomery 1996).

A study performed by Iqbal, et al., (2006) optimized parameters and forecasting performance measures in hard milling using an expert system. This study concentrated on improving the tool life and surface quality of the work-piece. The expert system technology was used for optimization of milling parameters such as work piece material hardness, tool's helix angle, milling orientation, and coolant in order to achieve the target of enhanced tool life and improved surface finish. The effectiveness of the expert system was proved based upon two modules, cited as "optimization module" and "prediction module". The expert system used was based on fuzzy logic theory to optimize the combination of milling processes to reach the optimal process setting. Also, the optimization module can forecast the performance measures of the parameters finalized by the optimization module.

Iqbal et al. (2007) used the expert system in order to optimize the cutting parameters based on the objective such as 'tool life maximization' and 'minimization of surface roughness.' Moreover, the authors mentioned that the expert system can be helpful and efficient for optimizing the hard milling process. It also can be useful in forecasting, thus it can develop the output quality and decrease the production cost. However, this research did not include any other cutting parameters such as cutting velocity, depth of cut, feed, or tool tilt angle.

Optimization of cutting parameters in turning operations was proposed by (Soni, et al., 2014). Multi-objective algorithm optimization method was used to find the optimal values of cutting parameters. This research perused the effects of speed, feed and depth of cut on the surface roughness and material removal rate in turning operations on aluminum. It was discussed by authors that Genetic Algorithm is the best multi-objective optimization method since it finds the best fit of several models. Nevertheless, other cutting parameters such as rake angle, shear angle and contact length of milling etc. were not considered in this study. Similar research was performed by Zeelan, et al., (2013) that focused on improving the quality of surface finish by forecasting machine parameters in turning operations. Genetic Algorithm and response surface were applied to examine the effect of different cutting parameters such as depth of cut, cutting speed and feed.

Nian, et al., (1999) studied the optimization of CNC turning processes by using Taguchi method considering various performance characteristics. Other optimization method was introduced by Lin, et al., (2001) which carried the study of a network model to find the surface roughness and cutting forces. Also, Wang, et al., (2010) examined the effect of tool nose vibration on surface roughness in turning processes.

As for a good example of the response surface methodology application in turning process, Soni, et al., (2014) used this method to develop mathematical models for surface roughness and material removal rate. Finally, it was determined by the authors that the parameters affecting the response surface are speed, feed and depth of cut.

2.8 Use of buffer inventory

The rise in the electricity demand and cost in manufacturing industries have been a critical issue. One of the causes of this problem is unbalanced distribution of the electricity use in different periods, which leads to the financial burden of investing for excessive power grid capacity in order to meet the demand during peak times. As for example, it is reported that by 2030, almost $697 billion investment is needed for the new electricity generation capacities to satisfy the rising demand (Chupka, et al., 2008).

One of the methods used in reducing both economics and environmental effects of increasing electricity demand is Demand Side Management (DSM). There are two forms of DSM, “energy efficiency management” and “load management”. Load management aims to achieve the same output while reducing energy consumption. Whereas, the energy efficiency management focuses on shifting the demand from peak periods with high financial cost to off-peak times (Gellings, 1985). It is reported that the average energy which can be saved in peak periods is almost 65 kWh per kilowatt of peak demand reduction; therefore, dynamic pricing methods such as Time of Use (TOU) rate are introduced. Likewise, it is predicted that industrial and commercial sectors can reduce energy consumption by 13% during peak periods (Faruqui, et al., 2007).

The methods of reducing energy consumption introduced previously in this chapter, are useful for a typical manufacturing system with several machines and buffers (Li, et al., 2012; Li et al., 2012b; Fernandez et al. 2013) or a single machine system. The majority of these studies focus on only commercial and residential building sectors (Ghatikar, 2010; Motegi, et al.,2007). The methodology introduced by (Braun, 1990; Houwing, et al., 2011) applied thermal storage in order to decrease the power demand of building in peak periods. A method which integrates the building load management into power grid was considered by (Corno, et al 2012). This model helps to manage the electricity consumption of buildings during peak periods. Moreover, manual or automatic control methods were used to reduce the electricity consumption in buildings during peak time.

A few studies have been done about load management. For instance, Logenthiran, et al., (2012) proposed a heuristic algorithm to develop a mathematical formula of the implementation of day-ahead load shift by minimizing the actual load curve and desired load curve for commercial, residential and industrial facilities. However, this model considered industrial facilities as mutually independent, thus this model cannot be used in complex manufacturing systems. A mathematical model by Ashok and Banerjee (2001) showed indicates the optimal production schedule for a flour plant by minimizing the total cost of energy consumption and other operation cost. Though, this model did not include the cost of demand, thus it cannot be referred to as a comprehensive optimization model.

Li, et al., (2012) evaluated the challenges of the load management system and concluded that the load management systems in industrial sector are not comprehensive. It was also demonstrated that the heuristic buffer utilization method can be used to decrease the electricity demand in manufacturing systems.

Another approach mentioned by Fernandez, et al,. (2013) as “Just-for- Peak” buffer inventory, which reduces the electricity required in manufacturing systems with several machines and buffers in peak period. Moreover, the objective function comprises the holding cos of the buffer inventory and electricity cost. A nonlinear integer programming is developed by the authors. The objective function (equation 2-29) is to minimize the sum of holding cost of “Just-for-Peak” buffer inventory and energy consumption cost during production. In equation 2-30, φ_i is the rated power of machine i, C_p is the on-peak energy consumption cost are ($/kWh), C_R is the off-peak energy consumption charge rate ($/kWh), C_D is the on-peak demand charge rate ($/kWh), K_i is the set of binary variables for machine i during the peak periods.

Objective: $\min T_C(K_i) = \min \left(\sum_{i=1}^{n-1} h_i \frac{(JT_i)^2 \; (1-K_i)K_i + 1(a_i+c_i)}{2a_ic_i(T+t_p)} + \sum_{i=1}^{n} E_i \right)$ **2-29**

$$E_i = \left(\frac{\varphi_i \times T \times r_i \times C_R + \varphi_i \times K_i \times t_p \times C_p + \varphi_i \times K_i \times C_D}{T + t_p} \right) \qquad \textbf{2-30}$$

This model is further developed in this thesis (study) since the total energy cost includes electricity consumption of machines in turning or milling operation. The electricity consumption of the machine process proposed by (Narita, et al., 2006; equation 2-31) is utilized in order to create a complete model for of energy consumption of machining process and the total cost of electricity consumption. Next, the capacity constraint introduced and added to this model which controls the buffer inventory in order to prevent failure in the real production line.

Another feature (constraint) added to the model used in this study is to predict the changes of the energy consumption in the production line with the changes in the market demand. Therefore, by considering the cost and energy consumption during the market demand fluctuations, a manager of a line can decide (plan) easier the necessary volume of production.

$$E_e = (\text{SME}+ \text{SPE} +\text{SCE}+\text{CME} +\text{CPE} +\text{TCE 1}+\text{TCE 2}+\text{ATCE}+\text{MGE}+\text{VAE}) \quad \textbf{2-31}$$

The new objective function developed in this study is:

$$\text{Objective: } \min T_C\,(K_i) = \min\left(\sum_{i=1}^{n-1} h_i \,\frac{(JT_i)^2\ (1-K_i)K_i + 1(a_i + c_i)}{2a_i c_i T_{total}} + \sum_{i=1}^{n} \left(\frac{E_e}{T_{total}} \times K_i \times C_{pD}\right) + \left(\frac{Ee}{T_{total}} \times C_R\right)\right) \quad \textbf{2-32}$$

Summary of literature review on this subject is presented in Table A- 21.

3 METHODOLOGY and APPROACH

3.1 Introduction

The growth in energy consumption and limitations in energy supply have become the major reasons for manufacturers to pay close attention to energy use, imposing limitations and process material while meeting quality. As a result, energy efficiency methods are introduced at different levels of manufacturing process to provide more energy efficient processes. In this study, the energy efficiency methods are considered at only two levels, such as enterprise and process level.

Firstly, one of the optimization solutions provided at the process level is to develop a simulation model of energy consumption by using system dynamics which can describe the behavior of a machine system and to improve the accuracy and consistency of energy consumption forecasting in milling and turning processes. Although, in this study foundation of the energy data and calculations are based on the static mathematical models, the models are simulated by SD in order to show the energy changes in the time frame.

A second method has also been developed in order to reduce energy and cost in milling and turning processes using buffer inventories during peak times of electricity usage. A nonlinear integer programming (NIP) is used in this study to minimize the cost of electricity while maintaining system throughput.

Improving the delivery of electricity is possible through 1) DSM options which are related to the efficiency on the user-side of the electricity meter; 2) supply side efficiency measures which is related to how electricity is generated by the supplier or conveyed to the users; 3) new supply alternatives (options), are introduced to replace current generation options (Eberhard, et al., 2000).

To have high performance of the electricity grid, electricity supply and demand must remain in balance in real time. Originally utilities requested power plants to increase power generation to meet growing demand. Demand-side management (DSM) includes energy efficiency and demand response (DR). Moreover, DSM pays energy users to decrease electricity consumption and utilities pay for demand-side management capacity since it is cheaper and easier to procure than the traditional (old) generation (enernoc, 2015).

Recent assessments as part of the United Nation Development program's (UNDP) World Energy Assessment (WEA), finalized in 2001, verified potential opportunities in electricity efficiency improvements in all countries. The technical potential in countries with high per capita consumption indicates modification to consumption and improved conservation behavior. Due to regulatory problems in North America and other regions, electric utilities made advancements in DSM programs to introduce more efficient technologies and decrease peak demands, and are striving to overcome informational, institutional, and other barriers. Many utility-run DSM programs accomplished major energy-savings at low costs, and expanded to account for 1% of utility costs in the US by 1990s (Eto, 1995).

According to Eberhard, et al., (2000) supply side efficiency is considering the electricity generated to its end-users while number of technical and non-technical losses can happen. The technical losses include the electricity consumption at the power station, step-up transformer losses, and transmission and distribution losses. These losses of electricity can account up to 35- 40% and they can be measured from what is delivered (sent out) from the power station to what is shown on the consumers' meters. Trying to make current transition and distribution systems to work more efficiently can lead to significant savings. For instance, in India, 35% of electricity produced is lost in the distribution and transmission system before reaching end-users.

3.1.1 System dynamics

System Dynamics is a useful technique for the analysis of complex systems, integrating the subsystems and parts into a whole, which can be simulated to improve insight into its dynamic behavior (Tang and Vijay, 2001). Even without simulation, the causal diagrams improve the understanding of the structure and the key determinants of system behavior. (Forrester, 1969) cites:

"System dynamics can provide a dynamic framework to give meaning to detailed facts, source of information, and human response. Such a dynamic framework provides a common foundation beneath mathematics, physical sciences, social studies, biology, history and even literature."

Other advantage of using system dynamics is that it is a computer-aided method to support precise analysis and design. It can be used when dynamic problems arise in any complex system. Basically, any dynamic system is categorized by interdependence, mutual interaction, information feedback, and circular causality.

Key features of systems dynamics

- It is useful to model a problem, issue, or evaluation questions but not to model the whole program
- It assumes that most problems have endogenous causes
- It assumes events are part of patterns, which are created by structures
- It is about testing hypothesis
- Choosing the systems boundary (limits) are essential (vital)
- Extent in time and space is usually more important than detail (Williams and Harris 2005).

Systems dynamics key differentiators

- The model and the real world have related structures
- The focus is on the effect of information feedback
- It is useful in simulation of the model to test hypotheses
- Models can contain quantitative and qualitative elements (Williams and Harris, 2005).

Feedback thinking

The feedback concept is at the heart of the system dynamics approach. Diagrams of loops of information feedback and circular causality are tools for developing the structure of a complex system and for communicating model-based insights (System Dynamics Society 2015)

Loop Dominance and Nonlinearity

The loop concept underlying feedback and circular causality by itself is not enough, however. The explanatory power and insightfulness of feedback understandings also rest on the notions of active structure and loop dominance (System Dynamics Society 2015).

The Endogenous Point of View

The internal change is fundamental concept in the system dynamics approach. It directs aspects of model formulation. The external disturbances are seen at most as triggers of system behavior. The causes are contained within the structure of the system itself (System Dynamics Society 2015)

System Structure

These ideas are captured in Forrester (1969) organizing framework for system structure:

1) Closed boundary
2) Feedback loops:
    2.1) Levels
    2.2) Rates:
        - Goal
        - Observed condition
        - Discrepancy
        - Desired action (System Dynamics Society, n.d.)

Application of systems dynamics in manufacturing

System dynamics model of a manufacturing system is provided by (Parnaby, 1979). Likewise, by Byrne and Roberts (1994) use SD to evaluate manufacturing performance in a kanban-based system. Towill has been a supporter of the value of Forrester's work, and much of Towill's research activity which was involved with developing the Forrester supply chain models (Towill, and Del Vecchio, 1994).

Edghill and Towill (1989) proposed a generic library of control theory-based models of manufacturing systems. They discussed that these models achieve the criteria of being meaningful and logical, since these three components give the general view that a manufacturing manager needs. Likewise, Baines (1994) considered the respective qualities of DES and SD for assessing the result of proposed changes to a manufacturing system. The author mentioned that even though DES appears to provide reliable models due to the level of detail that can be included in such models, SD model building times are considerably lower. Baines argues that when considering strategic issues within a manufacturing company, then SD has some distinctive advantages over DES.

3.2 Method 1 (process modeling using System Dynamics)

3.2.1 The model structure

Selecting the cutting parameter value is essential in machining to get the best quality, economical and productive process. Cutting parameters selected based on the required accuracy of the work piece, maximum production rate and minimum production cost (Gheorghita 1998; Gheorghe, et al. 1991) .

3.2.2 The model structure in turning process

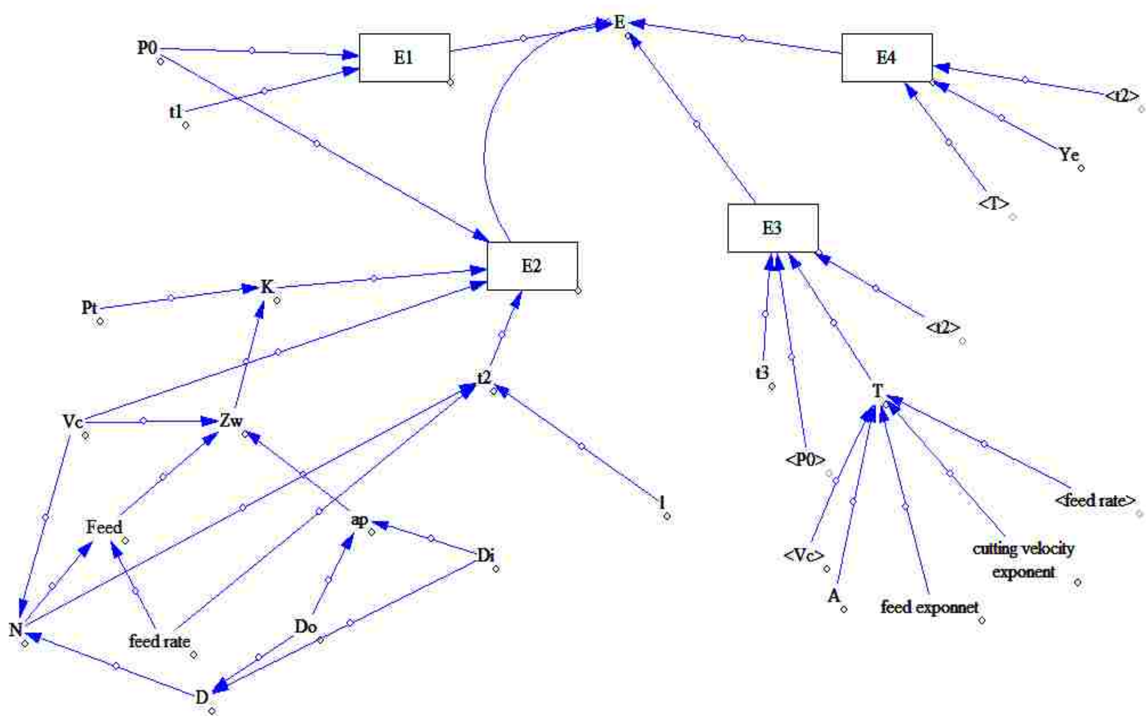

Figure 3-1 Energy consumption model of turning process in Vensim

The energy model in turning is introduced by (Equation3-1; Rajemi, et al., 2010). The authors explained that total energy (E) consumption in turning can be estimated from the energy consumption of the machine during setup operation E_1, during cutting operations E_2, during tool change E_3 and energy to produce cutting tool per cutting edge E_4, produce work piece material E_5. In practice, the workpiece material is fixed depending on the product. Similar to the research conducted by Campatelli (2009), the energy of the work piece material was not included because it is independent of the machining strategy and does not affect the optimization of production parameters.

$$E = E_1 + E_2 + E_3 + E_4 \quad \textbf{3-1}$$

In Equation 3-1, energy (E_1) is the energy consumed by a machine during setup, and is estimated by the power consumption of the machine and total time for set up tools and work piece. It is important to remember that during setup time the spindle speed has not yet been turned on (Rajemi et al. 2010).

The energy E_2 during machining is assessed based on the energy consumption of the machine modules and the energy for material removal as defined by Gutowski, et al., (2006) in equation 3-2.

$$E_2 = (P_0 + K \times MRR)\ t_2 \quad \textbf{3-2}$$

P_0 is the power consumption of machine modules (KW), k is the specific energy needed in cutting processes (kWh/mm^3), MRR is material removal rate (mm^3/s) and t_2 is time (s) taken for cutting.

The energy consumption in tool changing E_3 is estimated from a product of machine power and time for tool change. In turning operation, the tool is usually replaced when the spindle is turned off. Therefore, the power during tool change is equal to the power when the machine is in an idle state (Rajemi, et al., 2010).

The parameter E_4 indicates the energy footprint of the cutting tool divided by the number of cutting edges. This is evaluated from the energy embodied in the cutting tool material, the energy consumption in tool manufacturing and the energy of any supplementary processes namely, coating. Moreover, E_4 is estimated from the product of the energy per cutting edge y_E multiplied by the number of the cutting edges needed to finish the machining pass. In Equation 3-3, where t_1 is machine setup time (s), t_3 is tool change time (s) and T is the tool-life (s) (Rajemi, et al., 2010).

$$E = P_0\ t_1 + (P_0 + K \times MRR)t_2 + \ P_0 t_3 \left(\frac{t_2}{T}\right) + \ y_E(\frac{t_2}{T}) \quad \textbf{3-3}$$

Equation 3-3 can be expanded to equation 3-4

$$E = P_0 t_1 + P_0 \frac{\pi D_{avg} l}{f\, V_c} + K \frac{\pi l}{4}\left(D_i^{\,2} - D_o^{\,2}\right) + P0t3\, \frac{\pi D_{avg} l V_c^{(\frac{1}{\alpha}-1)} f^{(\frac{1}{\beta}-1)}}{A} + \frac{y_E \pi D_{avg} l V_c^{(\frac{1}{\alpha}-1)} f^{(\frac{1}{\beta}-1)}}{A} \qquad \textbf{3-4}$$

D_{avg} is the average work piece diameter and defined in 3-5 (Sheikh-Ahmad, 2009).

$$D_{avg} = \frac{D_i + D_o}{2} \qquad \textbf{3-5}$$

In brief, system dynamics is applied in this study in order to design and analyze the energy consumption model in cutting milling and turning operations. Moreover, SD is a useful tool to comprehend the behavior of the system. In this case, this method helps to understand sensitivity of the energy consumption to specific parameters.

3.2.3 The model structure in milling process

The simulation model of energy consumption of milling process on aluminum alloy is shown in Figure 3-2.

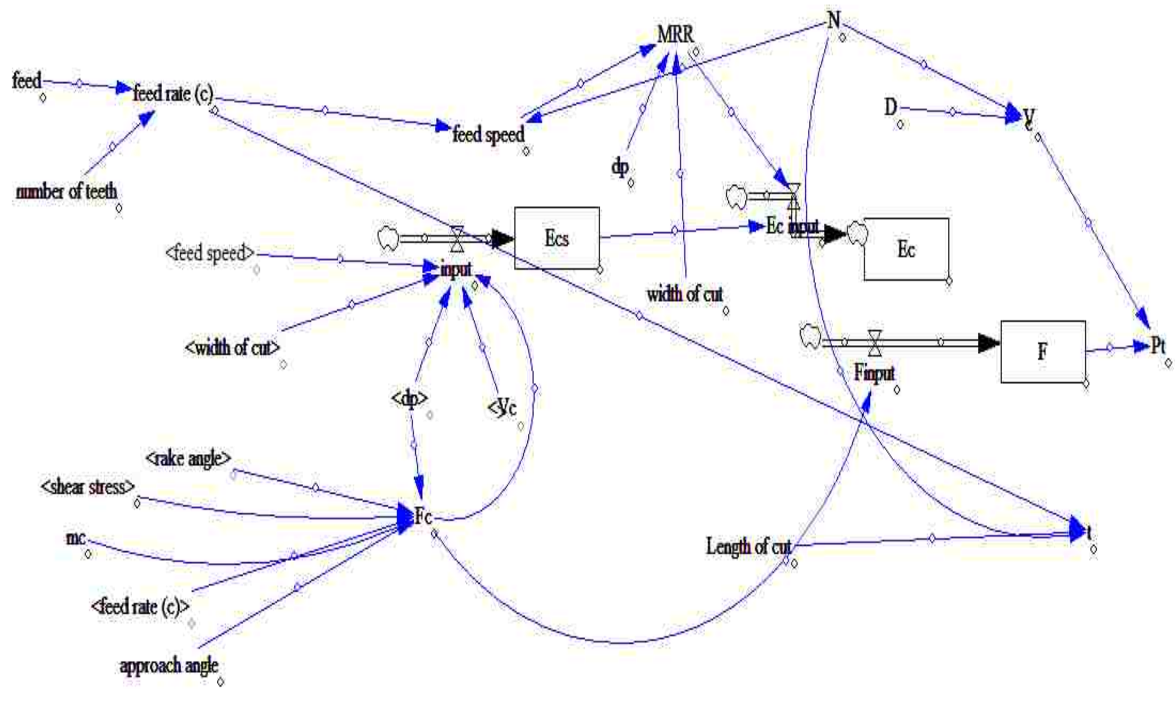

Figure 3-2 System dynamic model for energy consumption in milling operation

The cutting force model is adopted from Li and Kara (2011) in equation 3-6. The specific cutting force K_c is a function of the shear stress of the work piece material ($K_{c1.1}$) and the geometric properties of the cutting action (α_r, α; Li and Kara, 2011). The rest of the equations are adopted from (Scallan, 2003; He et al., 2012; Sheikh-Ahmad, 2009).

$$F_c = K_c \times \mathrm{f} \times \mathrm{d} = \frac{(1-0.01\times \text{rake angle})\times \text{shear stress}\times \text{feed rate (c)}\times \text{dp}}{(\text{feed rate (c)}\times \text{SIN(approach angle)})^{\mathrm{m_c}}} \tag{3-6}$$

$$Feed\ rate = feed\ \times \text{number of teeth} \tag{3-7}$$

$$Feed\ speed = feed\ rate \times \mathrm{N} \tag{3-8}$$

$$MRR = width\ of\ cut \times \text{feed speed} \times \text{dp} \tag{3-9}$$

$$t = \frac{Length\ of\ cut}{feed\ rate\ \times N} \tag{3-10}$$

$$P_t = F_c \times V_c/60 \tag{3-11}$$

$$V_c = \frac{\pi DN}{1000} \tag{3-12}$$

Cutting energy E_c can be calculated from the cutting power P_c, equation 3-13 (Peng and Xu, 2014)

$$\mathrm{E_c} = \mathrm{P}_c \times \mathrm{t} \times 6/1000 = \frac{(1-0.01\times \text{rake angle})\ \times \text{shear stress} \times \text{feed rate (c)}\ \times d_p)}{(\text{feed rate (c)}\ \times \text{SIN(approach angle)})^{m_c}}\ \times Vc\ \times t \times 0.006 \tag{3-13}$$

To find how the consumed energy absorbed from the power network, it is necessary to divide the power of main spindle, which is a function of force and speed, by the material removal rate (Draganescu, et al., 2003).

The specific cutting energy can be formulated as equation 3-14 introduced by (Polini & Turchetta 2004). The specific energy consumption (E_{cs}) indicates how the cutting power can be used. The cutting energy (E_c) in equation 3-15 is a function of material removal rate and specific cutting energy. The higher feed speed, width of cut and depth of cut is in better use of energy in milling process.

$$Ecs = \frac{F_c \times V_c}{(\text{feed speed} \times \text{width of cut} \times d_p) \times 60000} \quad \text{3-14}$$

$$E_c = E_{cs} \times \text{MRR} \quad \text{3-15}$$

3.3 Method 2 (Demand Side Management)

The second method proposed to reduce the energy in manufacturing processes is about controlling buffer capacities during the high electricity usage. In addition, it is about how much throughput can change when the energy consumption rate is declining and economic benefits of this optimization method. Therefore, the purpose is more about finding a trade-off between saving energy and throughput (market demand) in different settings. In other words, the linear equation provides the optimization process in response of market changes, energy consumption changes, or different changes in the machine operations such as speed.

3.4 Introduction:

Demand side management (DSM) has been offered by Federal Energy Regulatory Commission as “Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the cost of electricity overtime or to the incentive fees designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” (FERC, 2012).

Moreover, energy efficiency management and load management are proposed as the basis of DSM which the load management is about getting the same amount of output and saving energy usage. The EEM is also about moving the market demand from peak periods with high financial cost to off-peak period in order to reduce cost and energy (Gellings, 1985). However, due to complexities in manufacturing system and system throughput variation some issues in load management have not been solved yet. As for one of the obstacles, it can be noted that dynamic nature of varying demand in manufacturing processes cause difficulties in reaching the best results in load management. Next, keeping the system throughout at the same level is difficult when planning for load management and reduction in energy consumption and the cost related to it in peak times.

Figure 3-3 shows the summary of the methods applied in this study.

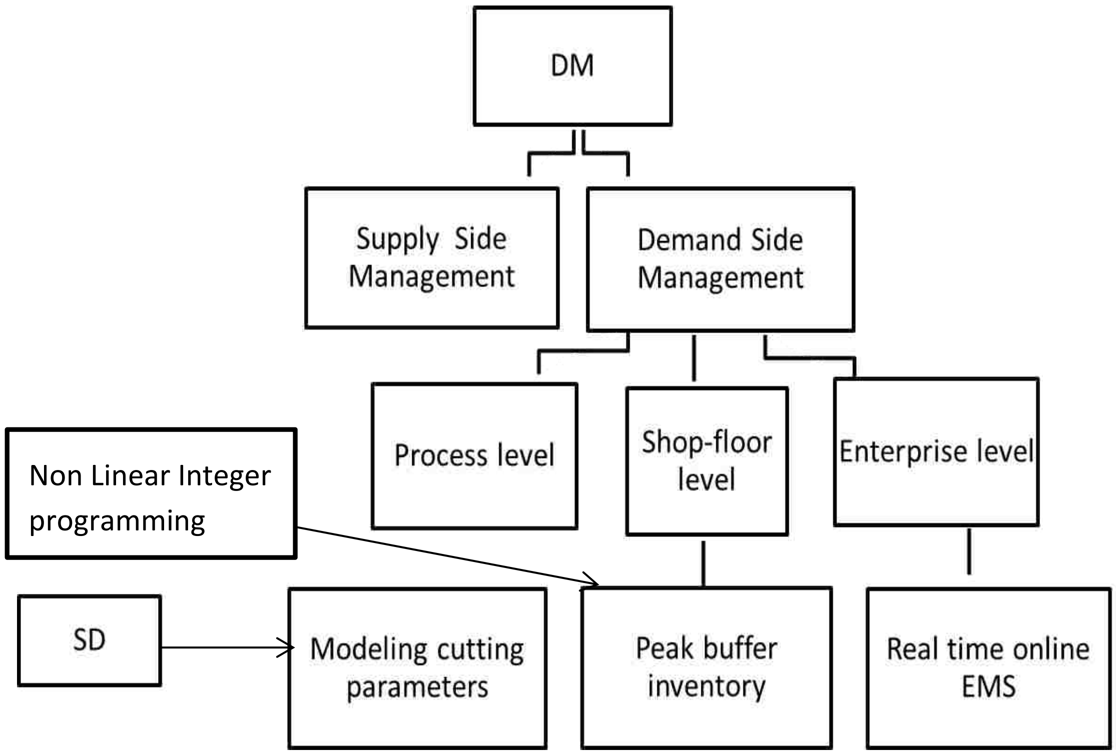

Figure 3-3 Energy management in machine process

3.5 Demand Side Management methodology and case studies:

3.5.1 Case study 1:

"Buffer inventory, also called buffer stock or safety stock, is a cushion of supply in excess of forecast demand" (Martin, 2007). Buffer inventory can be utilized to decrease the frequency or severity of stock-out situations in manufacturing process. It's also used in production or other inventory situations to ensure unexpected demands can be met with some degree of certainty.

The "Just-for-Peak" buffer inventory methodology is projected to reduce power demand in manufacturing processes with multiple machines and buffers during peak periods with the constraint of constant system throughput. Moreover, the holding cost of the buffer inventory and electricity bill cost are included in the objective function. Data for this case study is adapted from (Fernandez M, et al., 2013). In this method, there are n machines and n-1 buffers in a production line. The purpose of having buffers (B_i, i=1... n-1) between two machines is to reduce the impact of system failures of machines. In addition, the extra buffer locations (J_i, i=1…n-1) are introduced before as preventive maintenance by (Salameh and Ghattas, 2001). In Fernandez, et al., (2013) these buffers are used to save more buffer inventory during peak periods and reduce demand. Moreover, the production period is characterized as sum of a scheduled off peak period (T) and a follow up scheduled peak period (T_p).

By knowing the time length of T and t_p, before off peak period ends, if the inventory level in (B_i) is high, the inventory can be stored in corresponding buffer (J_i) as peak buffer inventory. Also, the upstream machines can stay off during peak periods by using buffer inventory to drop the demand during the high time of electricity usage. It is assumed that (c_i) is the consumption rate of the buffer inventory in (J_i) in high electricity demand time and (a_i) is the accumulation rate for peak buffer inventory accumulated in (J_i) in off peak periods. JT_i is the target unit of peak buffer inventory and it can be formulated as:

$$JT_i = C_i.t_p \qquad \textbf{Equation 3-16}$$

k_i is a set of binary variables to indicate the primary load management results for machine M_i in the beginning of peak period, which can be explained as

$$k_i = \begin{cases} 0, \text{turn off machine } M_i \text{ at the beginning of peak period} \\ 1, \text{maintain machine } M_i \text{ on in the begining of the peak period} \end{cases}$$

Therefore, for the example provided here there are 4 variables; Table 3-1 shows the variable values after the first run of this program:

Table 3-1 Variables

Variables	n=4	
	K_1	0
	K_2	0
	K_3	1
	k_4	1

The electricity consumption of machine process consists of electricity usage of both machine tools (E_e) and cutting tools (T_e).

- Electric consumption of machine tool (E_e)

The electric consumption of machine tool is calculated as it is presented before in Equation 2-31 (Narita, et al., 2006). According to equation 2-31, the electric consumption of exterior devices can be calculated from a running time. But one of servo and spindle motors is varied dynamically according to the machining process. Hence, a cutting force and a cutting torque models are applied to estimate the electric consumption for these motors.

$$\mathrm{Ee} = (\mathrm{SME} + \mathrm{SPE} + \mathrm{SCE} + \mathrm{CME} + \mathrm{CPE} + \mathrm{TCE\,1} + \mathrm{TCE\,2} + \mathrm{ATCE} + \mathrm{MGE} + \mathrm{VAE}) \quad \textbf{2-31}$$

The electricity consumption of servo motor (SME) is formulated as follows (Narita, et al., 2006):

$$\mathrm{SME}= \frac{2\pi.n.T_l.m_t}{60} \quad \textbf{3-17}$$

$$T_l = T_u + T_m \quad \textbf{3-18}$$

$$T_m= \frac{(\mu * M \pm f) * \cos\theta \pm (M-f) * l * sin\theta}{2\pi * t_b} \quad \textbf{3-19}$$

The electricity consumption of spindle motor (SPE) kWh is calculated as follows (Altintas 2000):

$$\mathrm{SPE}= \frac{\tau_s.d_p.h.\ V_{cij}.\ M_{tij}}{sin\emptyset_c.\cos(\emptyset_c+\beta_a-\alpha_r)} \quad \textbf{3-20}$$

In this case study the values of cutting processes are presented in

Table A- 20. There are two different work piece (W_1= Aluminum, W_2=Steel) and two machine operations (m_1= milling, m_2= turning)

- Electric consumption of cutting tool (Te)

Electricity consumption of a cutting tool is defined in milling and turning process (equation 3-13, 3-4 and 3-13):

$$T_{Emilling} = \frac{(1 - 0.01 \times \text{rake angle}) \times \text{shear stress} \times \text{feed rate (c)} \times d_p)}{(\text{feed rate (c)} \times \text{SIN(approach angle)})^{m_c}} \times V_c \times t \times 0.006$$

$$T_{Eturning} = P_0 t_1 + P_0 \frac{\pi D_{avg} l}{f V_c} + K \frac{\pi l}{4}\left({D_i}^2 - {D_o}^2\right) + P_0 t_3 \frac{\pi D_{avg} l V_c^{(\frac{1}{\alpha}-1)} f^{(\frac{1}{\beta}-1)}}{A} + \frac{y_E \pi D_{avg} l V_c^{(\frac{1}{\alpha}-1)} f^{(\frac{1}{\beta}-1)}}{A}$$

The calculation of energy consumption of machine operation is shown in the Appendix, Table A- 1, Table A- 2. Cutting forces are calculated according to the basic formula (equation 3-21) for cutting in machining from Altintas, (2000):

$$F = \frac{\tau_s d_p h}{\sin \emptyset_c \cos(\emptyset c + \beta_a - \alpha_r)} \qquad \textbf{3-21}$$

Table A- 5 and Table A- 6 show the buffer settings for this case study. By utilizing the optimal building policies of the buffer inventory and load management actions during the peak periods, the electricity demand can be reduced significantly. Additionally, the building policies of buffer inventory has to be considered before production line starts working, in order to specify the buffer locations B_i which can make the buffer inventory in J_i through off peak period T.

As it is explained before in equation 2-32, the purpose of this method is to minimize the holding cost of the buffer inventory and energy consumption cost in production. Where T_C (K_i) is the total cost per production time where *n* is the number of machines C_{pD} is the energy and demand charge rate during the peak times, which is considered 0.099 ($/kWh). C_R is the energy charge rate during off-peak period and it is considered as 0.0135 ($/kWh; equation 3-22):

$$\text{Objective: min Total cost } (K_i) = \min \left(\sum_{i=1}^{n-1} h_i \frac{(JT_i)^2 \ (1-K_i)K_i + 1(a_i + c_i)}{2a_i c_i (T_{total})} + \sum_{i=1}^{n} \left(\frac{E_{ei}}{T_{total}}\right) \times C_R + \left(\frac{E_{ei}}{T_{total}}\right) \times C_{pD} \times K_i \right) \qquad \textbf{3-22}$$

There are four constraints to be considered which are presented below:

1) Demand constraint which is considered as power reduction in peak periods should be greater than or equal to demand reduction (equation 3-23; Fernandez, et al., 2013):

$$\sum_{i=1}^{n} P_{mi}(1-K_i) \geq P_{saving} \qquad \textbf{3-23}$$

P_{saving} in equation 3-23 is power reduction requirement in peak times. Moreover, it can be explained that the purpose of having this constraint is to see whether the new load management system can save the power expected.

2) The second constraint is capacity constraint. In real time management system, the demand should be less than the capacity. Hence, total accumulated buffer inventory in off-peak period (T) should be greater than its consumption rate; otherwise, there should be a short notice to the system to make other machine work slower, so that the machine i can accumulate during this short period. The NIP equation is:

$$a_i T \geq c_i(1-k_i)k_{i+1} \qquad \textbf{3-24}$$

3) Capacity constraint which necessitates the buffer capacity be limited to a certain (level) quantity. Thus, the total buffer inventory capacity J_i^T needed must be less than or equal to its maximum buffer capacity. The NIP is shown in equation 3-25, considering $J_{i\,max}$ is the capacity of J_i (Fernandez, et al., 2013).

$$J_{i\,max} \geq J_i^T(1-k_i)k_{i+1} \qquad \textbf{3-25}$$

4) The fourth constraint is about to keep the production line keep processing without influence of peak times, Thus the last machine has to always be turned on during the machining. The NIP equation is K_n=1 (Fernandez, et al., 2013).

The cycle times, mean time between failure (MTBF), mean time to repair (MTTR), and the rest of information needed are given in the appendix Table A- 3 and Table A- 4. Some of the data is adopted from (Fernandez, et al., 2013).

$$\text{Min } Z= C_1X_1+C_2X_2+C_3X_3+C_4X_4 \qquad \textbf{3-26}$$

3.5.2 Case study 2:

The second part of the linear programming and the optimization process is about how to get the minimum amount of energy according to changes in the market demand. There are two types of work pieces (i) W_1 is Aluminum; W_2 is Steel and two milling and turning machines (j). t_{ij} is the machine time (hour). The process parameters are included in the appendix Table A- 1.

Coefficient (C_i) is the machine time for each process. Once the program is run, it provides the actual machine time for each process (t_{ij}). Then by having the machine time, X_{ij} can be achieved. X_{ij} defined as the production rate per hour or throughput which is formulated as equation 3-27:

$$X_{ij} = 1/t_{ij} \qquad \textbf{3-27}$$

The objective function is formulated as:

$$\text{Min } Z = C_1.X_1 + C_2.X_2 + C_3.X_3 + C_4.X_4 \qquad \textbf{3-28}$$

Thus, the objective is to minimize the energy output or minimize Z for Aluminum, Steel Alloy in milling and turning processes (equation 3-29).

$$\text{Min } Z = \sum_{i=1}^{2} \sum_{j=1}^{2} E_{eij} \,.\, T_{ij} \qquad \textbf{3-29}$$

After running the NIP equation for objective function the minimum amount of energy consumption is 0.015 (kWh).

The energy of each machine operation is calculated according to equation 2-31; adapted from Narita, et al., (2006). After calculation the results are shown in the Table A- 2.

There are demand and capacity constraints in this case study.

The demand constraint, which is considered as the number of work piece (i) machined by machine (j) should be more than or equal to the demand, defined in equation 3-30:

$$\sum_{i=1}^{2} \sum_{j=1}^{2} T_{ij} <= 1/D_{ij} \text{ , (i=1,2, j=1,2)} \qquad \textbf{3-30}$$

The total capacity for each machine should be greater than or equal throughput and defined as capacity constraint (equation 3-31):

$$\sum_{i=1}^{2}\sum_{j=1}^{2} T_{ij} \geq 1/C_{ij} \text{ , (i=1, 2, j=1, 2)} \qquad \textbf{3-31}$$

4 RESULTS and ANALYSIS

4.1 Milling Process: case study (Procedure)

The cutting tool and work piece material specification are adopted from (Draganescu, et al., 2003) as a reference model. The cutting tool used is a face mill with diameter of 250 mm, cutting tips: SPMR 120312 (K10/an = 8°, y_n = 18°) and the work piece material is Aluminum Alloy. During each cutting test, one of the cutting parameters will be changed and its effect will be reflected in the energy output.

Table 4-1 Initial Values for Cutting Parameters

Cutting parameters	
angle of immersion (rad)	10
edge contact length (mm)	2
K_c (N)	1000
N (rpm)	250
W (mm)	0.7
D_p (mm)	60

1) Cutting test is performed by varying the cutting speed and specific energy consumption (kWh/cm^3) in face milling using Aluminum Alloy; width of cut = 0.3 mm and M_t = 80 mm.

Table 4-2 Cutting Velocity & E_{cs}

V_c (m/min)	E_{cs} (w h/cm^3)	Log(E_{cs})
60	1.007	0.003
120	1.01	0.006
180	1.02	0.009
240	1.03	0.012
300	1.03	0.016
360	1.04	0.019

As Figure 4-1 shows, when the cutting speed increases, the energy consumption will increase slightly. The polynomial equation is:

$$E_{cs} = -3E\text{-}6x^2 + 5E\text{-}2x + 3E\text{-}6 \quad \textbf{4-1}$$

Moreover, there is a direct relationship between cutting speed and energy output. R^2 is 0.98 which points out that the linear equation is a good fit for this data and parameter.

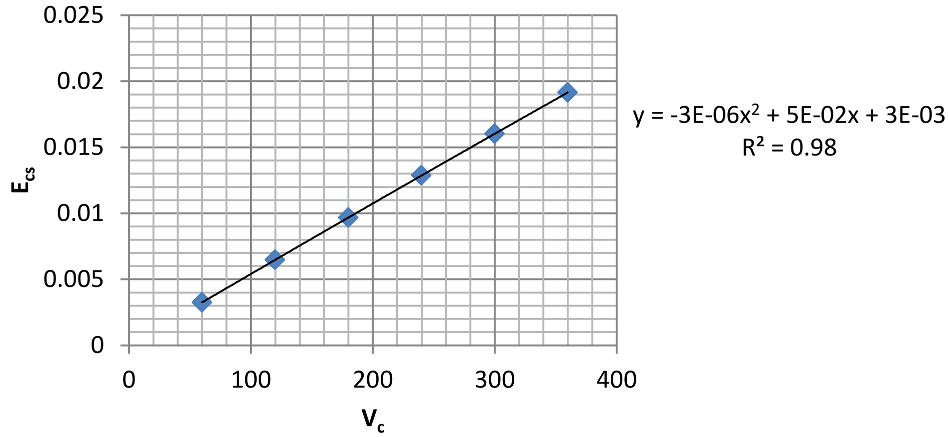

Figure 4-1 V_c & E_{cs}

2) Table 4-3 illustrates results of the simulation for feed per tooth, material removal rate and energy consumption relation.

Table 4-3 MRR, Feed Rate & E_{cs}

MRR(rpm)	n=1,E_{cs} (Wh/cm^3)	F(mm/min)
0.84	1.0021	0.2
1.05	1.0016	0.25
1.26	1.0013	0.3
1.68	1.0009	0.4
2.1	1.0006	0.5
2.52	1.0004	0.6
2.94	1.0003	0.7

The polynomial equation for energy consumption rate, feed per tooth is:

$$E_{cs} = 3.4x^2 - 4.5x + 1.7 \quad \textbf{4-2}$$

R^2 is 0.98 which indicates a good fit.

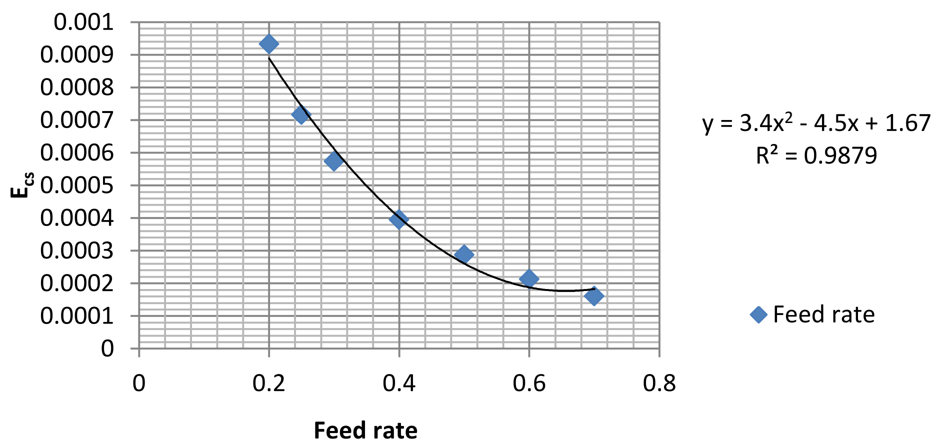

Figure 4-2 Feed rate & E_{cs}

3) Table 4-4 shows results of simulation with System Dynamics for depth of cut and E_{cs}:

Table 4-4 Depth of Cut & E_{cs}

D_p (mm)	E_{cs} (Wh/cm^3)
0.2	1.64
1.2	1.07
2.2	1.05
3.2	1.04
4.2	1.03
5.2	1.02
6.2	1.02
7.2	1.01

The scatter plot and polynomial equation show there is a negative relationship between depth of cut and energy consumption. The polynomial equation for this parameter is:

$$E_{cs} = 8x^2 - 78.9x + 18.8 \quad \textbf{4-3}$$

R^2 is 0.74 which indicates that this equation may be a fit for the data provided. Hence, more data is needed here to find a better fit and relationship between these parameters.

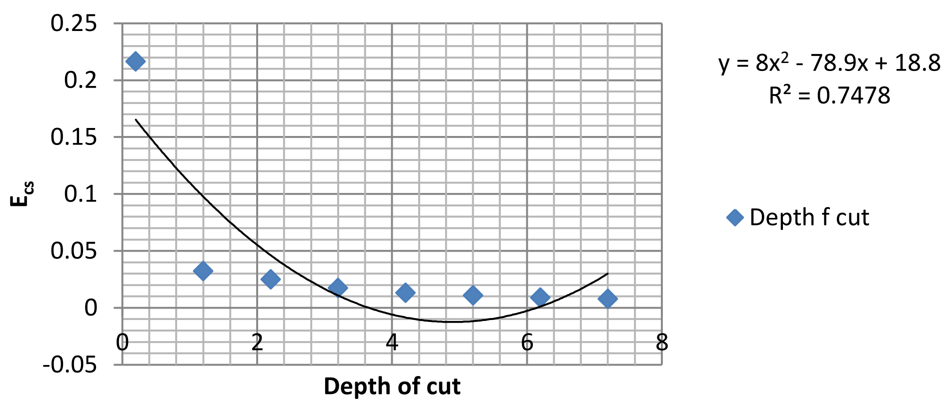

Figure 4-3 depth of cut & E_{cs}

4) Table of edge contact length and specific energy consumption:

Table 4-5 Edge Contact Length & E_{cs}

B (edge contact length) mm	E_{cs} (Wh/cm^3)
10	1.01
20	1.02
30	1.03
40	1.04
50	1.05
60	1.06
70	1.07
80	1.08
90	1.09
100	1.1

The graph below is showing the relationship between edge contact length of milling and energy. In addition, the polynomial regression equation indicates that there is a positive relationship between energy consumption and edge contact length.

$$E_{cs} = -2E\text{-}4x^2 + 0.5x + 2E\text{-}2 \quad \textbf{4-4}$$

R^2 is 0.99 which is a very good fit for this data

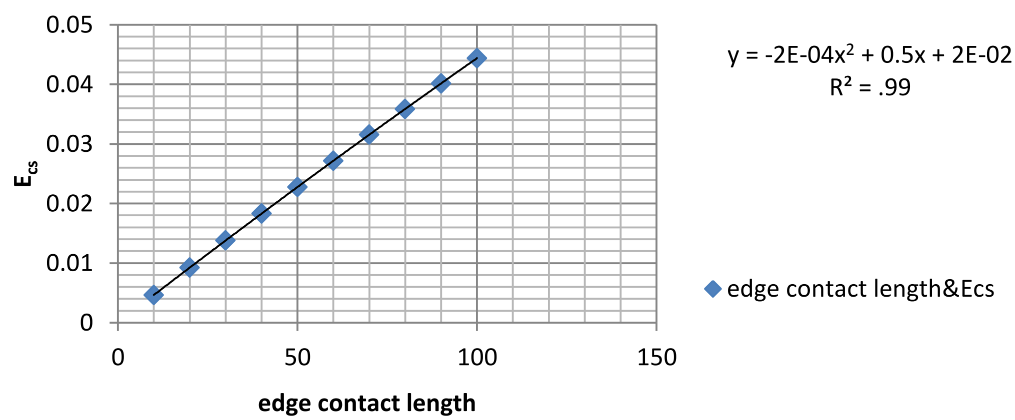

Figure 4-4 Edge contact length & E_{cs}

5) Table 4-6 Number of Teeth and Ecs illustrates the results for number of teeth and specific energy consumption:

As it can be observed from the Table 4-6 and Figure 4-5, energy and number of teeth have a reverse relationship.

Table 4-6 Number of Teeth and E_{cs}

Number of teeth	E_{cs} (Wh/cm^3)
1	1.024
2	1.012
3	1.007
4	1.005
5	1.004
6	1.003
7	1.003
8	1.002
9	1.002
10	1.002

The scatter plot and exponential regression equation for these parameters are:

$$E_{cs} = 0.2x^2 - 2.8x + 11.3 \qquad \textbf{4-5}$$

R^2 is 0.90 which is almost a good fit for the data and parameters provided. The polynomial regression trend line indicates a reverse relationship between number of teeth and energy consumption

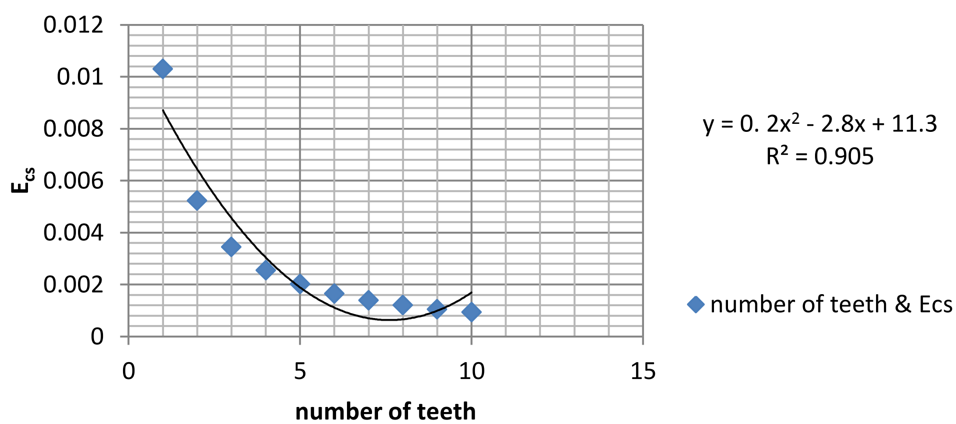

Figure 4-5 Number of teeth andE_{cs}

6) The effect of shear angle on the energy output has been shown in Table 4-7 with the specific cutting parameter set up:

Table 4-7 Specific Cutting Parameter Set Up

Shear stress 1 (N/m^2)	400
Width of cut (mm)	0.70
Length of cut (mm)	10
Depth of cut 1 (mm)	0.70
uncut chip thickness (h)	0.44
Vc_{ij} (m/min) (60-370)	120
T (machine time)	5
feed speed(mm/min),V_f	238.85
feed rate(mm/min)	0.20
spindle speed (rpm)	250
tool diameter (mm)	250
S_z (feed/tooth)	0.20
axial depth of cut (mm)	0.70
K_t (specific cutting coefficient)	1

The cutting test on the shear angle has been performed in a range of 10 and 38 (rad).

Table 4-8 Effect of Shear Angle and Shear Stress on Cutting Energy

shear angle (rad)	rake angle (rad)	cutting force (N)	Energy (wh/cm^3)
15.5	10	942.97	10.77
20.5	20	493.4	5.63
29.5	25	426.46	4.87
34.5	35	321.32	3.67
36	35	321.32	3.37
38	45	250.13	2.85

Figure 4-6 indicates the results of shear angle and E_{cs} simulation

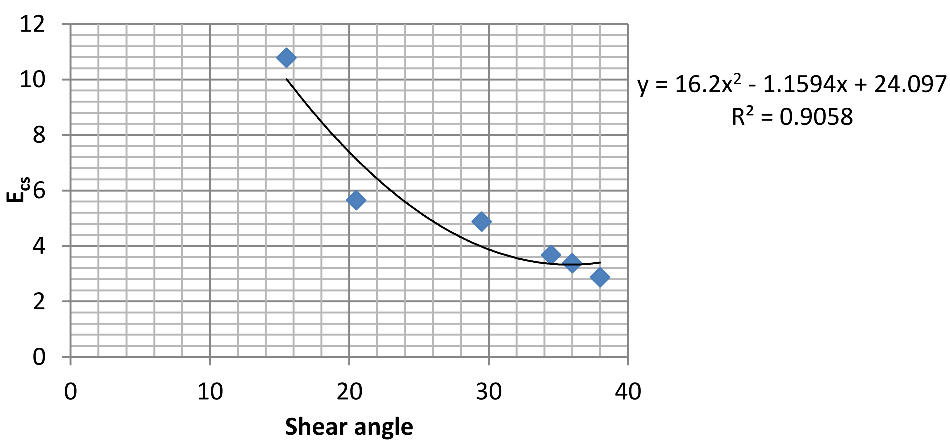

Figure 4-6 Shear angle & E_{cs}

7) The last cutting process has performed to show the effect of rake angle on the cutting parameter. The shear stress is 613 MPa. The regression trend line for the rake angle is:

$$E_{cs} = 9E\text{-}2x^2 - 0.06x + 6.33 \quad \textbf{4-6}$$

R square is 0.99 which indicates that the polynomial function is a very good fit for the data provided.

Table 4-9 Rake Angle & E_{cs}

rake angle (rad)	E_{cs} (wh/cm^3)
15	5.33
20	4.98
25	4.67
30	4.35
35	4.04
40	3.73
45	3.42

Figure 4-7 illustrates a decline in the specific energy consumption when the rake angle is growing.

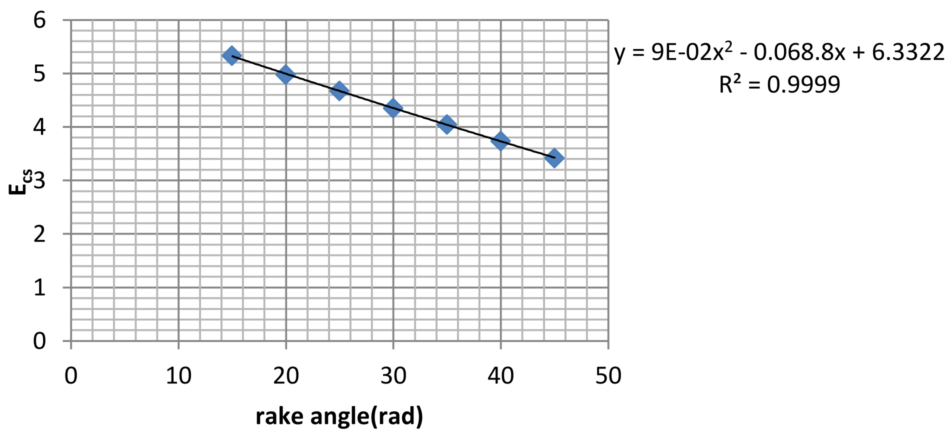

Figure 4-7 Rake angle & E_{cs}

In brief, it can be understood from the data presented before that there is a negative or reverse relationship in milling operation between energy consumption and depth of cut, number of teeth and feed rate but direct relationship with edge contact length and cutting velocity. By comparing the coefficient of each polynomial line, it can be concluded that feed rate and number of teeth are the most impactful factors in reducing the energy consumption.

4.2 Turning Process

- Selection of cutting parameters:

A study about turning process has been carried out in order to develop the energy model for this operation, the energy consumption was calculated and the effects of different cutting parameters presented here.

The cutting force is formulated based on the mathematical model and data from (Rajemi et al. 2010). This case study considered Aluminum as the work piece which was processed on an MHP CNC lathe machine. In addition, the cutting speed, spindle speed, depth of cut and feed rate has specific ranges according to the material used in this case.

Table 4-10 Initial Values for Cutting Parameters in Turning Process

P_0(kW)	4.7
t_1(s)	120
P_t(kW)	3
N(RPM)$\times 10^3$	1.2
D_i(mm)	45
D_o(mm)	44.5
t_3(s)	120
L (length of cut)(mm)	100
Y_e (N)	75
A(mm)	100
feed exponent	0.4
feed rate (mm/min)	0.1
D_p (mm)	0.2
V_c (initial/sec)	30

- Estimated energy consumption in turning:

In order to investigate the relationship of cutting parameters and energy consumption, their values have been changed and shown in the tables below and different analysis have been carried out.

1) Cutting test by varying the cutting speed and energy consumption in turning process using Aluminum:

Table 4-11 Cutting Speed & E_c

V_c (m/min)	E_c (kWh)
60	0.15
90	0.17
120	0.21
150	0.28
180	0.32
210	0.37
300	0.45
400	0.5
500	0.88

According to Table 4-11, when the cutting speed increases, the energy consumption declines. Furthermore, Table 4-8 presents the same results. The polynomial equation is:

$$E_c=1E\text{-}6x^2+0.0008x+0.11 \qquad \textbf{4-7}$$

There is a direct relationship between cutting speed and energy output. R^2 is 0.98 which points out that this equation is a good fit.

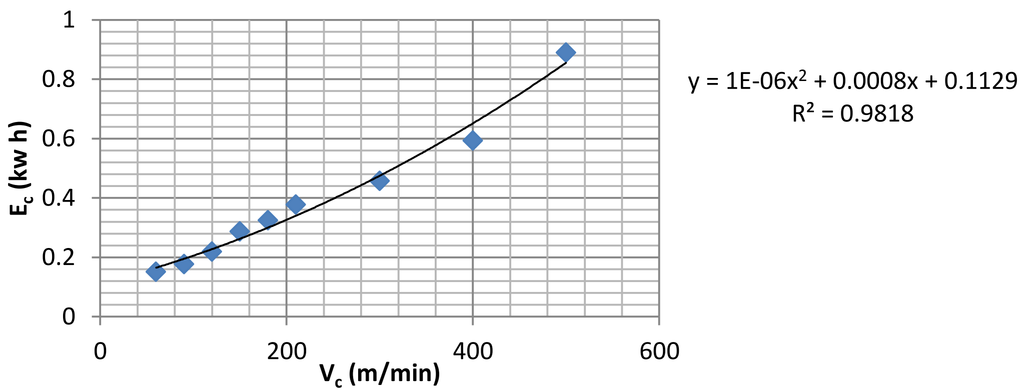

Figure 4-8 Cutting velocity & cutting energy

2) Table 4-12 shows the results of feed per tooth, material removal rate and energy consumption relation

Table 4-12 Feed Rate, MRR And Cutting Energy

feed rate (mm/min)	E (kWh)	MRR (cm^3/min)
0.1	0.002	235.5
0.15	0.0018	353.2
0.2	0.0015	471
0.25	0.0014	588.7
0.3	0.0012	706.5

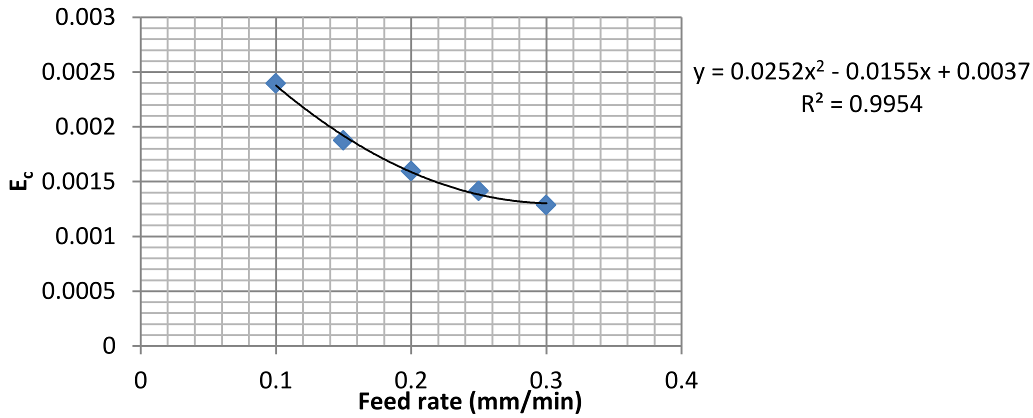

Figure 4-9 Feed rate & cutting energy

The polynomial equation for energy consumption rate, feed rate is:

$E_c = 0.02x^2 - 0.01x + 0.003$ **4-8**

Figure 4-10 shows the positive relationship between spindle speed and material removal rate.

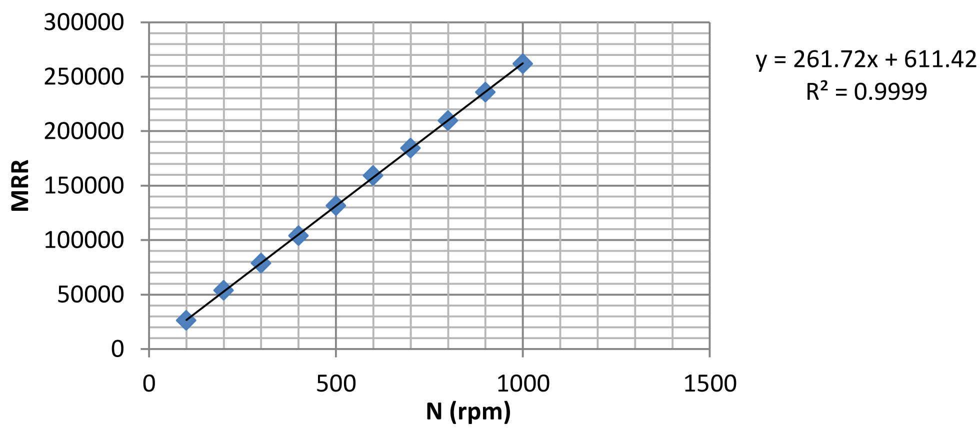

Figure 4-10 Spindle speed & cutting energy

3) Table 4-13 shows the effect of depth of cut and energy consumption:

The scatter plot and linear equation show there is a negative relationship between depth of cut and energy consumption. Also, the polynomial equation for these parameters is:

Table 4-13 Depth of Cut & Cutting Energy

D_p (mm)	E_c (kWh)
0.25	0.688
1.25	0.687
2.25	0.686
3.25	0.6867
4.25	0.6865
5.25	0.68651
6.25	0.686519
7.25	0.6864
8.25	0.68642

$$E_c = 4E\text{-}5x^2 - 0.0005x + 0.68 \quad \textbf{4-9}$$

R^2 is 0.92 which indicates that this equation is a good fit for the data provided. Hence, more data is needed here to find a better fit and relation between these parameters.

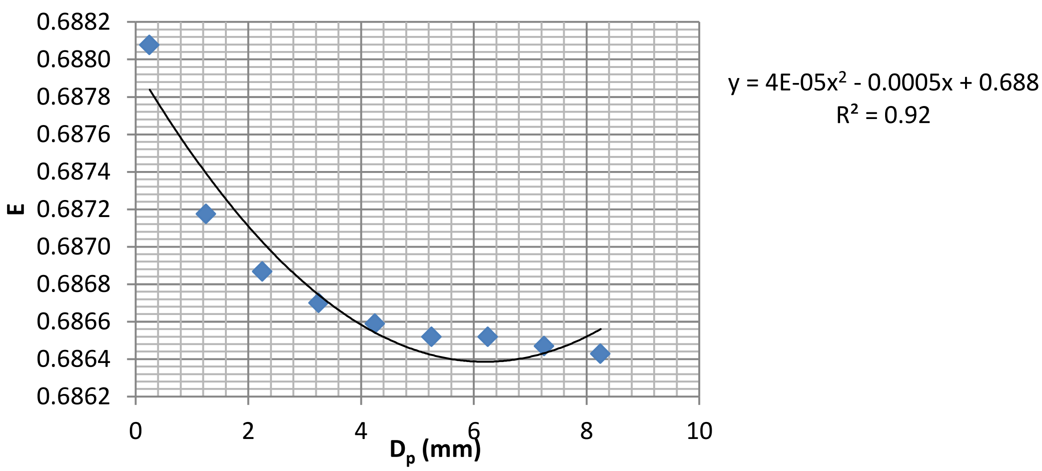

Figure 4-11 Depth of cut & cutting energy

4) Effects of spindle speed on energy consumption:
   The graph below is showing the relationship between spindle speed and energy. In addition, the polynomial regression equation indicates that there is a reverse relationship between energy consumption and spindle speed.

Table 4-14 Spindle Energy & Cutting Energy

N (rpm)	E (kWh)×10^{-3}
100	2
200	1
300	0.7
400	0.6
500	0.5
600	0.43
700	0.39
800	0.35
900	0.33
1000	0.31

The regression equation is:

$$y = 3E\text{-}6x^2 - 0.005x + 2.13 \quad \textbf{4-10}$$

R^2 is 0.87. The scatter plot is shown in Figure 4-12.

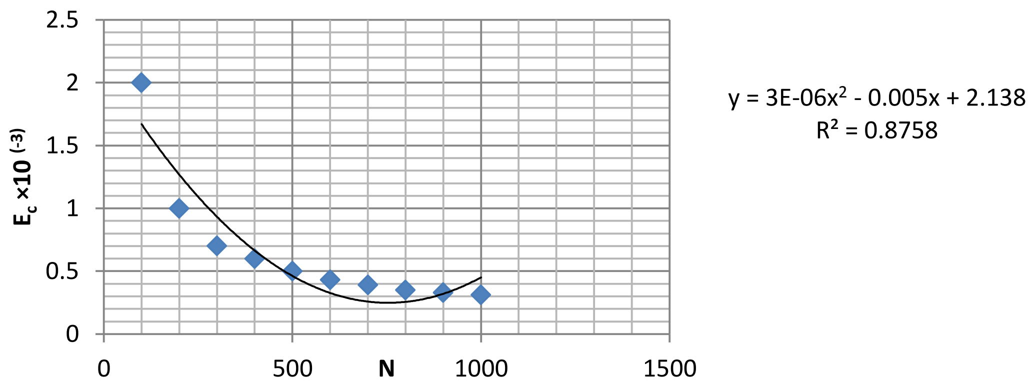

Figure 4-12 Spindle speed & E_c

5) Table 4-15 illustrates the results of simulation for material removal and energy consumption:

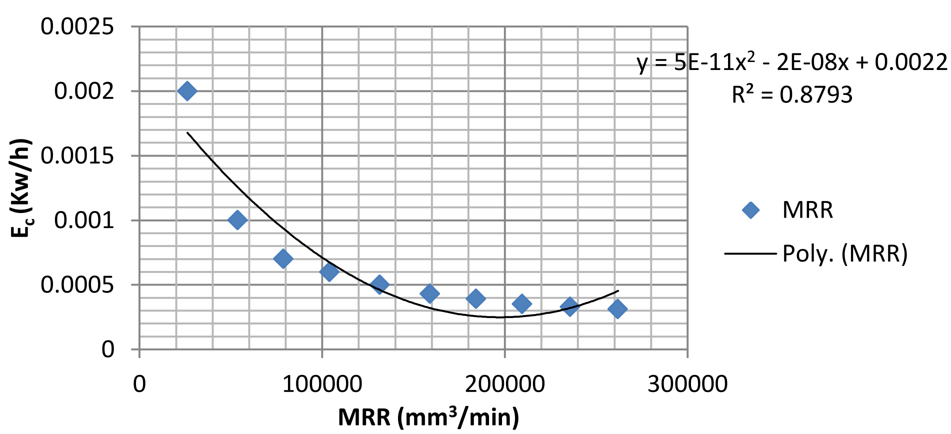

Figure 4-13 MRR & E_c

Table 4-15 Material Removal Rate &E_c

$MRR \times 10^3 (mm^3/min)$	E_c (kWh)
26.19	0.002
53.7	0.001
78.92	0.0007
104.14	0.0006
131.65	0.0005
159.16	0.0004
184.37	0.00039
209595	0.00035
235.79	0.00033
261.99	0.00031

It is showing the reverse relationship between energy and MRR.

E_c= 5E-8x^2 - 2E-5x + 2.2 **4-11**

R^2 is 0.88 which is almost a good fit for the data and parameters provided. The logarithmic regression trend line indicates a reverse relationship between number of teeth and energy consumption.

4.3 Sensitivity analysis & ANOVA

4.3.1 Sensitivity analysis in milling process

The purpose of sensitivity analysis is to find the relationship between the independent variables such as depth of cut, cutting speed, shear angle and the dependent variable such as power and energy needed to finish the particular machine operations.

The main goal of sensitivity analysis is to gain insight into which assumptions are critical and which assumptions affect choice. The process involves various ways of changing input values of the model to see the effect on the output value.

For the sensitivity analysis, in order to show the effects of different variables on the energy and power demand, the value of different parameters should be changed while showing the output results. Therefore, by comparing the outputs, the optimal parameters can be found.

In the test performed before, in order to have machine operations on Aluminum, specific cutting conditions should be considered as Table 4-16 (Draganescu et al. 2003):

Table 4-16 Cutting Parameters Ranges

Milling specification	
Cutting speed(m/min)	60-360
feed (per tooth) (S_z)	0.2-0.7
depth of milling (mm)	0.2-7.2
Edge contact length of milling (B)(mm)	10-100
Number of teeth	1-12

The table below indicates the changes in power consumption when the shear angle (rad) is changing from (5 to 25) and depth of cut is changing between 0.5 and 0.7 mm. The 3D plot shows the relationship between the nominal power, shear angle and depth of cut.

The initial values for these process parameters are adapted from (Altintas 2000) and presented in Table 4-17.

Table 4-17 Initial Setting for Cutting Parameter

edge contact length (mm)	10
k_{tc}	1000
k_{te}	800
k_{rc}	0.2
k_{re}	0.1
Angle of immersion (rad)	10
Number of teeth	1
Length of cut (mm)	10
D (mm)	250
N (rpm)	200
F_c (N)×10^3	1.57
W (mm)	0.7

What-if-analysis function in Excel has been used to find the output according to the input variables. Table 4-18 displays the changes in the specific energy consumption in milling process (kWh/cm^3) when the depth of cut (d_p) and shear angle are varying.

Table 4-18 Effects of Depth of Cut & Shear Angle on Power Consumption in Milling

Shear angle(rad) / Depth of cut(mm)	power	5	10	15	20	25
	0.05	170.76	85.7	57.5	43.51	35.21
	0.25	853.83	428.54	287.52	217.57	176.08
	0.3	1024.6	514.25	345.02	261.09	211.3
	0.4	1366.13	685.67	460.03	348.12	281.73
	0.7	2390.73	1199.93	805.06	609.22	493

It can be seen from Table 4-18 and Figure 4-14 that depth of cut and shear angle have significant effects on saving power in milling process.

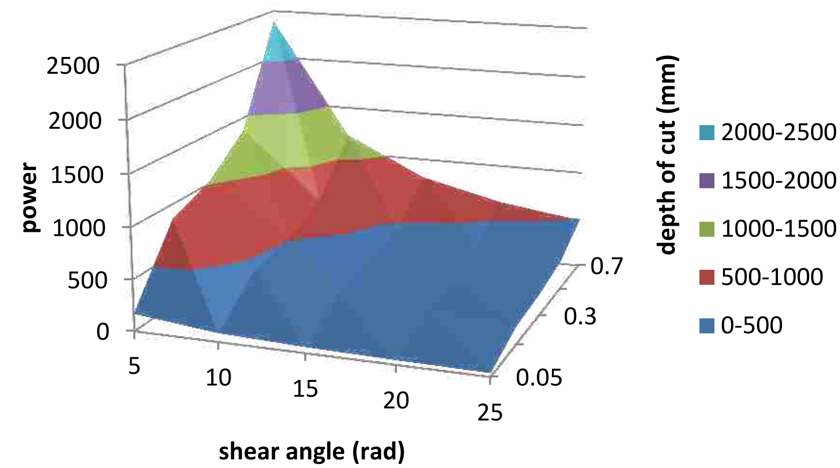

Figure 4-14 Effect of shear angle and d_p on power consumption

Table A- 9 displays the changes in the energy consumption (kWh/cm^3) when the cutting speed (v_c) and depth of cut (d_p) are changing.

The 3D surface plot and bar graph for energy use, cutting speed and depth of cut in milling process are illustrated in Figure 4-15 and Figure 4-16 :

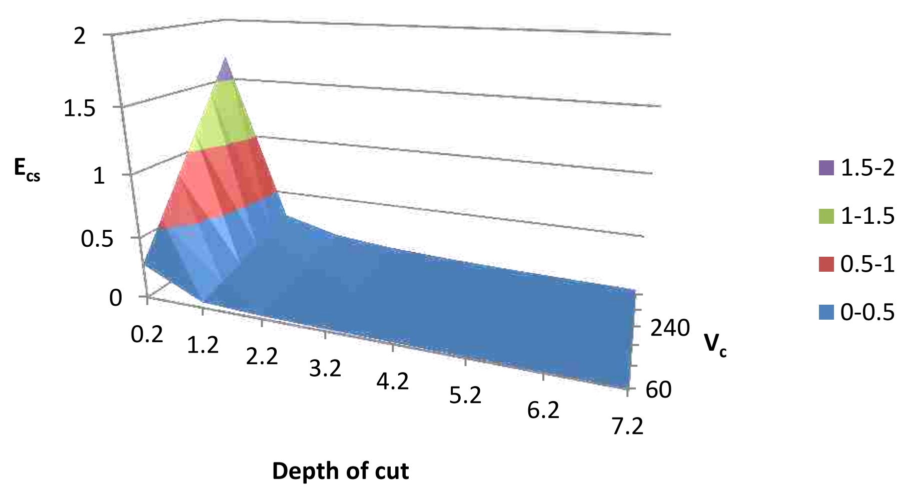

Figure 4-15 Depth of cut, V_c and E_{cs}

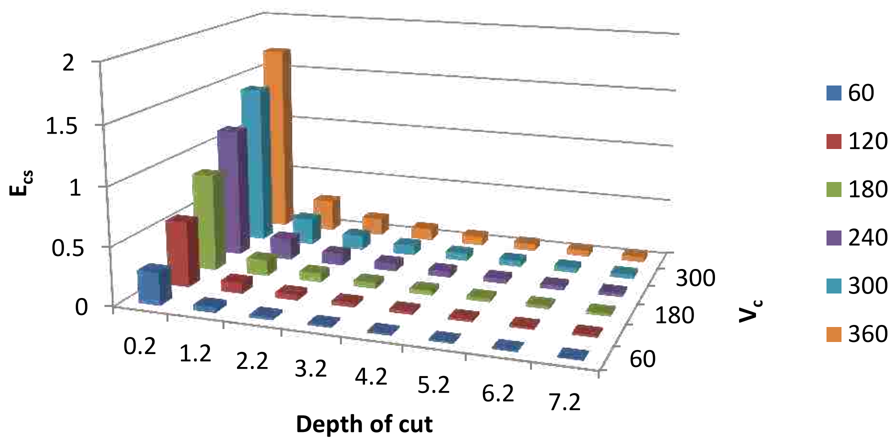

Figure 4-16 Depth of cut, V_c and E_{cs}

Table A- 10 indicates the changes in specific cutting energy (kWh/cm^3) when depth of cut and feed rate are changing in milling operation. Other process parameters are: cutting speed 60 m/min, spindle speed 200 rpm and cutting force considered as a constant factor which is 1382.39 N.

3D surface plot reflects the relationship between depth of cut, feed rate and specific energy consumption rate accordingly (Table A- 10).

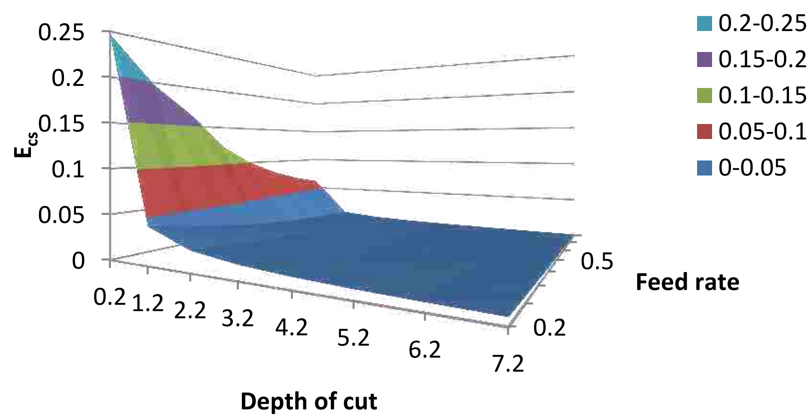

Figure 4-17 Depth of cut, feed rate and Ecs

Table A- 11 indicates the changes in specific cutting energy (kWh/cm^3) when feed rate and cutting velocity are changing. Other process parameters are; depth of cut at 0.2 mm, spindle speed 200 rpm, cutting force considered as a constant factor which is 1382.39 N.

3D surface plot (Figure 4-18) is reflecting the relationship between feed rate, cutting speed and specific energy consumption rate in milling process. In addition, it can be understood that energy consumption drops considerably with the increase of the feed rate whereas it rises when the cutting speed is increased.

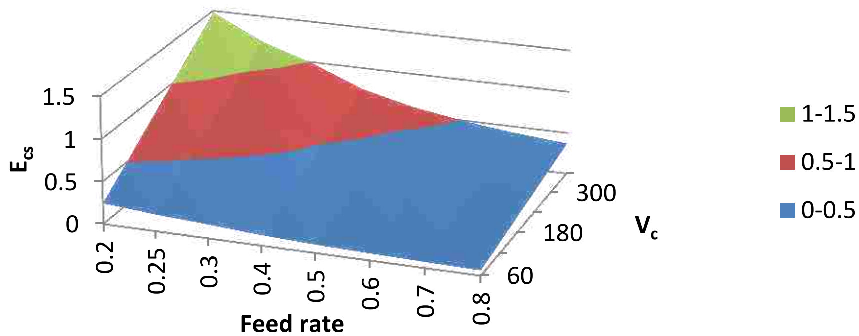

Figure 4-18 Feed rate & V_c and E_{cs}

4.3.2 Sensitivity analysis results

Sensitivity analysis approach is applied to find which cutting parameters in milling and turning operations have critical effect on the output. The table and graph below indicate that the effect of feed rate is the highest; then there is depth of cut and finally, the cutting velocity.

The regression equation for each cutting parameter is obtained from the data showed before for each parameter and presented in Table 4-19:

Table 4-19 Regression Equations for Cutting Parameters in Milling Process

Cutting parameter	Regression Equation	Coefficient
V_c	$y = -3\times10^{-6}x^2 + 5\times10^{-5}x + 3\times10^{-6}$	$-6\times10^{-6}x + 5\times10^{-5}$
D_p	$y = 8x^2 - 0.0789x + 0.18$	$16x - 0.07$
Feed rate	$y = 3.4156x^2 - 4.487x + 1.65$	$6.8x - 4.48$
Rake angle	$y = 9\times10^{-2}x^2 - 0.0688x + 6.33$	$1.8\times10^{-2}x - 0.06$
Edge contact length	$y = -2\times10^{-4}x^2 + 0.0005x + 2\times10^{-5}$	$-4\times10^{-4}x + 0.0005$
Number of teeth	$y = 0.2x^2 - 0.0028x + 0.01$	$0.4x - 0.002$

The x value of each variable is defined in a limited range which is positive. The first derivative of each polynomial equation (Table 4-19) can be compared and the bigger coefficient reflects the largest effect on the output (energy consumption). By comparing the coefficient of each equation, it is obvious that feed rate has the most significant effect on the energy consumption in milling operation using aluminum, followed by depth of cut; (D_P >Feed rate > V_C > Edge contact length> Rake angle> Number of teeth).

Regression analysis

Table 4-20 Regression Analysis Results for Milling Process

Regression analysis	
Multiple R	0.9
R Square	0.9
Adjusted R Square	0.9
Standard Error	0.08
Observations	14

According to Table 4-20, R^2 is almost 0.94 which shows a very good fit and means 94% of the variation in power is explained by the independent variables shear angle and depth of cut.

Analysis of variance

A statistical analysis tool that divides the total variability found within a data set into two components: random and systematic factors. The random factors do not have any statistical effect on the given data set, whereas the systematic factors do. The ANOVA test is used to determine the impact independent variables have on the dependent variable in a regression analysis. The ANOVA test is the initial step in identifying factors that are influencing a given data set. After the ANOVA test is performed, the analyst is able to perform further analysis on the systematic factors that are statistically contributing to the data set's variability(Investopedia2015).

Reliability of the result (statistically significant) can be checked by looking at significance F (1.74E-7) in Table 4-21. If this value is less than 0.05, the results are good. If significance F is greater than 0.005, it is probably better to stop using this set of independent variables.

Table 4-22 shows, p value is less than 0.05 therefore the equation for the power demand, shear angle and depth of cut is:

Power= 741.38 + 1465.011× d_p - 45.92 × shear angle **4-12**

Table 4-21 ANOVA Results for Milling Parameters

ANOVA					
	df	SS	MS	F	*Significance F*
Regression	2	507	253	35.74	1.74E-7
Residual	21	148	70935.97		
Total	23	656			

Table 4-22 ANOVA Results for Milling Parameters

Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
741.38	167.91	4.41	0.0002	392.19	1090.58	392.19	1090.58
1465.01	261.23	5.6	1.4E-5	921.73	2008.28	921.73	2008.28
-45.92	7.89	-5.81	9E-6	-62.34	-29.49	-62.34	-29.49

The residuals are presented in Table A- 8, which demonstrates how far away the actual data points are from the predicted data points. For example, the first data point is -269.7. Using the above equation, the predicted data point equals 355.41.

In the second example, the relationship between cutting speed, depth of cut and energy consumption is considered. The regression analysis (Table 4 23) shows that as for R^2 the value is 0.89 which is a good fit. 89% of the variation in energy consumption is explained by the independent variables cutting speed and depth of cut.

Table 4-23 Regression Analysis for V_c and D_p in Milling Process

Regression Statistics	
Multiple R	0.94
R Square	0.89
Adjusted R Square	0.88
Standard Error	2.63
Observations	42

Table 4-24 ANOVA for D_p and V_c in Milling Process

ANOVA	df	SS	MS	F	Significance F
Regression	2	2199.81	1099.9	158.89	1.79E-19
Residual	39	269.97	6.92		
Total	41	2469.78			

Table 4-24, the significance F (1.79E-19) is less than 0.005; therefore the data used here is acceptable and can present a good relationship between independent and dependent variables

Table 4-25 ANOVA Results for V_c & D_p in Milling Process

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-10.02	1.22	-8.16	5.7E-10	-12.5	-7.53	-12.5	-7.53
V_c	0.05	0.005	10.97	1.7E-13	0.04	0.06	0.04	0.06
d_p	16.70	1.18	14.05	7.5E-17	14.29	19.10	14.29	19.10

From Table 4-25, the equation which shows the relation between energy, cutting speed and depth of cut is as follows:

$$E=0.0002+1.74E\text{-}13\times V_c+7.57E\text{-}17\times d_p \quad \textbf{4-13}$$

4.3.3 Sensitivity analysis in turning process

The initial values of cutting parameters for turning process are shown in Table A- 17:

The change in the energy consumption (kWh) is displayed in Table A- 12 when the depth of cut (d_p) and feed rate are varying.

As it can be observed from Figure 4-19, depth of cut and feed rate have substantial effects on saving energy consumption in turning process.

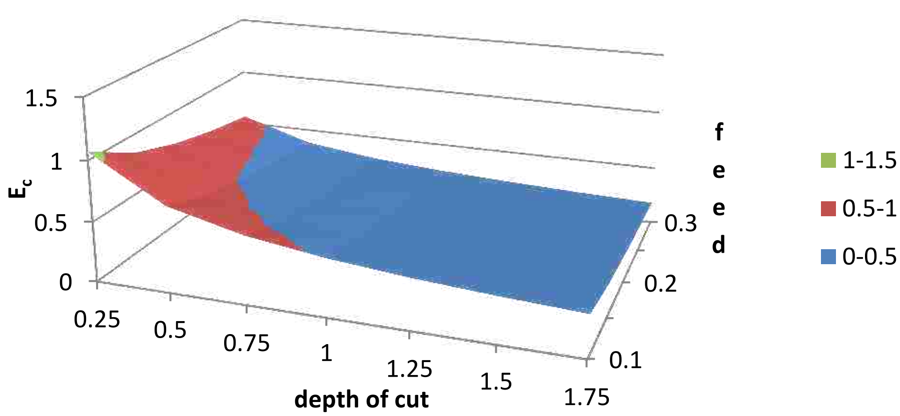

Figure 4-19 Depth of cut, feed rate and E_c in turning process

Table A- 13 shows the changes in the cutting energy (kWh) in turning process when the depth of cut (d_p) and cutting speed are changing within the range.

As it can be seen from Table A- 13 and Figure 4-20, depth of cut and cutting speed have significant effects on reducing energy consumption in turning process.

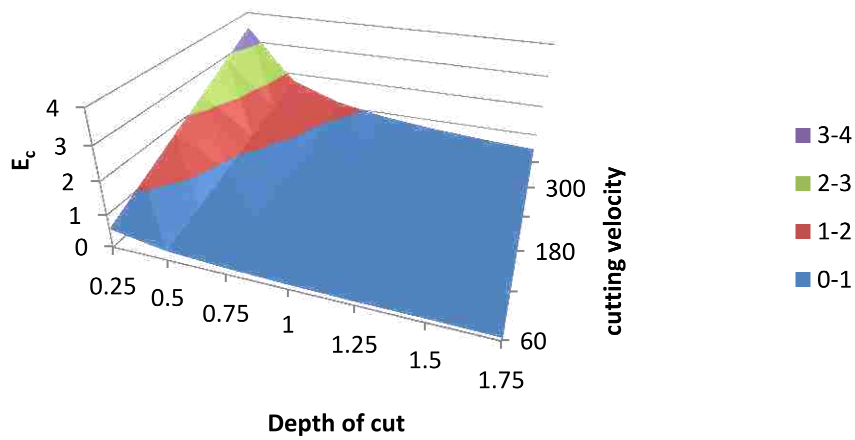

Figure 4-20 D_p, V_c and E_c in turning process

Table 4-26 displays the regression equations of cutting parameters in turning process:

Table 4-26 Regression Equations for Cutting Parameters in Turning Process

Cutting parameter	Regression Equation	Coefficient
V_c	y = 1E-03x2 + 0.8x + 0.11	2E-3x
Spindle speed	y = 3E-03x2 - 5x + 2.13	6E-3x
D_p	y = 4E-02x2 - 0.05x + 6	8E-2
Feed rate	y = 25.2x2 - 15.5x + 3.7	50.4

The first derivative (coefficient) of each polynomial equation (Table 4-26) can be compared and the bigger coefficient reflects the largest effect on the output (energy consumption). By comparing the coefficient of each equation, it is resulted that feed rate has the most significant effect on the energy consumption in milling operation using aluminum, followed by depth of cut; (Feed rate > D_p > Spindle speed > V_c).

4.3.4 Analysis of variance and regression analysis:

Regression analysis

The regression analysis for depth of cut, cutting speed and feed rate in turning process is illustrated in the Table 4-27:

Table 4-27 Regression Analysis for D_p, V_c and E_c in Turning Operation

Regression Statistics	
Multiple R	0.93
R Square	0.86
Adjusted R Square	0.83
Standard Error	0.009
Observations	17

R Square

In the regression analysis (Table 4-27), R square is 0.86 which is almost a good fit; 86% of the variation in power is explained by the independent variables feed rate, cutting speed and depth of cut.

Table 4-28 ANOVA Results in Turning Process

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.007	0.002	27.98	6.08E-6
Residual	13	0.001	9.02E-5		
Total	16	0.008			

The analysis of variance results are presented in Table 4-28. According to this table, the significance F (6.08E-06) is less than 0.005, therefore the data used here is acceptable and present a good relationship between independent and dependent variables.

Table A- 14 which shows the relation between energy, cutting speed, feed rate and depth of cut is as shown below; moreover, the p values are less than 0.05 which are acceptable and indicate that these parameters contribute in energy reduction in turning.

$$E_C = -0.06 + 0.149\text{Feed rate} + 0.0002V_c + 0.062D_p \quad \textbf{4-14}$$

4.4 Response Surface Methodology (RSM)

Response surface methodology (RSM) is a collection of mathematical and statistical methods for practical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by various independent variables (input variables; Montgomery 1996). Originally, RSM was developed to model experimental responses (Box and Draper, 1987), and then migrated into the modelling of numerical experiments. The difference is in the type of error generated by the response.

Response Surface Method (RSM) is one of the methodologies used in structured design of experiments (DOE) to make sufficient and complete experiments which helps to understand the effects of changes in different cutting parameters on the output. Statistical analysis resulted from measurements in different experiments leads to finding the final mathematical model of results (energy consumption here) depending on input (cutting parameters here).

For the optimization method, response surface methodology is used for this study with the goal of minimizing the energy consumption while finding the best level of input parameters such as X_1= cutting speed (m/min), X_2= feed rate (mm/rev), X_3= rake angle (rad) and X_4= depth of cut (mm). The energy consumption rate is the function of these input parameters as follows:

$$y = f(X_1, X_2, X_3, X_4) + \varepsilon \qquad \textbf{4-15}$$

Where ε represents the noise or error perceived in the response (y). The surface represented by $f(X_1, X_2, X_3, X_4)$ is a response surface.

4.4.1 Experimental Values for RSM in milling process

The method of response surface methodology has been used to conduct the experiments and improve the mathematical model for prediction of optimal cutting parameters and energy consumption. The parameters are:

Input parameters:

X_1=cutting speed (m/min)

X_2=feed rate (mm/rev)

X_3=Rake angle (rad)

X_4= depth of cut (mm)

Output parameter: energy consumption (y)

Process parameters and the levels used in RSM:

In this experimental analysis of milling process parameters has been conducted in three levels -1, 0, 1 and represented in Table 4-29.

Table 4-29 RSM Three Level Table for 4 Cutting Parameters in Milling Process

Cutting parameters	Unit	-1	0	1
Cutting speed	m/min	60	120	360
Rake angle	rad	10	22.5	35
Feed rate	mm/rev	0.25	0.52	0.8
Depth of cut	mm	0.2	0.4	0.6

As well, design table (Table A- 18) and data provided to determine the relationship between rake angle, cutting speed and feed rate.

Fit summary

After performing analysis by Design Expert 9.0, it can be concluded from Table 4-30 and Table 4-31 that the quadratic and linear model are the best fits for the data given in table A-19. Moreover, because a linear regression model is not always appropriate for the data, the residuals should be assessed. Basically, the difference between the observed data for dependent variable (y) and the predicted value (y) is known as the residual. There is one residual for each data point presented in figure A-1. Because the points in a residual plot are randomly dispersed around the horizontal axis, a linear regression model is appropriate for the data; otherwise. Hence, this model is useful in predicting the actual value of output.

Table 4-30 Fit Summary for Data Table 4-36

Sequential Model Sum of Squares [Type I]						
	Sum of		Mean	F	p-value	
Source	Squares	df	Square	Value	Prob > F	
Mean vs Total	11.72	1	11.72			
Linear vs Mean	6.69	4	1.67	25.47	< 0.0001	Suggested
2FI vs Linear	0.66	6	0.11	2.13	0.09	
Quadratic vs 2FI	0.48	4	0.12	3.53	0.03	Suggested

Cubic vs Quadratic	0.50	9	0.05	33.69	0.0002	Aliased
Residual	9.8E-3	6	1.6E-3			
Total	20.06	30	0.67			

The summary of R^2 resulted for each model is presented in Table 4-31. The quadratic model is applied as a best fit for mathematical model since it has higher R Square 0.93.

Table 4-31 Model Summary Statistics

	Std.		Adjusted	Predicted		
Source	Dev.	R-Squared	R-Squared	R-Squared	PRESS	
Linear	0.26	0.8	0.77	0.68	2.63	Suggested
2FI	0.23	0.88	0.82	0.57	3.54	
Quadratic	0.18	0.93	0.88	0.55	3.67	Suggested
Cubic	0.04	0.99	0.99			Aliased

Statistical Analysis

The effects of cutting speed, feed rate, and rake angle on energy consumption were analyzed with the analysis of variance (ANOVA). Table A- 16 indicates that the parameters experimented are statistically significant.

In Table A- 16, model’s F-value of 54.89 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. Values of "Prob > F" less than 0.05 indicate that model terms are significant.

The Model F-value of 12.14 implies the model is significant. Values of "Prob > F" less than 0.05 indicate model terms are significant. In this case A, C, D, AB, AD, BC, CD, A^2 are significant model terms.

Final equation

Factorial designs can be used for fitting quadratic models. A quadratic model can significantly improve the optimization process when a second-order model suffers lack of fit due to interaction between variables and surface curvature. The quadratic mathematical model is developed using the experimental values and responses to predict the energy consumption. A general quadratic model is defined as (Montgomery 1996):

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum \sum_{i<j=2}^{k} \beta_{ij} x_i x_j + \sum_{j=1}^{k} \beta_{ij} {x_j}^2 + \varepsilon \quad \textbf{4-16}$$

Where x_i and x_j are the design variables and β_{ij} are coefficients.

Equations were formed using Design Expert 9.0 software for energy consumption in milling process (Y):

$$Y=\beta_0+ \beta_1x_1+ \beta_2x_2+ \beta_3x_3+ \beta_4x_4+\beta_{12}x_1x_2+ \beta_{13}x_1x_3+ \beta_{14}x_1x_4+ \beta_{23}x_2x_3+ \beta_{24}x_2x_4+ \beta_{34}x_3x_4+\beta_{11}x_1^2+ \beta_{22}x_2^2+ \beta_{33}x_3^2+ \beta_{44}x_4^2 \quad \textbf{4-17}$$

$$Log\_10(E_{milling})=1.039+2.7E\text{-}003\times V_c\text{-}0.067\times d_p\text{-}0.88\times f+0.013219\times \alpha_r+3.34E\text{-}003\times V_c\times d_p+6.058E\text{-}004\times V_c\times f+5.33E\text{-}005\times V_c\times \alpha_r\text{-}1.82\times d_p\times f\text{-}9.901E003\times d_p\times \alpha_r\text{-}0.029\times f\times \alpha_r\text{-}6.48E\text{-}006\times V_c\text{^}2+0.032\times d_p\text{^}2+1.0006\times f\text{^}2+1.32E\text{-}006\times \alpha_r \text{^}2 \quad \textbf{4-18}$$

The 3D plots made by Design Expert 9.0 (Figure 4-21 and Figure 4-22) present the relationship between cutting parameters and energy consumption in milling process.

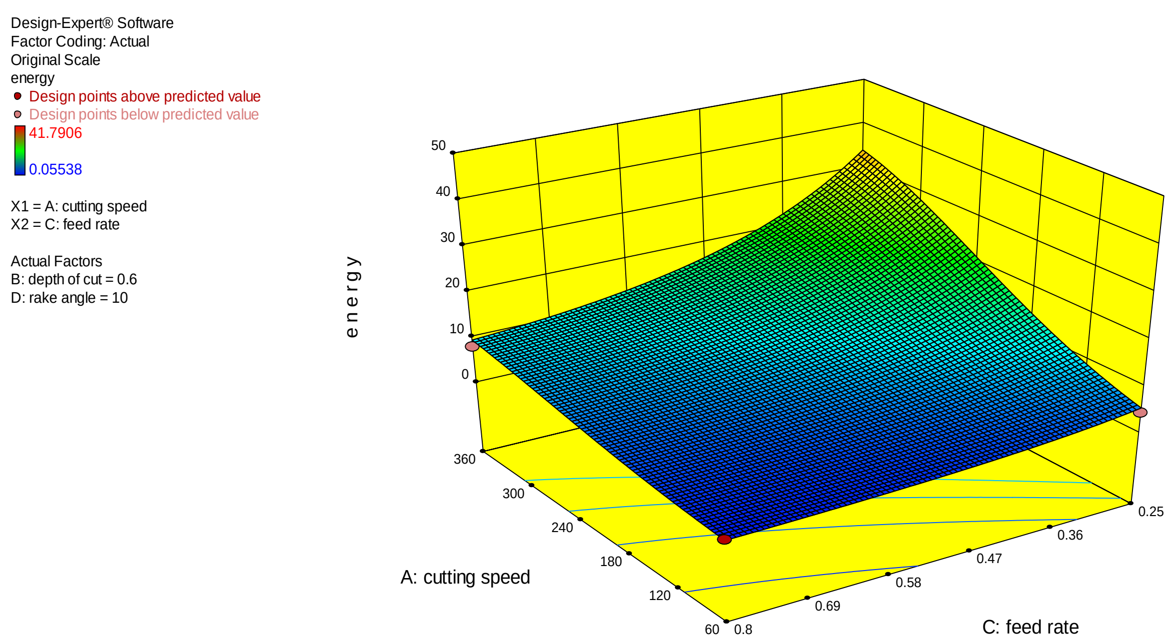

Figure 4-21 3D plot of feed rate, cutting speed and energy in milling process

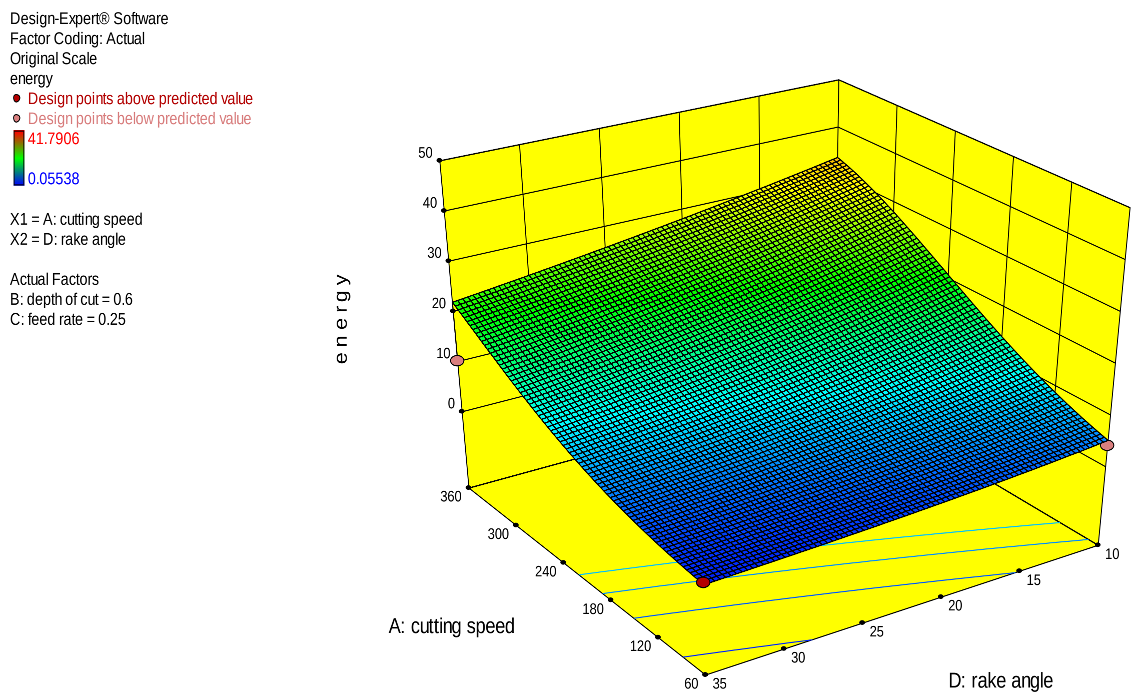

Figure 4-22 3D plot for rake angle, cutting speed and energy consumption

Confirmation Report

The confirmation report (Table 4-32 and Table 4-33) shows that the confidence level of 95% is preferred for the factors. Therefore these factors can be used to predict and show the relationship between the energy output and cutting parameters.

Table 4-32 Confirmation Report Table

Confirmation Report						
Two-sided Confidence = 95%, n =1						
Factor	Name	Level	Low Level	High Level	Std. Dev.	Coding
A	cutting speed	210	60	360	0.00	Actual
B	depth of cut	0.4	0.20	0.6	0.00	Actual
C	feed rate	0.53	0.25	0.8	0.00	Actual
D	rake angle	22.5	10	35	0.00	Actual

Table 4-33 Predicted Results for Energy Consumption in Milling Process

Response	Predicted Mean	Predicted Median	Observed	Std Dev	n	SE Pred	95% PI low	Data Mean	95% PI high
energy	4.89	4.49	-	1.98	1	N/A	1.71		11.76

Predicted vs actual results

The data obtained from simulation is used to predict the energy consumption in milling process by developing the regression model and design of experiment. The Figure 4-23 shows that the energy demand responses obtained from actual and prediction lies closer in normal line, therefore the process parameters optimized for energy consumption has been achieved best result.

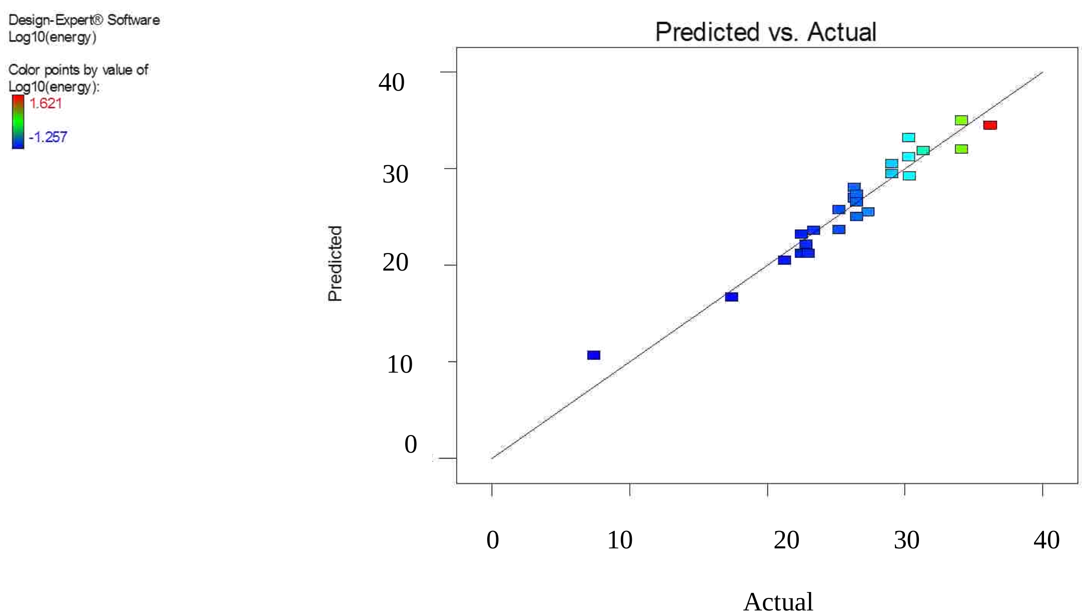

Figure 4-23 Predicted vs actual results for milling process

4.5 RSM for turning process

Response Surface Methodology is used for turning process to build a mathematical model of energy consumption and related cutting parameters.

Input parameters:

X_1=cutting speed (m/min)

X_2=feed rate (mm/rev)

X_3=depth of cut (mm).

Output parameter: energy consumption

Process parameters and the levels used in RSM:

The case study analysis of turning process has been performed with Design Expert 9.0 in three levels -1, 0, 1 and represented in Table 4-34.

Table 4-34 RSM Three Level Table for Turning Process

Cutting parameters	Unit	-1	0	1
Cutting speed (m/min)	m/min	60	120	180
Depth of cut (mm)	mm	0.25	0.5	0.75
Feed rate (mm/rev)	mm/rev	0.1	0.2	0.3

Table 4-35 presents the design table and data made to show the relationship between rake angle, cutting speed and feed rate.

Table 4-35 Design Table Values with Response for Turning Process

		Factor 1	Factor 2	Factor 3	Response 1
Std	Run	A:Feed rate	B:Vc	C:Dp	Energy
11	1	0.1	60	0.75	1.36
4	2	0.3	60	0.75	4.07
3	3	0.1	120	0.75	2.71
19	4	0.3	120	0.75	8.15
9	5	0.1	60	0.5	2.71
14	6	0.3	60	0.5	8.15
2	7	0.1	120	0.5	5.43
12	8	0.3	120	0.5	16.31
7	9	0.1	180	0.5	8.15
15	10	0.3	180	0.5	24.47
16	11	0.1	60	0.25	4.07
10	12	0.36	60	0.25	12.23
8	13	0.1	120	0.25	8.15
20	14	0.3	120	0.25	24.47
18	15	0.1	180	0.25	12.23
1	16	0.3	180	0.25	36.71

Fit summary

After performing analysis by Design Expert software, it can be stated that the second order model is the best fit or mathematical model type for the data given in Table 4-35. Residual plot displayed as figure A-2. Since the points in a residual plot are randomly dispersed around the horizontal axis, a linear regression model is appropriate for the data; otherwise, a non-linear model is more appropriate.

Table 4-36 Summary Fit Table

	Sum of		Mean	F	p-value	
Source	Squares	df	Square	Value	Prob > F	
Mean vs Total	2013.74	1	2013.74			
Linear vs Mean	1191.94	3	397.31	18.92	< 0.0001	
2FI vs Linear	236.54	3	78.85	45.74	< 0.0001	Suggested
Quadratic vs 2FI	9.75	3	3.25	3.38	0.09	
Cubic vs Quadratic	5.77	5	1.15	3.35E+8	< 0.0001	Aliased
Residual	3.4E-9	1	3.4E-9			
Total	3457.74	16	216.11			

4.5.1 Statistical Analysis

The effects of cutting speed, feed rate, and depth of cut on energy consumption were investigated and calculated with the analysis of variance (ANOVA; Table A- 17). The results of the table indicates that the parameter experimented are statistically significant. According to Table A- 17, values of "Prob > F" less than 0.05 indicate model terms are significant.

Regression equation

The equation in terms of actual factors can be used to make predictions about the response for given levels of each factor. Here, the levels should be specified in the original units for each factor. The second order mathematical model is developed using the experimental values and responses to predict the energy consumption

Regression equations were formed using Design Expert 9.0 software for Energy consumption (Y) is:

$$y = \beta_0 + \sum_{j=1}^{k} \beta_j x_j + \sum \sum_{i<j=2}^{k} \beta_{ij} x_i x_j + \sum_{j=1}^{k} \beta_{ij} x_j^{\ 2} + \varepsilon \qquad \textbf{4-19}$$

$$E_{turning} = -6.845 + 22.182 * f + 0.077 * V_c + 18.711 * d_p + 0.593 * f * V_c - 75.104 * f * d_p - 0.205 * V_c * d_p \qquad \textbf{4-20}$$

The 3D plots present the relationship between cutting parameters and energy consumption in the turning process (Figure 4-24).

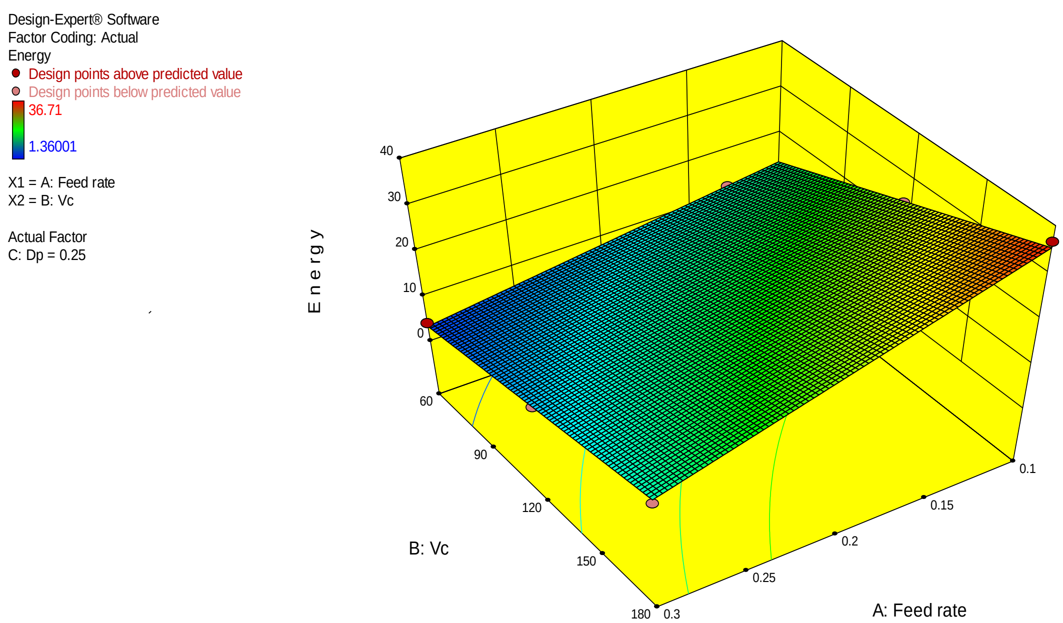

Figure 4-24 Feed rate, V_c and cutting energy in turning

Predicted vs actual results

The obtained data from simulation is used to predict the energy consumption in turning process by developing the regression model and design of experiment. The Figure 4-25 indicates that the energy demand responses obtained from actual and prediction lies closer in normal line, therefore the process parameters optimized for energy consumption has been achieved best result.

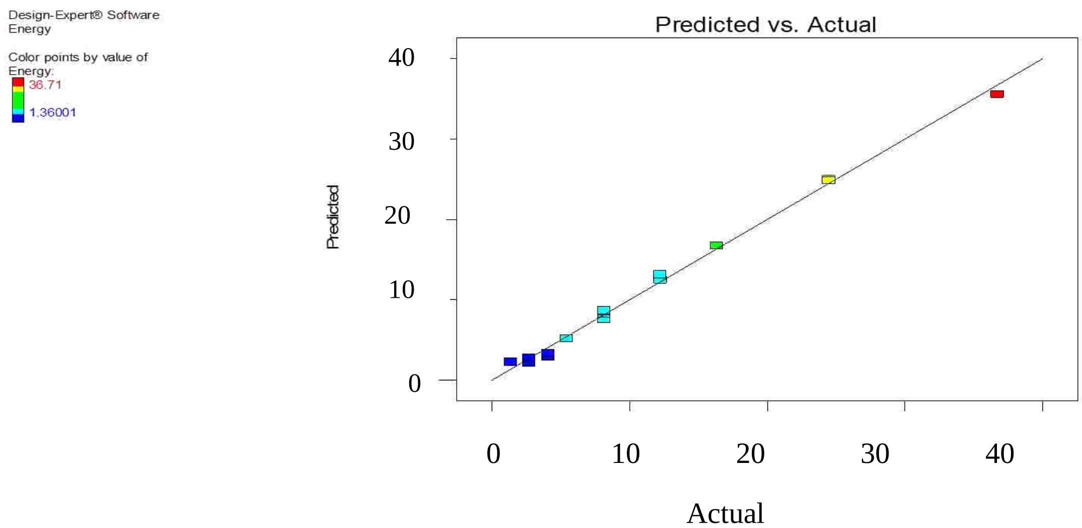

Figure 4-25 Predicted vs actual results for turning process

4.6 Demand side management (case study1):

There are four constraints in this case study and the results after running the optimization model are as below:

1) The first constraint is demand constraint. The power reduction in peak periods should be greater than or equal to demand reduction (equation 3-23):

$$\sum_{i=1}^{n} P_{mi}(1 - K_i) \geq P_{saving}$$

Table 4-37 shows the results after running demand constraint for two different work piece (aluminum and steel) and two machine operations. The total power reduction in peak times (71.7053) is greater than demand reduction requirement which by default is 16 (kW).

Table 4-37 Results after Running Equation 3-23

Constraint 1	71.7	>=	16
M_1	31.7		
M_2	39.9		
M_3	0		
M_4	0		

2) The second constraint is to control the production of the downstream machines throughput at the same level (equation 3-24):

$a_i T \geq c_i(1 - k_i)k_{i+1}$

Table 4-38 represents the same example and the constraint for three machine operations are shown in the table below:

Table 4-38 Results for the Second Constraint

Constraint 2			
Machine 1	296	>=	0
Machine 2	126.4	>=	60
Machine 3	56	>=	0

3) Capacity constraint which necessitates that the target buffer inventory J_i^T must be less than or equal to the peak buffer capacity. After running equation 3-25 with the constraint and three different machine operations:

   $J_{i\,max} \geq J_i^T(1 - k_i)k_{i+1}$

   Table 4-39 shows that the target buffer inventory in peak periods are less than the buffer location capacities:

Table 4-39 Results after running the Third Constraint

Constraint 3			$J_{i\,max}$
M1	0	<=	80
M2	60	<=	85
M3	0	<=	60

4) Next, the constraints are calculated according to equation 3-22 and results are shown in Table 4-40:

Table 4-40 Cost Coefficients

C1	0	0	0
C2	0.09	0	0
C3	0	0.03	0.02
C4		0.06	0.04

Considering this objective function developed to optimize the cost of electricity consumption during high electricity demand (equation 3-26):

Min $Z = C_1X_1+C_2X_2+C_3X_3+C_4X_4$

After running the NIP equations the optimal value is: min Z= 1.1758

By comparing the energy consumption of a base line model and proposed model, it can be seen that there is almost 30% reduction in the electricity charges.

Table 4-41 Energy Comparison of Rate of a Base Line Model and Proposed Model

Model	Energy consumption charge ($/kWh)
Base line model	1.78
Electricity reduction model	1.17

4.7 Demand side management (case study2):

The second part of the linear programming and the optimization process is about how to achieve the minimum amount of energy according to changes in the market demand. It is considered that there are 2 work pieces (i) and 2 machines (j). The coefficients are defined in

Table 4-42:

Objective function: Min Z= $C_1X_1+C_2X_2+C_3X_3+C_4X_4$ **3-26**

Table 4-42 Cutting Coefficient

C	C_1	C_2	C_3	C_4
	0.07	0.06	0.05	0.05
t_{ij}	0.06	0.07	0.06	0.05

(C_i) is the coefficient for each process. Once the program is run, it generates the actual machine time for each process (t_{ij}). Then by having the machine time, X_{ij} can be achieved. X_{ij} is the number of work piece i produced by machine j per hour and defined in equation 4-21.

$$X_{ij} = 1/t_{ij} \quad \textbf{4-21}$$

Table 4-43 displays the throughput for each process after running the program.

Table 4-43 Throughput for Each Process

X_{11}	17
X_{12}	14
X_{21}	15
X_{22}	17

The energy of each machine operation is calculated according to equation 2-31; Narita, et al., (2006). The results are shown in Table A- 2.

There are demands and capacity constraints in this case study; the demand constraint and its results are presented in (Table 4-44). This constraint is defined in equation 3-30.

Table 4-44 Demand Constraint

Demand per hour (D_{ij})	0.06	<=	0.09
	0.07	<=	0.07
	0.06	<=	0.09
	0.05	<=	0.07

The capacity constraint is (equation 3-31). Table 4-45 indicates the results of running capacity constraint for this case study:

Table 4-45 Capacity Constraint

Capacity (C_{ij})	0.06	>=	0.06
	0.07	>=	0.07
	0.06	>=	0.06
	0.05	>=	0.05

After running the NIP equation for objective function (equation 3-25) the minimum amount of energy consumption is 0.015 (kWh).

5 MODEL VALIDATION

Model validation is an essential, but often controversial characteristic of any model-based methodology. Moreover, in the model-based simulation, the results are highly related to the model validation (Barlas, 1996). One of the methods of validation discussed by Barlas, (1989) is the structure-oriented behavior test which evaluates the validation of the structure indirectly by using certain behavior tests on the model-behavior generated patterns. This test presents a simulation of the entire system with sub-models. Also, it involves strong behavior test that helps in uncovering potential structural flaws.

Behavior sensitivity test comprises determining parameters in which the model is very sensitive. Thus, by applying the sensitivity method, it can be understood whether the real system can show the similar high sensitivity to parameters fluctuations or not.

According to Barlas (1989) and Senge (1997), modified behavior forecast is accomplished if it is possible to find data about the behavior of a modified version of the real system. The model passes this test if it can produce similar modified behavior, when simulated with structural modifications that reflect the structure of the “modified” real system.

A good example of behavior sensitivity application and extreme-condition testing is presented by Carson and Flood (1990). The authors used “Qualitative Features Analysis” to a model fluid/electrolyte balance in the human body.

Structure-oriented behavior tests are strong behavior tests that can provide information on potential structural flaws (Barlas 1989). Their key advantage over direct structure tests is that these tests are easier to be formalized and quantified. Direct structure tests, though powerful in concept, have the disadvantage of being too qualitative and informal by the structure. Since structure-oriented behavior tests combine the strength of structural orientation with the advantage of being quantifiable, they seem to be the most promising direction for research on model validation.

Hence, structure-oriented behavior test is utilized in this study to demonstrate the validation of the simulated milling and turning models.

5.1 Structure-oriented behavior test and comparative analysis:

To validate the results, as well as, practicality of the model, structure-oriented behavior test has been used. Each cutting parameters and related data resulted from the simulation in Vensim are evaluated through this test.

In comparative analysis, it is recommended by (Law, 2007) that if a system similar to the one of interest exists, then data should be acquired from it for use in building the model. Then the data resulted from the system (simulation model) are compared to those from the existing system. If the two sets of data compare "closely," then the model of existing system is considered "valid." The model is modified so that it presents the proposed system. The greater the commonality between the existing and proposed systems, the greater our confidence in the model of the proposed system (Law 2009).

Since the model presented in this study is similar to the reference model developed by Draganescu, et al., (2003), some of the data used is from the reference model for comparison. Then the simulation models have been run for a variety of settings and the outputs were checked to see if they are reasonable and resemble the same trend that the reference model has.

Initial values of cutting parameters in milling process are presented in Table 4-1, and Table 4-10 illustrates the initial values for turning process. Parameter values in the reference model for milling are shown in Table 4-16.

E_{cs1} in milling and E_{c1} in turning present the results from Vensim simulation and E_{cs2} and E_{c2} show the model adapted from the references (reference model). Some of these references are Guo et al. (2012); Li & Kara (2011); Soni et al. (2014) in turning process. For milling process, models by Draganescu, et al., (2003) and Mori et al. (2011) were considered for the case validation.

1) The cutting speed and energy use simulation model are compared with the reference model. These references are Draganescu, et al., (2003) for milling process and Guo et al. (2012) for turning process (Figure 5-1 and Figure 5-2).

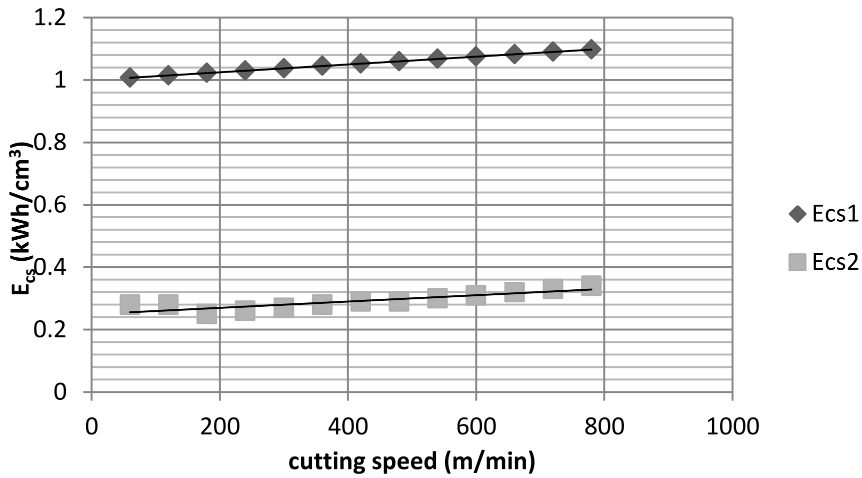

Figure 5-1 Effect of cutting speed on E_{cs} in milling process

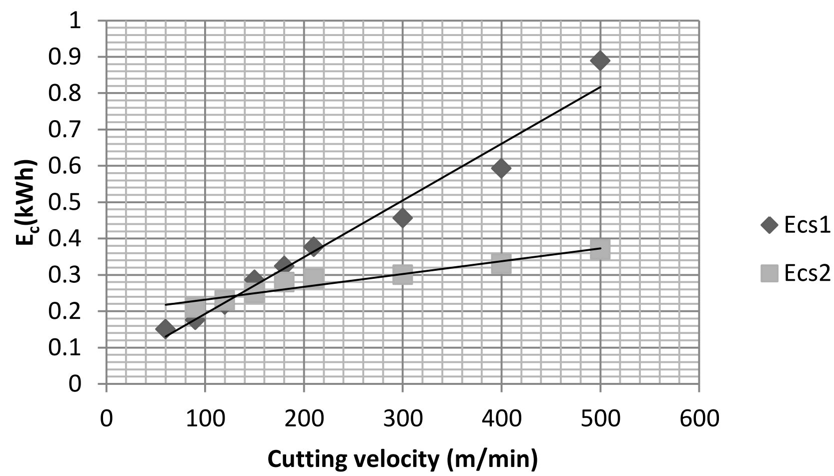

Figure 5-2 Effect of cutting speed on E_c in turning process

As it can be observed from Figure 5-1 and Figure 5-2, both models have the same trend. Besides, models show the growth in energy consumption in milling and turning operations when the cutting speed is increased.

2) The effect of feed rate on energy usage resulted from the simulation models are presented in Figure 5-3 and Figure 5-4. These models are compared with the reference models which are demonstrated by Draganescu, et al., (2003) in milling operation and by Guo et al. (2012) in turning operation.

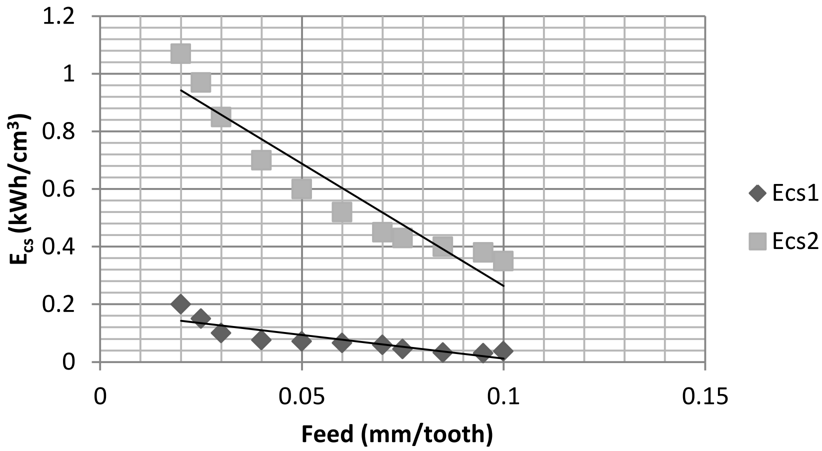

Figure 5-3 Effect of feed rate on energy consumption in milling process

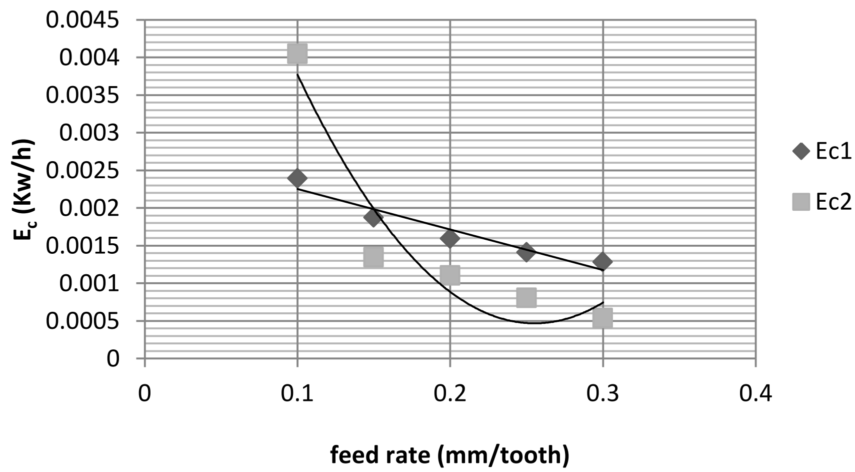

Figure 5-4 Effect of feed rate on energy consumption in turning process

It can be understood from Figure 5-3 and Figure 5-4 that both models have the same trends and similar ranges for the energy output. Models indicate the reduction in energy consumption in milling and turning operations when the feed rate is increased.

3) The relationship between depth of cut and energy demand resulted from the simulation model in SD are compared with the reference model. The reference model in milling is presented by Draganescu, et al., (2003) and turning processes discussed by (Guo et al. 2012).

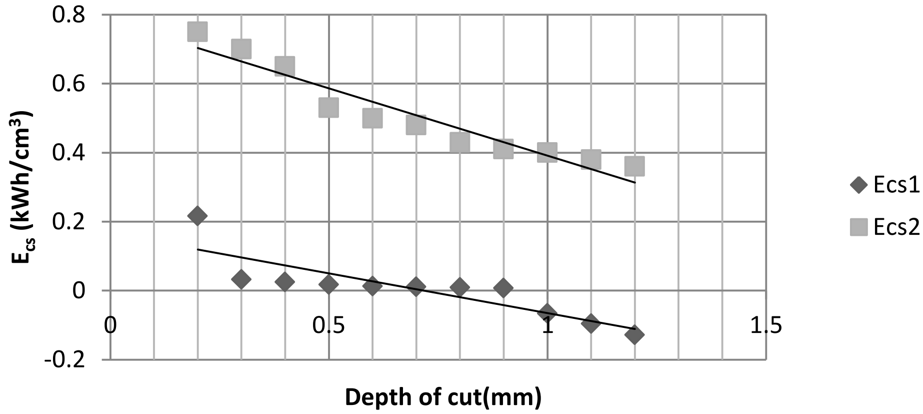

Figure 5-5 Effect of depth of cut on energy use in milling

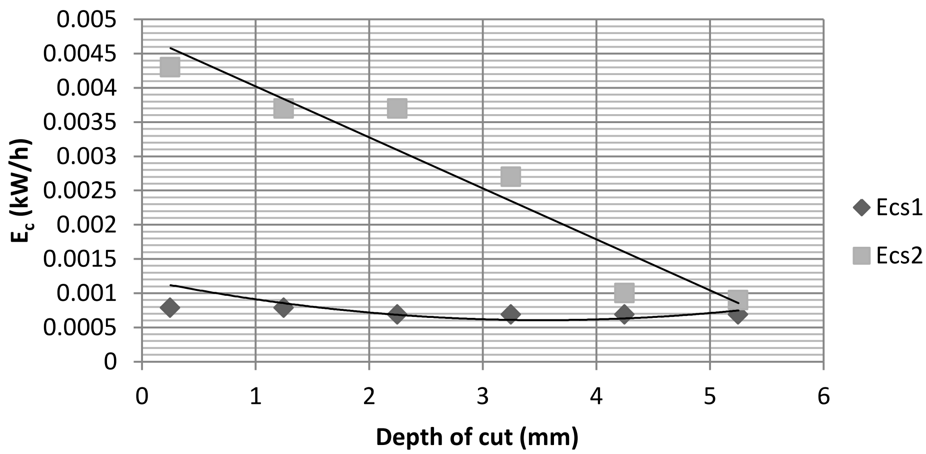

Figure 5-6 Effect of depth of cut on energy use in turning

As it can be observed from Figure 5-5 and Figure 5-6, both models have the same trend. Although, the energy in turning process decreases with a slighter slope than that of the reference model but these two models have a similar trend. Models show the decline in energy usage in milling and turning operations when depth of cut is increased.

4) Effect of "number of teeth" on energy consumption from SD simulation model and the reference model Draganescu, et al., (2003) have been presented in Figure 5-7 for milling processes. Here, both models resemble similar trend as well.

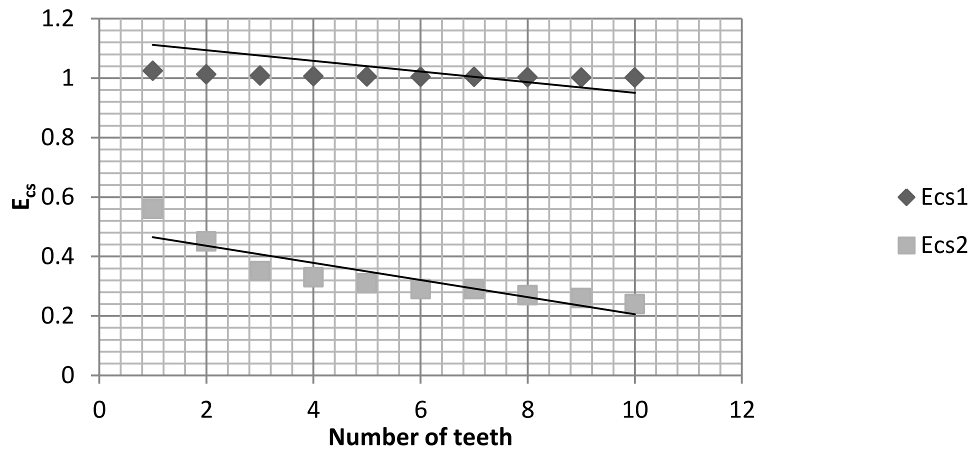

Figure 5-7 Number of teeth & E_{cs} in milling process

5) The effect of material removal rate on energy consumption in turning and milling processes were compared with reference models introduced by Li & Kara (2011) regarding turning process and the work defined by Diaz et al. (2011); Polini & Turchetta (2004) in milling process. Both models discuss the same issues which show reduction in energy consumption with the increase in material removal rate.

6) The effect of edge contact length which is shown in this study is compared with the model developed by Draganescu, et al., (2003). Both models have similar trend, which is the increase in the energy consumption with the growth in edge contact length.

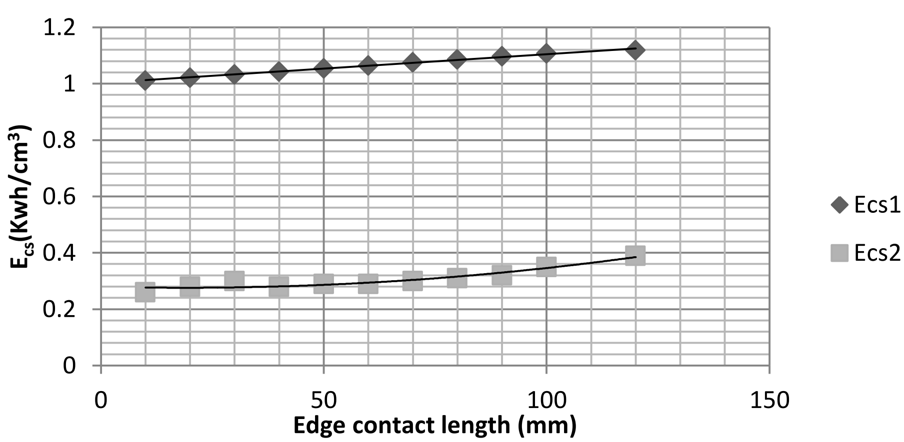

Figure 5-8 Edge contact length & E_{cs}

5.2 Comparative analysis for optimization model (DSM case)

For the second part of this study, the comparative analysis has been applied to compare the result of the optimization model and the existing model. As explained before, comparative analysis is a useful method.

Data resulted from the optimization models can be compared to those from the existing systems (models). According to Law (2009), if there is no big difference between the proposed model and existing model, the model is valid. Therefore, the same method was used in this case to show the validity of the results.

After running the NIP equations, the optimal value (E) is 1.1758 (kWh). By comparing the energy consumption of a base line model adopted from Fernandez et al. (2013) and proposed model, it can be concluded that there is almost 30% reduction in the electricity charges; Table 4-41 and Figure 5-9.

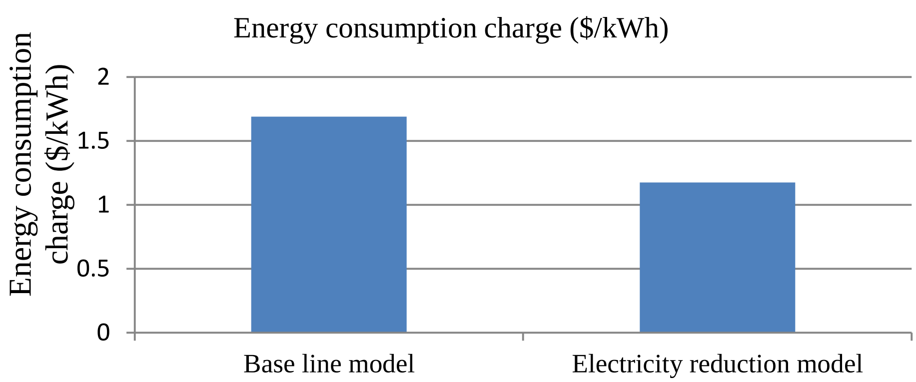

Figure 5-9 Comparison of energy consumption of base line and proposed model

6 CONCLUDING REMARKS

6.1 Summary

Developing a dynamic model of energy consumption for CNC machines in automotive industries helps to reduce the energy consumption in these machines.

In CNC machines, there are several parameters for milling and turning operations which play significant roles in reducing energy consumption. In the first case study presented, parameters of machine tools are changed and the energy consumption is measured to identify the parameters that have the greatest impact on saving energy. An energy consumption model is developed by using system dynamics (Vensim) in order to understand the behavior of complex system. Next, using the data from the first case study and it is demonstrated how buffer inventories can help manufacturers to save more energy during high electricity demand.

6.2 Conclusions

- The growth in the energy demand and cost in automotive industry have obliged manufacturers to think about better solutions for reducing energy consumption. Moreover, environmental burden of machine tools such as GHG emissions necessitate the need of making new policies and strategies in reducing the energy consumption. To achieve this goal in machining processes, energy flow is addressed in three-level structure while two major methods are recommended in shop floor level and process level.
- In order to understand the machining process in the process level, the effects of various cutting parameters on energy demand should be explored. Therefore, the System Dynamics tool was applied for both milling and turning processes on aluminum to build a dynamic model based on the static cutting formulas introduced in past research to investigate the effect of different cutting parameters on the output (energy consumption).
- ANOVA and regression analysis were applied to the data resulting from the SD simulation to demonstrate the relationship between independent variables and dependent variables. Regression equations showed how much each variable contribute to the changes in energy consumption.

- Sensitivity analysis was utilized to demonstrate which parameters were most impactful on the energy consumption. The results of sensitivity analysis confirmed that feed rate is the most significant factor in reducing energy in turning process, while depth of cut has the highest impact on energy reduction in milling process followed by feed rate, spindle speed and cutting speed.

  Therefore, by using the outcome of the sensitivity analysis in machining processes, the manufacturers should focus on finding (calculating) the optimal response according to the changes of these critical parameters.

- Response surface methodology (RSM) helps to build a practical energy model based on the data and cutting parameters for milling and turning processes (by careful design of experiments.) By using this method, the optimized model of the output variable which is influenced by various independent variables can be obtained. By applying the mathematical model, the manufacturers can find the actual and predicted energy consumption in milling and turning operations.
- Different analysis methods mentioned before determine whether the data resulted from the simulation lead to a conductive conclusion or methodology for turning and milling processes which can be used by manufacturers to reduce energy according to the data set, cutting parameters and material used.
- Another saving opportunity can be considered at the enterprise level and it is about saving energy costs during peak times of electricity demand in cutting, milling and turning processes. A nonlinear integer programming (NIP) was used in this study to minimize the cost of electricity while maintaining system throughput. Therefore, this methodology can help the manufacturers to keep the production level consistent while reducing energy consumption and its cost. Furthermore, using buffer inventories during high electricity demand and applying load management policies can help to manage the electricity usage and lower the inventory holding cost. The results of the optimization model indicated almost 30% reduction in the cost of electricity demand comparing to the base model.
- Another important issue in the manufacturing processes is how to minimize the energy consumption with the market demand fluctuations. A linear programming

model developed in this study to optimize energy consumption accordingly. Thus, by applying this model, manufacturers can save energy consumption significantly while they can produce products according to the changes of demand.

6.3 Limitations

- The data provided in this study was adopted from online sources. Data resulted from real experiment can help more to find further precise results.
- The effects of other cutting parameters, namely chip thickness, temperature of work material, hardness of the work piece and different materials such as steel was not included in this study.
- There are other types of cutting processes such as drilling and end-milling which were not considered in this analysis.
- The results of the study were obtained through simulation. These should be eventually verified by a planned experiment.

6.4 Future work

Future extension of this study should perhaps explore further explore the production line and balancing concept. A production line is balanced if every machining task spends the same percentage of time. Line balancing is a manufacturing-engineering function in which the whole collection of production line tasks is divided into equal portions. Well-balanced lines avoid labor idealness and improve productivity. The recommended approach in this study is how the results from first methodology can help to minimize the time and energy consumed in machining processes in production line. This strategy discusses how changes in the cutting parameters can change the machine time and power demand; thus, help to make the production line more balanced.

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APPENDICES

Table A- 1 Energy Consumption of Machine Operation

Parameter	machine1, W_1 (milling, Aluminum alloy)	machine2, W_1 (turning, Aluminum)	machine1, W_2	machine2, W_2
SME (electric consumption of servo motor (kWh)	0.03	0.03	0.01	0.03
SPE (Electric consumption of spindle motor (kWh))	3.06	6.80	0.99	3.34
SCE (electric consumption of cooling system of spindle (kWh))	0.45	0.45	0.35	0.35
CME (electric consumption of compressor kWh)	1	1	1	1
CPE (electric consumption of coolant pump kWh)	0.25	0.25	0.25	0.25
TCE1 (electric consumption of lift up chip conveyor in machine tool KWh)	0.14	0.14	0.16	0.16
TCE1 (electric consumption of chip conveyor in machine tool kWh)	0.60	0.60	0.60	0.60
E_e (kWh)	**5.49**	**9.24**	**3.25**	**5.61**

Table A- 2 Table Shows The Values of Cutting Parameters and SPE

n (motor rotation speed rpm)	1592.356	1990.445	530.785	1194.267	
t (part per time hr) machine time	0.06	0.07	0.06	0.05	
p (electric consumption kWh)	31.70	39.99	16.03	39.14	
Shear stress 1(N/m^2)	400	400	460	460	
Length of cut (mm)	12	12	12	12	20
Depth of cut 1 (mm)	1.25	1.90	2.80	4.70	5
Uncut chip thickness (h)	0.44	0.44	0.20	0.20	0.30
V_{cij} (m/min) (60-370)	60	75	20	45	30
t (machine time) h	0.06	0.07	0.06	0.05	0.05
Shear angle (rad), cutter rotation angle	20	20	25	25	
Friction angle (rad)	26	26	16	16	
Rake angle (rad)	5	5	4	4	
SPE(kWh)	3.06	6.80	0.99	3.34	

Drill diameter (mm)					4

Table A- 3 Cutting Parameters and Results for Calculating Cutting Forces

cutting force in axes					
S_z (feed/tooth)	0.2	0.7	0.2	0.8	0.1
axial depth of cut (mm)	1.2	3.4	2.8	4.7	5
K_t (specific cutting coefficient)	1	1	1	1	1
cutting forces (N)$\times 10^3$	1.3	2.1	2.9	4.9	0.2

Table A- 4 Basic Setting of Machines

	Cycle time (min)	Power (kw)
Machine 1	0.06	31.76
Machine 2	0.07	39.93
Machine 3	0.06	16.00
Machine 4	0.05	39.00

Table A- 5 Buffers Setting

off peak period T (h)	8
peak period t_p (h)	0.70
T_{total} (h)	8.70
demand reduction requirement p saving (kWh)	16
on peak demand charge rate C_d ($/kW)	9.50
on peak electricity consumption charge rate C_p ($/kWh)	0.02
C_{pd} cost of peak electricity demand and charge rate	9.60
off peak electricity consumption charge rate C_r ($/kWh)	0.01
buffer 1 , target units of buffer inventory J_{it}	67
buffer 2, target units of buffer inventory J_{it}	60
buffer 3, target units of buffer inventory J_{it}	64

Table A- 6 Buffers Setting

Buffer	capacity of B_i	initial content of B_i	Capacity of J_i	Accumulation rate a_i	consumption rate C_i	Holding cost h_i
Buffer 1	80	43	80	37	187	0.07
Buffer 2	85	35	85	15.80	178	0.07
Buffer 3	60	47	60	7	140	0.07

Table A- 7 Cutting Parameters, Power and Force

Parameter	machine 1, W 1 (milling, Aluminum alloy)	machine2, W1 (milling, Aluminum)	machine 1, W 2	machine 2, W 2
Allowance for tool approach	3.80	3.80	3.09	3.09
feed rate (m/min)	0.50	0.60	0.20	0.40
D (mm) tool diameter	12	12	12	12
n ($\times 10^3$) (rpm)	1.50	1.90	0.50	1.10
T_u (axis friction torque) (Nm)	4	4	3	3
Friction coefficient of slide way	0.01	0.01	0.01	0.01
Transmissibility of ball screw system (mm)	0.90	0.90	0.90	0.90
l (ball screw lead) (mm/rev)	0.005	0.005	0.006	0.006
M (Moving part weight) (lb)	30	30	40	25
f ($\times 10^3$) (N)	1.30	2.10	2.90	3.70
Gradient angle from horizontal plane (rad)	15	15	25	25
T_M (application torque of ball screw NM)	-0.80	-1.20	1.40	1.80
T_L (load torque of servo motor NM)	3.17	2.74	4.44	4.82
N ($\times 10^3$) (rpm)	1.50	1.90	0.50	1.10
t (h) machine time	0.06	0.07	0.06	0.05
p (electric consumption Wh)	31.70	39.9	16	35

Table A- 8 Residual Output for Shear Angle & Depth Of Cut

RESIDUAL OUTPUT			
Observation	Predicted power (kW)	Residuals	Standard Residuals
1	355.41	-269.7	-1.05
2	125.80	-68.3	-0.26
3	-103.80	147.31	0.57
4	-333.41	368.62	1.44
5	878.03	-24.19	-0.09
6	648.42	-219.87	-0.86
7	418.81	-131.28	-0.51
8	189.2	28.37	0.11
9	-40.40	216.49	0.85
10	951.28	73.31	0.28
11	721.67	-207.41	-0.81
12	492.06	-147.03	-0.57
13	262.45	-1.35	-0.005
14	32.84	178.46	0.70
15	1097.78	268.35	1.05
16	868.17	-182.49	-0.71
17	638.56	-178.52	-0.70
18	408.95	-60.82	-0.23
19	179.34	102.39	0.40
20	1537.28	853.45	3.35
21	1307.67	-107.74	-0.42
22	1078.06	-272.99	-1.07
23	848.45	-239.23	-0.94
24	618.84	-125.80	-0.49

Table A- 9 V_c, D_p and Energy Use in Milling

V_c(m/min) / D_p(mm)	0.2	1.2	2.2	3.2	4.2	5.2	6.2	7.2
60	0.20	0.04	0.02	0.01	0.01	0.01	0.009	0.007
120	0.50	0.09	0.05	0.03	0.02	0.02	0.01	0.01
180	0.80	0.14	0.07	0.05	0.04	0.03	0.02	0.02
240	1.12	0.18	0.10	0.07	0.05	0.04	0.03	0.03
300	1.40	0.23	0.12	0.08	0.06	0.05	0.04	0.03
360	1.69	0.28	0.15	0.10	0.08	0.06	0.05	0.04

Table A- 10 Feed Rate, Depth of Cut and E_{cs}

D_p(mm) / Feed rate(mm/min)		Fc=1382.39 N		N=200 rpm	Vc=60 m/min				
	z	0.2	1.2	2.2	3.2	4.2	5.2	6.2	7.2
	0.20	0.24	0.04	0.02	0.015	0.01	0.009	0.007	0.006
	0.25	0.19	0.03	0.017	0.012	0.009	0.007	0.006	0.005
	0.30	0.16	0.027	0.014	0.01	0.007	0.006	0.005	0.004
	0.40	0.12	0.02	0.011	0.007	0.005	0.004	0.003	0.003
	0.50	0.09	0.016	0.008	0.006	0.004	0.003	0.003	0.002
	0.60	0.08	0.013	0.007	0.005	0.003	0.003	0.002	0.002
	0.70	0.07	0.01	0.006	0.004	0.003	0.002	0.002	0.001
	0.80	0.06	0.01	0.005	0.003	0.002	0.002	0.001	0.001

Table A- 11 V_c, Feed Rate and E_{cs}

Feed rate (mm/min) / V_c (m/min)		F=1382.39 (N)	d_p=0.2 (mm)	N=200 (rpm)					
	z	0.20	0.25	0.30	0.40	0.50	0.60	0.70	0.80
	60	0.24	0.19	0.16	0.12	0.09	0.08	0.07	0.06
	120	0.49	0.39	0.32	0.24	0.19	0.16	0.14	0.12
	180	0.74	0.59	0.49	0.37	0.29	0.24	0.21	0.18
	240	0.98	0.78	0.65	0.49	0.39	0.32	0.28	0.24
	300	1.23	0.98	0.82	0.61	0.49	0.41	0.35	0.30
	360	1.48	1.18	0.98	0.74	0.59	0.49	0.42	0.37

Table A- 12 Sensitivity Analysis for D_p, Feed Rate and E_c iIn Turning Process

d_p(mm) / Feed rate (mm/min)							
0.96	0.25	0.5	0.75	1	1.25	1.50	1.75
0.1	1.073	0.71	0.56	0.47	0.41	0.37	0.34
0.15	0.84	0.56	0.44	0.37	0.33	0.29	0.27
0.2	0.71	0.47	0.37	0.31	0.28	0.25	0.23
0.25	0.62	0.41	0.33	0.28	0.24	0.22	0.20
0.3	0.56	0.37	0.29	0.25	0.22	0.19	0.18

Table A- 13 Sensitivity Analysis Considering D_p, V_c and E_c in Turning Process

D_p (mm) / V_c(m/min)								
337.087	0.25	0.50	0.75	1	1.25	1.50	1.75	
60	0.57	0.28	0.19	0.14	0.11	0.11	0.09	
120	1.15	0.57	0.38	0.28	0.23	0.19	0.16	
180	1.73	0.86	0.57	0.43	0.34	0.28	0.24	
240	2.31	1.15	0.77	0.57	0.46	0.38	0.33	
300	2.89	1.44	0.96	0.72	0.57	0.48	0.41	
360	3.47	1.73	1.15	0.86	0.69	0.57	0.49	

Table A- 14 Regression Analysis

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%	
Intercept	-0.06	0.01	-6.1	3.5E-5	-0.08	-0.04	-0.08	-0.0	
0.1	0.10	0.02	6.4	2.2E-5	0.09	0.19	0.09	0.19	feed rate
60	0.0002	4.8E-5	5.3	0.0001	0.0001	0.0003	0.0001	0.0003	cutting speed
0.25	0.06	0.01	5.3	0.0001	0.03	0.08	0.03	0.08	depth of cut

Table A- 15 Residual Output for Energy Consumption and Cutting Parameters in Turning Process

RESIDUAL OUTPUT		
Observation	Predicted 0.003	Residuals
1	0.009	0.0005
2	-0.004	0.011
3	0.02	-0.004
4	0.01	-0.0007
5	0.04	-0.01
6	-0.004	0.01
7	0.02	-0.004
8	0.01	0.002

9	0.04	0
10	0.02	-0.006
11	0.05	0.004
12	0.01	-0.0007
13	0.04	-0.01
14	0.02	-0.006
15	0.05	0.004
16	0.04	-0.01
17	0.07	0.01

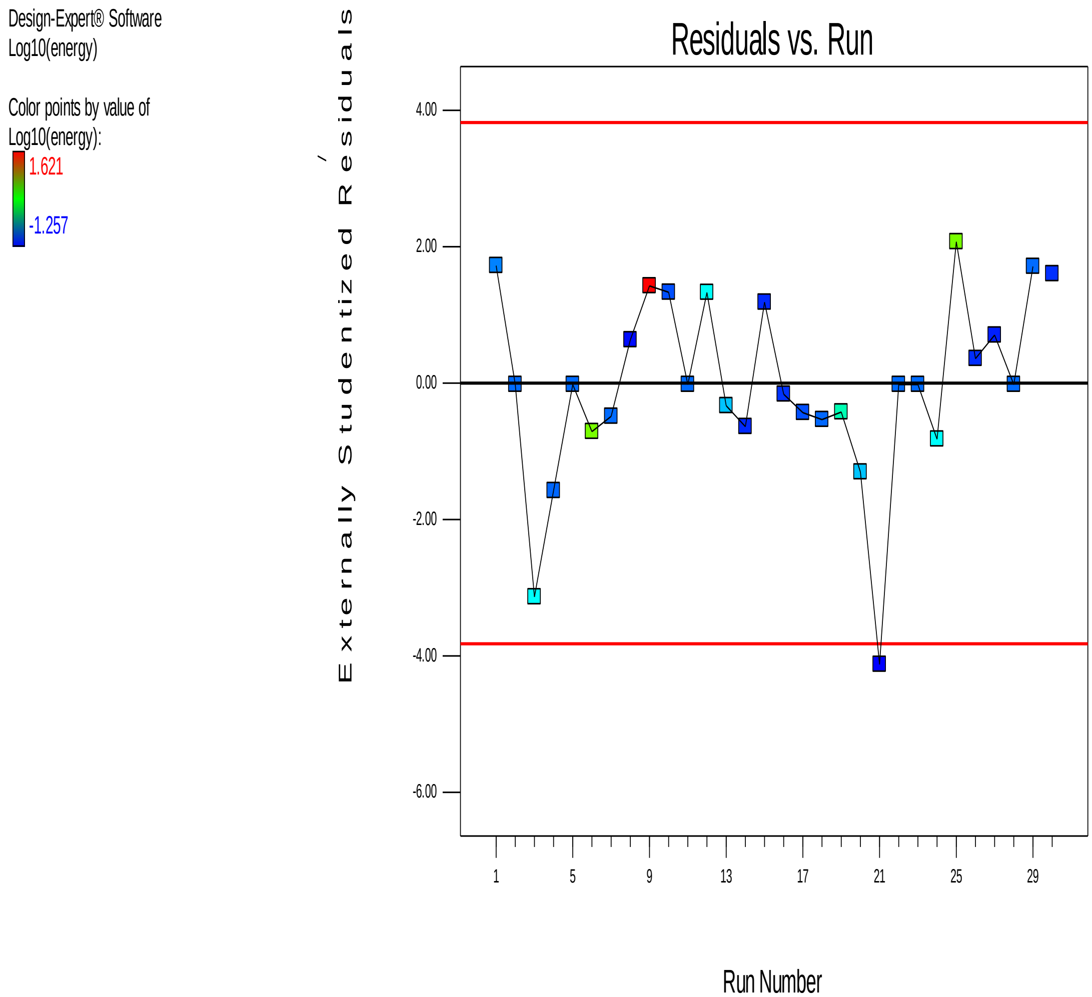

Figure A- 1 Residuals vs. Run Plot for Energy Consumption (kW/h) in Milling Process

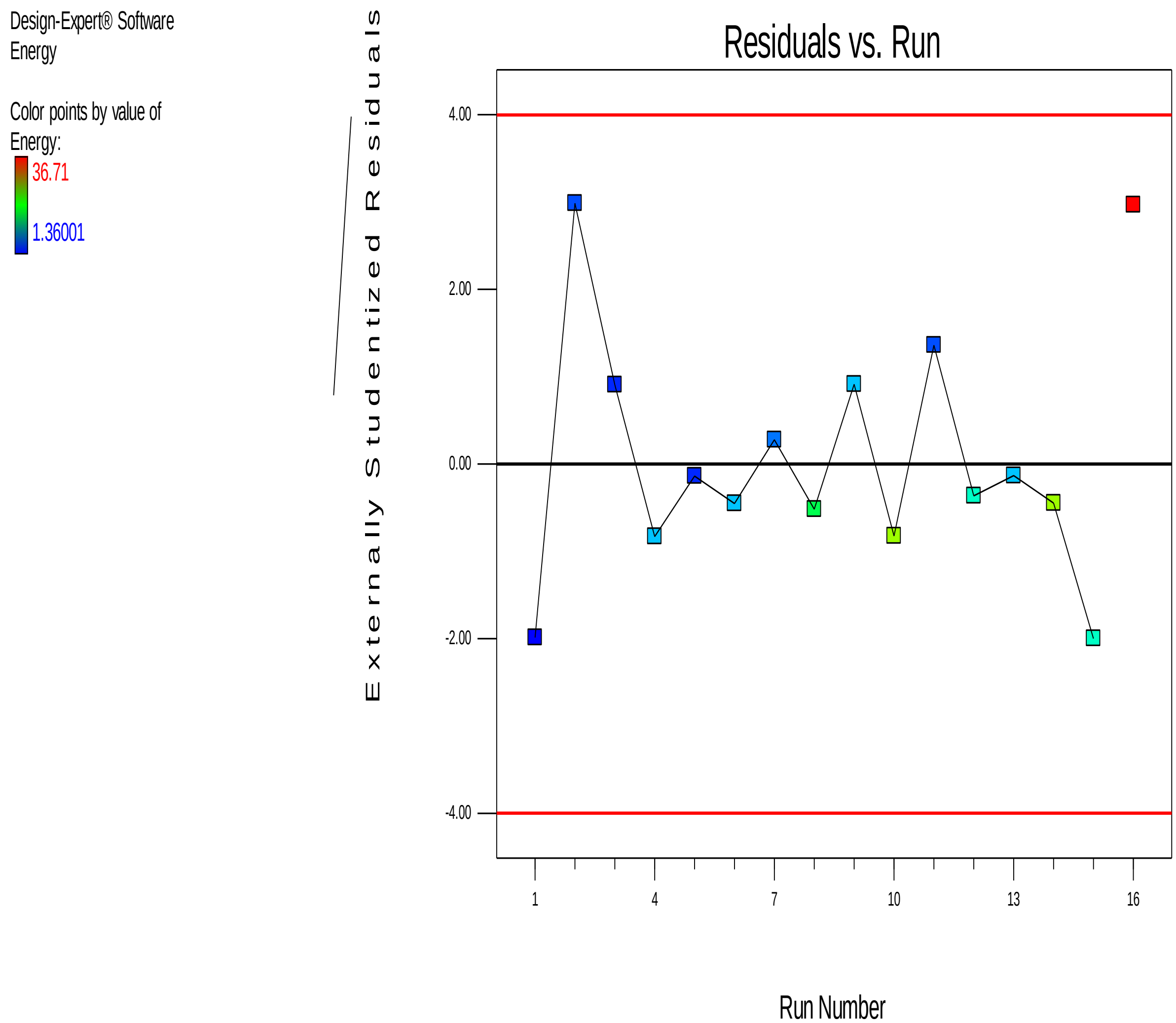

Figure A- 2 Residuals vs. Run Plot for Energy Consumption (kW/h) in Turning Process

Table A- 16 ANOVA for Response Surface 2FI Model

ANOVA for Response Surface Quadratic model						
Analysis of variance table						
	Sum of		Mean	F	p-value	
Source	Squares	df	Square	Value	Prob > F	
Model	7.83	14	0.56	16.6	< 0.0001	significant
A-cutting speed	3.25	1	3.25	96.43	< 0.0001	
B-depth of cut	0.11	1	0.11	3.2	0.0901	
C-feed rate	2.08	1	2.08	61.7	< 0.0001	
D-rake angle	1.68	1	1.68	50.01	< 0.0001	
AB	0.16	1	0.16	4.70	0.04	
AC	9.9E-3	1	9.9E-3	0.30	0.5	
AD	0.16	1	0.16	4.70	0.04	
BC	0.16	1	0.16	4.70	0.04	
BD	9.8E-3	1	9.8E-3	0.20	0.59	
CD	0.16	1	0.16	4.70	0.04	
A^2	0.34	1	0.34	9.90	0.006	
B^2	2.6E-5	1	2.6E-5	7.9E-4	0.97	
C^2	0.14	1	0.14	4.10	0.06	
D^2	1.2E-6	1	1.2E-6	3.5E-5	0.99	
Residual	0.51	15	0.03			
Lack of Fit	0.51	10	0.05			
Pure Error	0.0	5	0.0			
Cor Total	8.34	29				

Table A- 17 ANOVA Table for Cutting Parameters and Turning Process Using RSM

ANOVA for Response Surface 2FI model						
	Sum of		Mean	F	p-value	
Source	Squares	df	Square	Value	Prob > F	
Model	1428.48	6	238.08	138.10	< 0.0001	significant
A-Feed rate	477.54	1	477.54	277.01	< 0.0001	
B-Vc	246.11	1	246.11	142.76	< 0.0001	
C-Dp	212.06	1	212.06	123.01	< 0.0001	
AB	137	1	137	79.47	< 0.0001	
AC	38.06	1	38.06	22.08	0.001	
BC	41.43	1	41.43	24.03	0.0008	
Residual	15.52	9	1.72			
Cor Total	1444	15				

Table A- 18 Values of Cutting Parameters in Turning Process Using Aluminum

P_0 (kW)	3.6
t_1 (s)	2
P_t (kW)	3
N (rpm) $\times 10^3$	1.2
D_i (mm)	45
D_o (mm)	44.5
t_3 (s)	120
l (length of cut)	50
Y_e (kW/h)	2
A (mm)	100
feed rate (mm/min)	0.1
D_p , a_p (mm)	0.2
V_c initial (m/min)	100
E_c (kWh)	0.01
cutting velocity (m/min)	0.4
feed exponent	1.8
D_{avg} (mm)	44.7
K_c (N)	500
width of cut (mm)	15
F_c (N)$\times 10^3$	0.3
E_c (kWh)	0.9
h_{eq} (mm)	0.3
V_c constant (m/min)	0.4

Table A- 19 Design Table Values with Response for Milling Process

		Factor 1	Factor 2	Factor 3	Factor 4	Response 1
Std	Run	A:cutting speed (m/min)	B:depth of cut (mm)	C:feed rate (mm/min)	D:rake angle (rad)	Energy (kW/h)
5	1	60	0.20	0.80	10	5.30
30	2	210	0.40	0.52	22.50	4.40
12	3	360	0.60	0.25	35	10.60
1	4	60	0.20	0.25	10	4.30
29	5	210	0.40	0.525	22.50	4.40
4	6	360	0.60	0.25	10	25.80
19	7	210	0.20	0.525	22.50	4.40
13	8	60	0.20	0.80	35	0.50
21	9	210	0.40	0.025	22.50	41.70
16	10	360	0.60	0.80	35	3.30
26	11	210	0.40	0.52	22.50	4.40
18	12	510	0.40	0.52	22.50	10.80
8	13	360	0.60	0.80	10	8
9	14	60	0.20	0.25	35	1.70
11	15	60	0.60	0.25	35	1.70
22	16	210	0.40	1.07	22.50	2.10
14	17	360	0.20	0.80	35	3.30
3	18	60	0.60	0.25	10	4.30
23	19	210	0.40	0.525	-2.50	13.60
6	20	360	0.20	0.80	10	8
15	21	60	0.60	0.80	35	0.05
27	22	210	0.40	0.50	22.50	4.40
28	23	210	0.40	0.52	22.50	4.40
10	24	360	0.20	0.25	35	10.60
2	25	360	0.20	0.25	10	25.80
17	26	90	0.40	0.52	22.50	1.90
7	27	60	0.60	0.80	10	1.30
25	28	210	0.40	0.52	22.50	4.40
20	29	210	0.80	0.52	22.50	4.40
24	30	210	0.40	0.52	47.50	1.90

Table A- 20 Cutting Parameters and Cutting Force Results

Parameter	machine 1, W_1 (milling, Aluminum alloy) M_1	machine2, W_1 (turning, Aluminum) M_2	machine 1, W_2 M_3	machine 2, W_2 M_4
Allowance for tool approach	3.09	3.09	3.09	3.09
feed rate (m/min)	0.50	0.60	0.20	0.40
D (mm) tool diameter	12	12	12	12
N $\times 10^3$ (motor speed)	1.50	1.90	0.50	1.10
T_u (axis friction torque)	4	4	3	3
Friction coefficient of slide way	0.01	0.01	0.01	0.01
Transmissibility of ball screw system (mm)	0.90	0.90	0.90	0.90
l (ball screw lead) (mm)	5	5	6	6
M (Moving part weight) (lb)	30	30	40	25
f $\times 10^3$ (N)	1.30	2.10	2.90	4.90
Gradiant angle from horizontal plane (rad)	15	15	25	25
T_M (application torque of ball screw) (NM)	-0.80	-1.20	1.40	2.30
T_L (load torque of servo motor NM)	3.10	2.70	4.40	5.30

Table A- 21 Literature review table

Paper	Cite	Manufacturing	Automotive	Cutting (milling, turning)	Energy &cost	Environmental burden	Energy and Force model	Optimization of machine operations (para)	Tool life optimization	MRR	Cutting parameter
1-1(Sullivan., et al.,2010)	15	×	×			×			×		
1-2 (Lee, et al., 1995)	268	×		× M			× F				×
1-3(Anderberg, et al., 2009)	7	×			Electricity×			×		×	×
1-4 (Abhang and Hameedullah, 2010)	13	×	×	× T			× P	×			×
1-5 (Camposeco-Negrete, 2013)	1	×		×T				× robust design		× constant MRR	× (V,f,d)
1-6(Anderberg, et al., 2012	9	×			×	×		× process planning		×	
1-7 (Mativenga and Hon, 2005)	24	×		× M			Dynamic force model				× chip thickness, flank wear
1-8 (Dietmair and Verl, 2009) given application scenario	71	×				×	×P, E	× Energy efficiency		×	× cutting length, width
1-9 (Jeswiet and Kara, 2008)	98	×				×	× T	× CES			
1-10 (Dahmus and Gutowski, 2004)	286	× System level		×		×				×	

1-11(Weinert, et al., 2011)	80	×		×			× Energy prediction model	× Energy Blocks methodology, Process planning		× process parameter	
1-12 (Herrmann and Thiede, 2009)	128				×	×		×Process chain simulation Systematic approach		×	
1-13 (Rahimifard, et al., 2010)	100	×			×	×	× framework for modelling Embodied Product Energy during manufacture	×	×	×	
1-14 (Duflou, et al., 2012).	174	×	×		×	×	×	×optimized process control	×		× Process parameter
1-15 (Seow and Rahimifard, 2011)	57	×			×	×	× energy framework	×	×		
1-16 (Zhou and Ang, 2008) Data envelopment analysis (DEA)	154	×			×	×	× framework of both desirable and undesirable outputs	× Data development analysis			
1-17(Vijayaraghavan and Dornfeld, 2010		×			×	×	data sources Event stream		×		

							processing techniques				
1-18 (Rajemi, Et al., 2010)	119	×		× T	×		×	×	×		×
1-19 (Balogun and Mativenga, 2012)	47	×		× M, T		×	×	×	×	×	×
1-20 (Diaz, et al., 2009)		×		×		×	×	× process parameter optimization			× feed rate
1-22 (He et al., 2011)	28	×		× M			×			×	
1-23 (Astakhov and Xiao, 2008)	24	×		× T			force and energy				
1-24 (Santos, et al., 2010)	43	×		×		×	×	×	×	×	×
1-25 (Draganescu, et al., 2001)	107	×		×M			×			×	
1-27 (Iqbal, et al., 2006)	67	×		× M				× Fuzzy set theory			
2-1 (Wang and Li, 2013)	9	×			×	×		× demand-responsive production scheduling			
2-2 (Colledani, et al., 2014)	NA	×	×					× high quality			
2-3 (Fernandez, et al., 2013)	11	×			× holding cost			"Just-for-Peak" buffer inventory			
2-4 (Sun and Li, 2013, 2014)	6	×	×		×	×	× power demand	× Real time electricity	×		×

							reduction	demand response Markov Decision Process			
2-6 (Bego, et al., 2013	6	×			×		×	Mixed Integer Nonlinear Programming electricity demand response Critical Peak Pricing;			
2-7 (Wang and Li, 013) TOU (time-of use) based electricity demand response programs	9	×			×	×		× demand-responsive production scheduling			

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