CHAPTER 2

SYSTEMATIC LITERATURE REVIEW ON MACHINING ENERGY

This chapter provides a systematic literature review on the energy aspects of machining processes. The machining energy characteristics are reviewed to address the four key research areas of machining energy: (i) classification, (ii) modelling, (iii) saving strategies, and (iv) efficiency evaluation measures.

2.1 INTRODUCTION

Energy efficiency has become a key objective for the manufacturing industry since the last two decades due to rising energy prices, stringent environment policies, and increasing customer awareness. Despite the development of green energy technologies, fossil fuels are still the major resources for energy generation. The use of large amount of fossil fuels contributed 29.3 Gigatonnes carbon emissions in 2008; expected to rise to 35.4 Gigatonnes in 2035 (Campatelli et al., 2015).

According to a study conducted by International Energy Agency (IEA), manufacturing industries account for one-third of global energy consumption and 36% of net global carbon emissions (IEA, 2007). In 2015, the U.S. Energy Information Administration estimated the total global electricity consumption to be 72734 Petajoules (EIA, 2017). The industry sector accounted for 42% (30548 Petajoules) of the total energy consumption. As a sub-sector of industry sector, manufacturing consumed 27493.45 Petajoules; within manufacturing sector, approximately 20620 Petajoules electricity was consumed by machining activities. Machine tools are dominant end users of electrical energy in manufacturing, and responsible for high carbon emissions (Li et al., 2015; Zhou et al., 2016). Machine tools generally operate at less than 30% efficiency (He et al., 2012), and have a high potential for energy saving. The energy efficiency of the machine tools has direct impact on the productivity and economic efficiency of the CNC machining processes (Anderberg et al., 2010). Energy efficiency of machine tools improves economic and environmental performance of the machining activities, therefore it has become a focus area of research for industry as well as academia.

Understanding energy consumption characteristics provides the basis for energy saving of CNC machine tools. A large number of studies addressing the machining energy consumption characteristics and improvement strategies have been conducted in the recent years. However, a comprehensive analysis of the current state of knowledge and a structured methodology to understand the energy characteristics of the machine tools is lacking. Since the literature is very vast and fragmented, it is the time to delve into the current advancement in the research area and provide directions for future academic work and policy makers. As a step towards providing a clear understanding of machining energy characteristics, the current study provides a detailed analysis of the literature on machining energy characteristics encompassing 226 research articles from a variety of academic journals and conference proceedings published during last 25 years (1994-2018). The energy classification criteria, energy modelling approaches, energy saving strategies, and energy efficiency measures have been reviewed carefully. To the best of authors' knowledge, it is the first systematic literature review focusing on review and holistic classification of the reference literature focusing on energy aspects of the machine tools and machining processes. The study can also be helpful for the researchers to derive new research interest in the area. The basic objective of literature review is to identify the potential research gaps on a specific topic by identifying and evaluating the existing knowledge on the topic (Tranfield et al., 2003). It is vital to define and justify the research topic, design, objective, and methodology (Hart, 1998). Literature review is an integral part of any academic study, either as a standalone review work or as element in the introduction, methodology or results analysis sections (May et al., 2017).

2.2 RESEARCH METHODOLOGY

Eight types of literature review techniques are defined in the literature: state of the art, conceptual, realistic, systematic, narrative, critical, expert, and rapid literature review (Sangwa and Sangwan, 2018). The authors reviewed these techniques to select the best suited literature review technique based on the objectives of the study. In the current study, a systematic literature review was conducted to analyze and evaluate the current state and research trends in the field of energy efficient machining. The reference papers were analyzed to answer the following major questions:

i) How the machining energy consumption should be classified for better understanding and transparency?
ii) What are the energy modelling approaches for the machine tool energy consumption?
iii) What are the strategies used for reducing the machining energy?
iv) How to evaluate the energy efficiency of the machine tools?

A four phased approach was followed to carry out the systematic literature review: (i) planning, (ii) literature search, (iii) data analysis and synthesis, and (iv) interpretation. In the planning phase, the research area and scope of the study were defined, and the research questions were formulated. The literature search was conducted to prepare the database for literature review. In the third phase, descriptive and content analyses were done. Finally, the findings of the review and future research directions were discussed and presented in the interpretation phase.

The literature search methodology for the present study is presented in Figure 2.1. The literature search was done using Scopus database because it allows for quick and customized literature search for high quality articles. The literature was searched using the keywords (‘energy’ OR ‘power’) AND (‘machining’ OR ‘machine tool’ OR ‘machine tools’ OR ‘milling’ OR ‘turning’ OR ‘cutting’) in the title of the paper. The keyword ‘energy’ included the studies focusing on various energy aspects such as energy efficiency, energy saving, energy monitoring, energy modelling, energy efficient machining, etc. The search was limited to articles published in English language only. The Boolean keyword search in Scopus database allows to include different but relevant keywords and excludes irrelevant keywords in the same search. The excluded keywords were ‘ball’, ‘micro’, ‘stone’, ‘laser’, ‘plasma’, ‘stone’, ‘rice’, ‘granular’, ‘atomic’, ‘beam’, ‘discharge’, and ‘composite’. The present study considered the scholarly articles till 2018.

The first attempt for keyword search resulted into 1539 articles. The search was further refined based on title reading. This removed 1130 articles which were focused on composite manufacturing, non-metal machining, chemical operations, etc. and not related to metal machining processes. In the third step, the search was limited to articles published in six databases – Science direct, Springer, Taylor and Francis, Emerald, SAGE, and ASME. This reduced the articles to 302. In the fourth step, the search was refined by reading the abstracts and conclusions and a list of 245 articles was obtained. In the fifth step, a set of 219 articles was obtained by filtering the articles after reading the full articles. Later, seven additional articles were found to be important and relevant for the study which were highly cited in the reference literature. This provided a set of 226 articles for the review and critical observations. The literature search was terminated when the snowball approach started leading towards the articles already included in the database. These 226 articles are called reference articles throughout this thesis. Next, a descriptive analysis of these 226 articles was carried out and presented in the next section. The detailed content analysis is presented in subsequent sections.

Figure 2.1. Research methodology for the systematic literature review

2.3 DESCRIPTIVE ANALYSIS

The data from the literature was analyzed to provide meaningful patterns and trends over the period of time, as follows:

2.3.1 Distribution across Journals, Conferences and Books

The distribution of reference papers across journals and conferences has been shown in Figure 2.2. It is observed that 87% of the reference papers are from peer reviewed journals, 7% of the reference papers are from conference proceedings and 6% reference papers are published as book chapters.

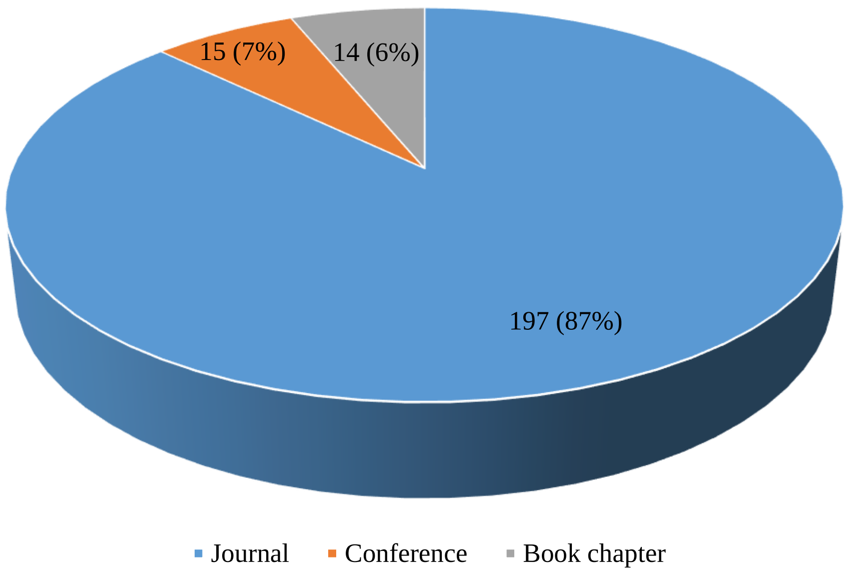

Figure 2.2. Distribution of reference articles across journals, conferences and books

The distribution of the reference papers among scientific journals and conference proceedings is provided in Table 2.1. The 226 reference papers are published in 29 journals, 10 conference proceedings and 5 books. It is observed that 65% of the total reference papers are published in six journals, and Journal of Cleaner Production accounts for highest (54) number of articles among them. Procedia CIRP has the second highest number of articles (33), followed by 27 articles in the International Journal of Advanced

Manufacturing Technology, 14 articles in Journal of Engineering Manufacture Part B, 11 articles in Energy, and 9 articles in CIRP Annals Manufacturing Technology. It shows that only few specific journals focusing on technical aspects of machining are preferred by the researchers. The specialized journals on energy efficiency, applied energy and environmental research have lesser publications. It shows that the environmental aspects of energy efficient machining should be highlighted.

Table 2.1. Distribution of reference literature across journals and conferences

Source title	Number of articles
J. Clean. Prod.	54
Procedia CIRP	33
Int. J. Adv. Manuf. Technol.	27
Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.	14
Energy	11
CIRP Ann. – Manuf. Technol.	9
CIRP J. Manuf. Sci. Technol.	6
Int. J. Precis. Eng. Manuf. - Green Technol.	4
Int. J. Prod. Res.	4
J. Intell. Manuf.	4
J. Manuf. Sci. Eng.	4
Int. J. Precis. Eng. Manuf.	3
Procedia Manuf.	3
ASME Int. Des. Eng. Tech. Conf.	3
Others (with less than 3 publications)	47

2.3.2 Distribution along the Timeline

The distribution of reference papers along the timeline shows the occurrence of research chronologically. The distribution of publications from 1994 to 2018 is shown in Figure 2.3. It is observed here that the first article on machining energy efficiency was published by Bayoumi and Hutton (1994) where specific cutting energy of a machining process was used as a measure of energy efficiency. Earlier, specific cutting energy of a material, defined as the amount of energy required per unit volume of material removed, was used as a measure of machinability of metals. After a considerable gap of nine years, second paper on the topic was published by Draganescu et al. (2003), which provided statistical models for energy efficiency and specific energy consumption at spindle level.

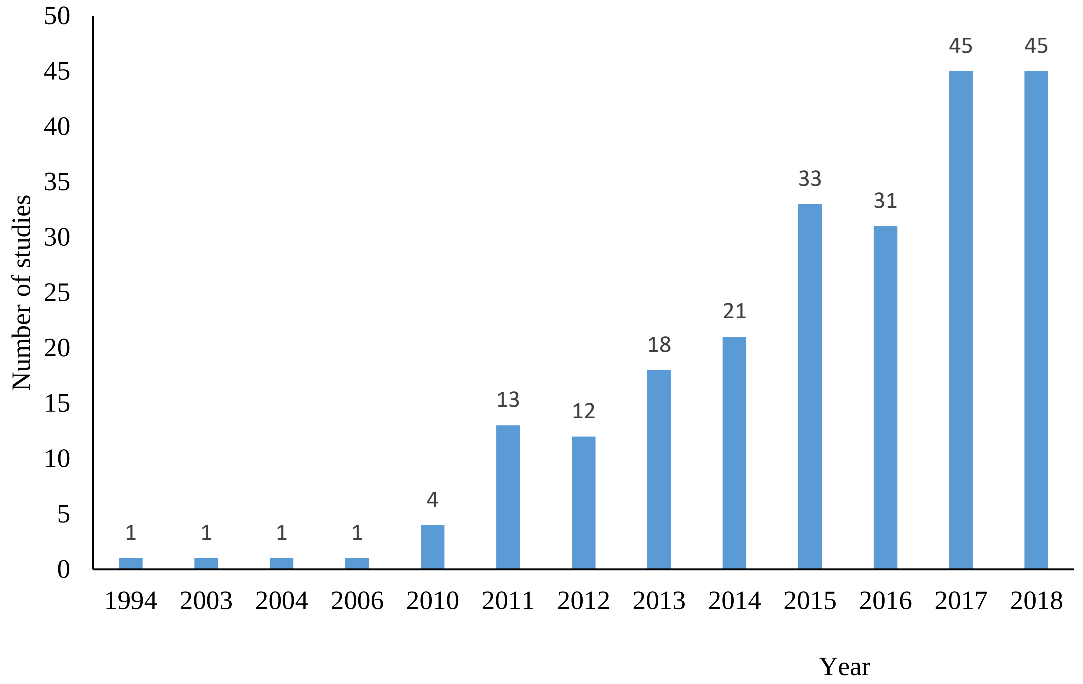

Figure 2.3 Distribution of reference articles along timeline

The fundamental study addressing the cutting and non-cutting energy for a machining process was provided by Gutowski et al. (2006). The intensity of research on the topic increased only during the second decade of the 21st century. The number of articles increased exponentially after 2010. The number of articles increased to 13 in 2011 from four in 2010, and in 2018 the number was 45. It can be noted here that 68% of the total reference articles appeared in the last four years only. This sustained growth may be attributed to increased concern towards energy efficient machining from both academia and industry. In recent years, many national and international research initiatives and energy policies have come into action to improve the energy efficiency of machining processes. For example, ISO initiated the ISO 14995 series to study the energy consumption and environmental performance of the machine tools (ISO, 2016, 2014). The European union has listed machine tools as one of the ten important product groups with high potential for energy saving and carbon emission reduction, in the Eco-design directive (EcodesignDirective, 2008). France, UK, USA, European union, and India have implemented many energy saving policies for SMEs (Aramcharoen and Mativenga, 2014). Similar initiatives have been introduced in China, Korea and Australia (Tuo et al., 2018a).

2.3.3 Distribution across Geography and Authorship

This section provides an overview of reference articles as per their distribution according to their country of origin and authorship (Figures 2.4 – 2.5). Most of articles are from China followed by USA, UK, and Germany. South Korea and India are at the fifth and sixth positions, respectively.

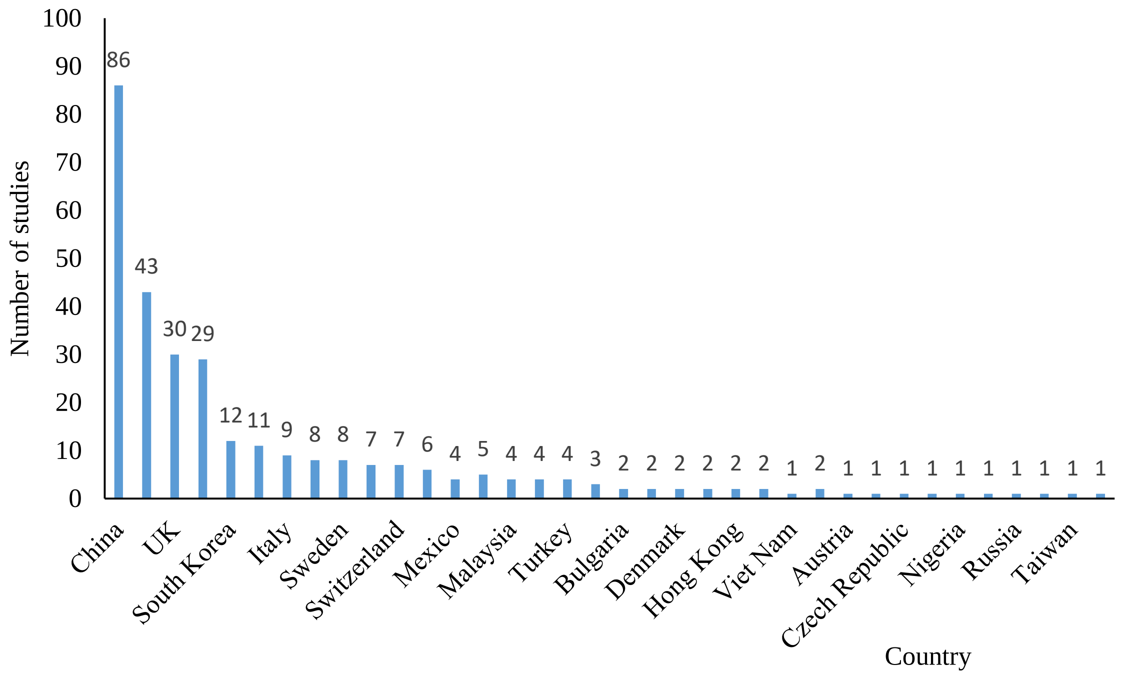

Figure 2.4. Geographical distribution of the reference articles

It shows that the machining energy research is mainly focused in China, USA, UK, and Germany. The number of research articles from China has increased exponentially from eight articles in 2015 to 37 articles in 2018. The research articles from USA and UK have also increased in the recent years. However, the research topic has proliferated to most of the countries and it can be expected that in coming times, most of the countries will focus on machining energy research. The distribution of authorship shows the number of articles published by each researcher. It is observed that most of the leading authors are Chinese.

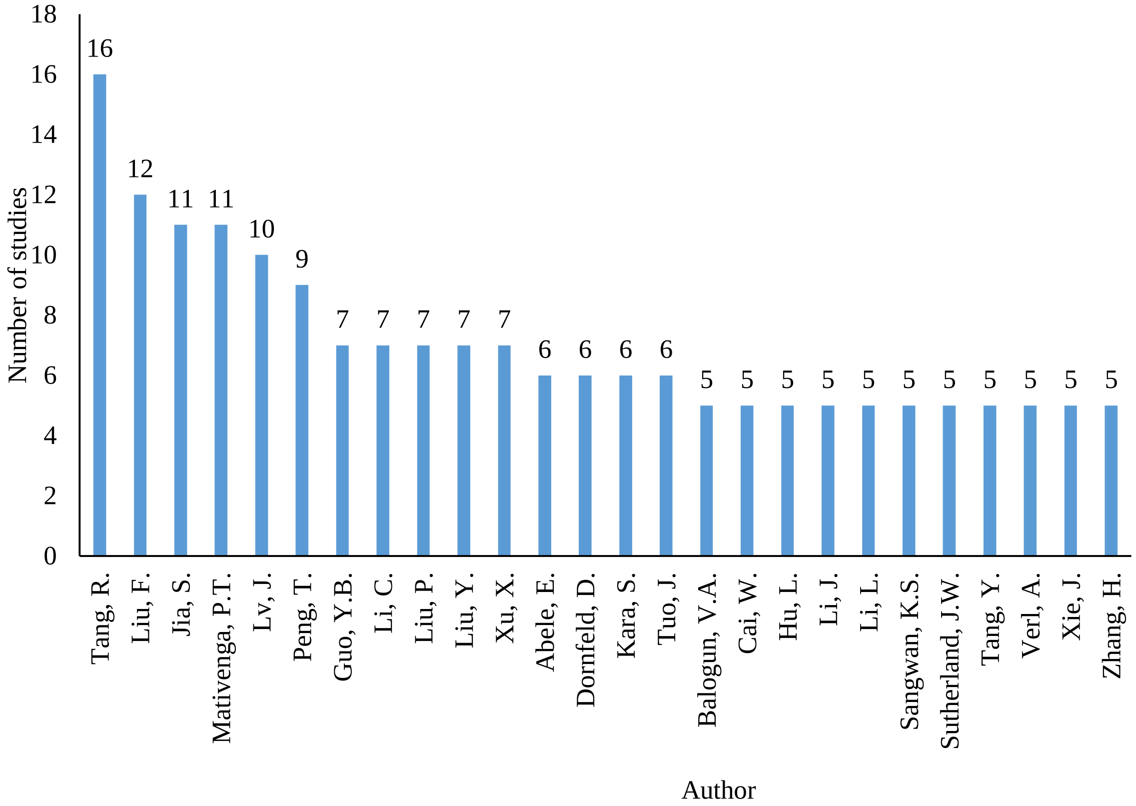

Figure 2.5. Distribution of articles across authorship

2.4 EXISTING REVIEW STUDIES

The literature search on the topic of machining energy efficiency provided seven review articles. These review articles were reviewed and a summary of the findings of these review articles is provided (Table 2.2) to position the present study accordingly. The first state of the art review article addressing the energy modelling and monitoring techniques, and energy saving strategies for machining processes was presented by Yingjie (2014). This paper classified energy modelling techniques based on the level of study at machining system, machine tool, and component levels. The challenges in assessment and modelling of energy consumption of machine tools were discussed. The study concluded that modern manufacturing industries need to improve energy and cost efficiency by rapid design, construction and reconfiguration of a machining system in order to maintain the competitive ability at the global level.

Peng and Xu (2014a) presented a critical review of energy efficient machining systems. The study focused on energy management at facility level and reported that the energy analysis becomes more complex with consideration of higher classification levels. Energy efficiency at machine tool level requires more research effort to improve the energy efficiency of day-to-day operations at shop floor.

Zhang (2014) presented a comprehensive literature review on energy efficiency of machine tools focusing on energy modelling and saving strategies. The energy monitoring approaches were reviewed to get an insight into the energy flow in a machine tool. The study outlined the challenges towards improvement in machining energy efficiency and highlighted the importance of energy consumption analysis at the machine tool level.

Yoon et al. (2015) proposed a novel hierarchical model for energy efficiency strategies based on ease of applicability, decision making and process levels for a single device/machine tool. The study mainly focused on the energy saving measures and energy assessment models are not discussed. It presented six hierarchical levels as assessment and modelling, software-based optimization, control technology, cutting improvement, hardware-based optimization, and design for environment.

Table 2.2 Summary of the existing review articles and the present study

Reference study	Journal	Type of review	Number of articles reviewed†	Energy classification	Energy modelling	Energy saving strategies	Energy efficiency evaluation
Yingjie (2014)	Int J Adv Manuf Technol	State of the art review	41†	Single classification criteria: level of machining system	-	Improve machine tool functionality, optimization and reconfiguration of the machining systems	-
Peng and Xu (2014a)	Int J Adv Manuf Technol	Critical review	117†	-	Theoretical, empirical, discrete event based, and hybrid models	Optimization and energy efficient process planning	-
Zhang (2014)	Proc Inst Mech Eng B J Eng Manuf	Comprehensive literature review	42†	-	Theoretical and experimental models in brief	Improve machine tool functionality, optimization, and reconfiguration of the machining systems	-
Yoon et al. (2015)	Renew sust energ rev	-	155†	-	-	Hierarchical approach at machine tool level	-
Moradnazhad and Unver (2017a)	Proc Inst Mech Eng B J Eng Manuf	Comprehensive literature review	101†	-	Theoretical and empirical models in brief	Optimization of cutting parameters	-
Zhou et al. (2016a)	J Clean Prod	Comprehensive literature review	108†	Five classification criteria: operational status, component, energy attribute, subsystem, and functional movement	Linear, process oriented, and cutting energy based models	Energy efficient design, optimization, and scheduling management	-
Zhao et al. (2017)	Energy		84†	Three classification criteria: different level, operating state, and component	Specific energy based models at machine tool, spindle, and process levels	Optimization of machine tool energy components and process parameters, improvement in peripheral component efficiency	-
Present study			226	Six classification criteria: level, energy attribute, cutting attribute, operating state, machining sub-system/ activity, and component/ Therblig	Detailed review of energy consumption models based on specific cutting energy of machine tool, cutting energy, operating state, and individual components	Energy saving strategies are clearly classified based on implementation phase for better understanding	Energy efficiency evaluation measures are discussed

†Total number of articles referred in the paper (the actual number of papers reviewed are not given)

Moradnazhad and Unver (2017a) provided a comprehensive review of the theoretical and empirical energy models for machine tools. Optimization of cutting parameters was identified as an important strategy to improve the energy efficiency of machine tools, and various parameter optimization approaches such as design of experiments and artificial intelligence techniques were discussed.

Zhou et al. (2016a) provided a comprehensive review of the energy efficiency of machine tools and the strategies to improve it. The study was divided into three parts. In the first part, the connotation of energy efficiency in context to machine tools was discussed. In the second part, various strategies used to improve the machining energy efficiency in design and use phase were discussed. In the third part, the energy assessment models were discussed. The study emphasized the need to develop a scientific evaluation index for assessment of energy efficiency of machine tools.

Zhao et al. (2017) provided a systematic overview on the energy classification, prediction models, and energy saving strategies for machining processes. The existing review studies, published during 2014-2017, provide a good starting point for the researchers but not without the following limitations:

- The reviewed articles were limited and the studies were not comprehensive.
- Energy efficiency evaluation models were not provided by any of the studies

To bridge these gaps, this chapter presents a systematic literature review of 226 papers on machining energy, from 1994 to 2018 with an aim to explore the different energy classification, energy modelling, energy improvement strategies, and energy efficiency evaluation of machine tools.

2.5 MACHINING ENERGY CLASSIFICATION

The understanding of different types of energy flows and energy classification is essential to reduce the energy consumption of machine tools (Bharambe et al., 2015). Energy measurement and monitoring is the first step towards energy analysis and saving. Therefore, innovative and effective energy monitoring and management approaches are required to promote energy efficient machining. Studies have been conducted to acquire, monitor and store the energy information of machine tools in standard formats to explain the flow of energy within the machining systems (Peng et al. 2013; Kolar et al. 2016; Abele et al. 2015b; Lenz et al. 2017; Zein et al. 2011). Eberspächer et al. (2014) integrated power data, control signals, and information from simulation models to develop a power monitoring concept for machine tools for detailed classification of the energy data. Event stream mapping has been used as an efficient approach for automated energy monitoring of the machine tools (Vijayaraghavan and Dornfeld, 2010).

Energy consumption of the machine tools is a well-researched area during the last decade and many classification criteria have been proposed in the literature. Wang et al. (2015) proposed a framework to explain the diverse energy characteristics of machine tools under three categories: energy specific characteristics of the process, state specific characteristics of the machine tool, and operation specific characteristics of the workpiece. Energy specific characteristics are generally used for measuring and managing the energy consumption of the machine tools, state specific characteristics are used to monitor the operating states of the machine tools, and operation specific characteristics are used to monitor the progress of machining process. A few studies have classified the machine tool energy consumption up to the component level. The energy classification provided in reference literature has been carefully analyzed and divided into six groups based on their classification criteria.

The first group classified the energy consumption based on three levels: machine tool, spindle and process (Y. Cai et al., 2018a; Z. Y. Liu et al., 2018b; Sealy et al., 2016; Wu et al., 2017). At process level, the energy required for actual material removal or tool-tip energy is studied. At spindle level, the energy consumption by the spindle unit is studied which involves the energy required for unloaded spindle rotation, additional losses due to load along with tool-tip energy. The energy analysis at spindle level facilitates the analysis of spindle motor efficiency. At machine tool level, the energy consumption by the entire machine tool is analyzed. It includes the energy consumed by machine tool control systems, feed systems, auxiliary components, spindle unit, and material removal.

The second group classified the energy consumption by the machine tool to manufacture a product based on the energy attribute as direct and indirect energy consumption (Arif et al., 2013; Hu et al., 2015; Mativenga and Rajemi, 2011; Peng and Xu, 2014b; Wang et al., 2014a). Direct energy is the energy consumed by the machine tool to realize the necessary operations to manufacture a product, whereas the indirect energy is the embodied energy of the cutting tool, coolant, and workpiece material. The indirect energy comprises the energy consumed for acquisition of raw or recycled materials and process them to manufacture the workpiece blank, coolant, or cutting tool.

The analysis of direct energy at machine tool level is important to assess and improve the energy efficiency of the machine tools. The third group classified the direct energy consumption at machine tool level, based on the cutting attribute, as cutting and non-cutting energy. The cutting energy is the energy required for material removal, and non-cutting energy is the fixed energy consumed by the machine tool when it is switched on, irrespective of the cutting load. The power consumption during cutting is variable and depends upon the tool-workpiece material and cutting conditions. A study of machining energy requirements at Toyota states that almost 85% of the energy is consumed as fixed energy in idling state, including energy consumed by control systems, lights, axis feed motors, spindle motor, coolant and lubrication pumps, etc. Only 14.8% of the total energy consumed is used for actual cutting (Gutowski et al., 2005).

It was observed that there exists one more state between machine tool start up and cutting states, which is responsible for the readiness of the machine tool for cutting operation, termed as machine-ready state (Balogun and Mativenga, 2013). It includes the power consumption by unloaded spindle rotation and feed axis movement. Machine tools exhibit a complex and dynamic power profile. The energy consumption is calculated by integration of the power profile over time or the area under the power curve and time axis. Due to the dynamic nature of power profile, the surface area needs to be decomposed properly to obtain the energy consumption. Therefore, the fourth energy classification criteria was based upon the operating state of the machine tool. With advancements in energy analysis of machine tools, the energy classification included higher number of operating states such as spindle acceleration/deceleration, tool change, air cutting, tool positioning, etc. for better understanding. A few studies have used various machine learning approaches for determining the operating state of a machine tool (O'Driscoll et al., 2015; Sihag et al., 2018). The energy data is processed and classified into pre-defined classes using various classifiers such as support vector machine (SVM), tree classifier, k-nearest neighbour (k-nn), etc. Hidden Markov models have also been explored to develop an expert system for identification of the energy efficiency state of machine tools (Y. Cai et al., 2018b). Frigerio et al. (2013) developed an automata based approach to model the function modules and operating states of the machine tools. The operating state based energy classification addressed by the reference studies is presented in Table 2.3.

Table 2.3 Energy classification based on operating state of the machine tool

Reference articles	**Startup**	**Stand –by**	**Spindle acceleration/deceleration**	**Idling**	**Air cutting**	**Cutting**	**Cutting tool change and setting**	**Additional load loss**	**Other**
Altıntaş et al., (2016); Avram and Xirouchakis, (2011); Balogun et al., (2013, 2015); Balogun and Mativenga, (2013a); Behrendt et al. (2012); Edem and Mativenga, (2017a); Rajemi et al., (2010); Rentsch and Heinzel, (2015); Salonitis and Ball, (2013a); (Vijayaraghavan and Dornfeld, 2010); Wang et al., (2014c); Zhang et al., (2017a)		x		x		x			
Zhou et al., (2018)		x			x	x			x
Moradnazhad and Unver, (2017b)		x		x		x			x
Balogun and Mativenga, (2013a)		x		x	x	x			x
Huang et al., (2016); F. Liu et al., (2015)	x			x		x			
Lv et al., (2016)		x		x	x	x			
Zein et al., (2011)		x			x	x			
Li et al., (2011)		x			x	x		x	
Li and Yuan, (2013); Lv et al., (2018); Zhang et al., (2016)		x		x		x		x	
Li et al., (2016a)		x			x	x	x	x	
Zhang et al., (2018)		x		x		x	x		
C. Li et al., (2017)	x			x	x	x	x		
Li et al., (2016b)		x			x	x	x		
Kianinejad et al., (2015)		x		x	x	x	x		
Tuo et al., (2018a)		x	x	x	x	x		x	
N. Xie et al., (2016)	x		x		x	x			
Tuo et al., (2018b)		x	x	x		x			
L. Li et al., (2017a)	x	x	x		x	x			
Chen et al., (2018)	x	x	x		x	x			
Mori et al., (2011)			x			x	x		
Total†	6	31	6	27	15	36	5	5	3

†Total number of reference articles for each operating state

The fifth energy classification criteria was based upon the machine tool sub-systems/functional modules/composition systems. Albertelli et al. (2016) classified the energy consumption modules as stand-by, cutting, and functional modules. Functional module consists of energy consumed by various machine tool components. The energy consumption modules were also classified as motion and auxiliary modules (Shen et al., 2018). Motion modules support the movements of machine tool components and material removal process. Spindle and feed modules are defined as motion modules. Auxiliary modules include the CNC, cooling, lubrication, hydraulic, and accessory modules, which facilitate the completion of the processing task. The machine tool sub-systems can also be classified as mechanical, electrical, hydraulic, and pneumatic sub-systems. Another criteria is to decompose the energy consumption based on functions of machine tool sub-systems such as drive train, cooling system, hydraulic system, compressed air, auxiliary system, control system, etc. The different machine tool modules and the studies addressing them are presented in Table 2.4.

Table 2.4 Energy classification based on machine tool sub-systems

Reference study	**Stand-by module**	**Spindle module**	**Feed module**	**Cooling module**	**Hydraulic module**	**Lubricati on module**	**Cutting module**	**Auxiliary module**
Shen et al., (2018)	x	x	x	x	x	x		x
Zhang et al., (2017b)	x	x	x				x	x
Mohammadi et al., (2017)		x		x	x	x		Compressed air and chip conveyor
Albertelli et al., (2016)	x	x	x				x	
Zhao et al., (2018)	x	x	x	x			x	x
Götze et al., (2012)	x	x	x	x				Tool and waste handling modules

One or more sub-systems are active during each operating state of the machine tool. Each composition system is comprised of one or more machine tool components like coolant motor, axis feed motor, controller, chip conveyor, automatic tool changer, etc. The sixth energy classification criteria was based on machine tool components. The machine tool components were classified as core/driver and auxiliary/peripheral. Core/driver components are responsible for material removal and motion transmission while auxiliary/peripheral components support the auxiliary operations. The machine tool components can also be classified as steady or transient, based on their power consumption characteristics. Some studies performed classification for individual components. Peng and Xu (2016) explained the energy consumption of a machining system in two stages. In the first stage, the total energy consumption was classified for different machining states, and, in the second stage, the energy consumption in each machining state was divided into machine tool components. A hybrid energy model was developed by combining lower level component models and higher level state models. O'driscoll et al. (2013) presented an elementary study to use statistical pattern recognition approach for classification of machine tool components based on their energy features. The studies classifying the energy consumption of the machine tools based on their components are summarized in Table 2.5.

It is interesting to note that it is still a challenge for researchers to identify where and how the energy is consumed during a machining process due to the complex structure of the machine tools and large number of energy consuming components in a machine tool. Based on the analysis of the reference articles and the classification criteria used by them, a six step hierarchical model for machining energy classification has been provided in the present study (Figure 2.6). This model can help to understand the energy classification at six hierarchical levels.

Table 2.5. Energy classification based on machine tool components

Tier 1									
Schmitt et al., (2011); Triebe et al., (2018)	Core	Auxiliary							
Tier 2	**Basic**	**Spindle motor**	**Feed-axis motor**	**Coolant pump**	**Hydraulic motor**	**Chip conveyor**	**ATC**	**Cutting**	**Others**
Wei et al., (2018)		x	x	x	x				display screen, ventilation fans, pilot lamp
Moradnazhad and Unver, (2017b)		x		x		x	x		milling head, turret, lubricant pump
Zhang et al., (2017a)	x	x	x	x				x	
Lee et al., (2015)	x	x	x	x				x	
Zhong et al., (2016a)	x	x	x	x			x		
Aramcharoen and Mativenga, (2014)	x	x	x	x			x	x	
Li et al., (2013)	x	x						x	
Y. He et al., (2012)	x	x	x	x			x		
Braun and Heisel, (2012)	x	x	x	x				x	
Frigerio et al., (2013)		x	x	x		x	x		part clamp, control cabinet, chiller
Calvanese et al., (2013)		x	x			x	x	x	clamp pallet, chiller, NC drives
Total	7	11	9	9	1	3	6	6	4

2.6 MACHINING ENERGY MODELLING

Due to complex energy characteristics of machine tools, it is important to develop precise and accurate energy consumption models for understanding and reducing the machining energy consumption. A large number of studies have focused on energy modelling of machining processes during the last decade. This section presents review of

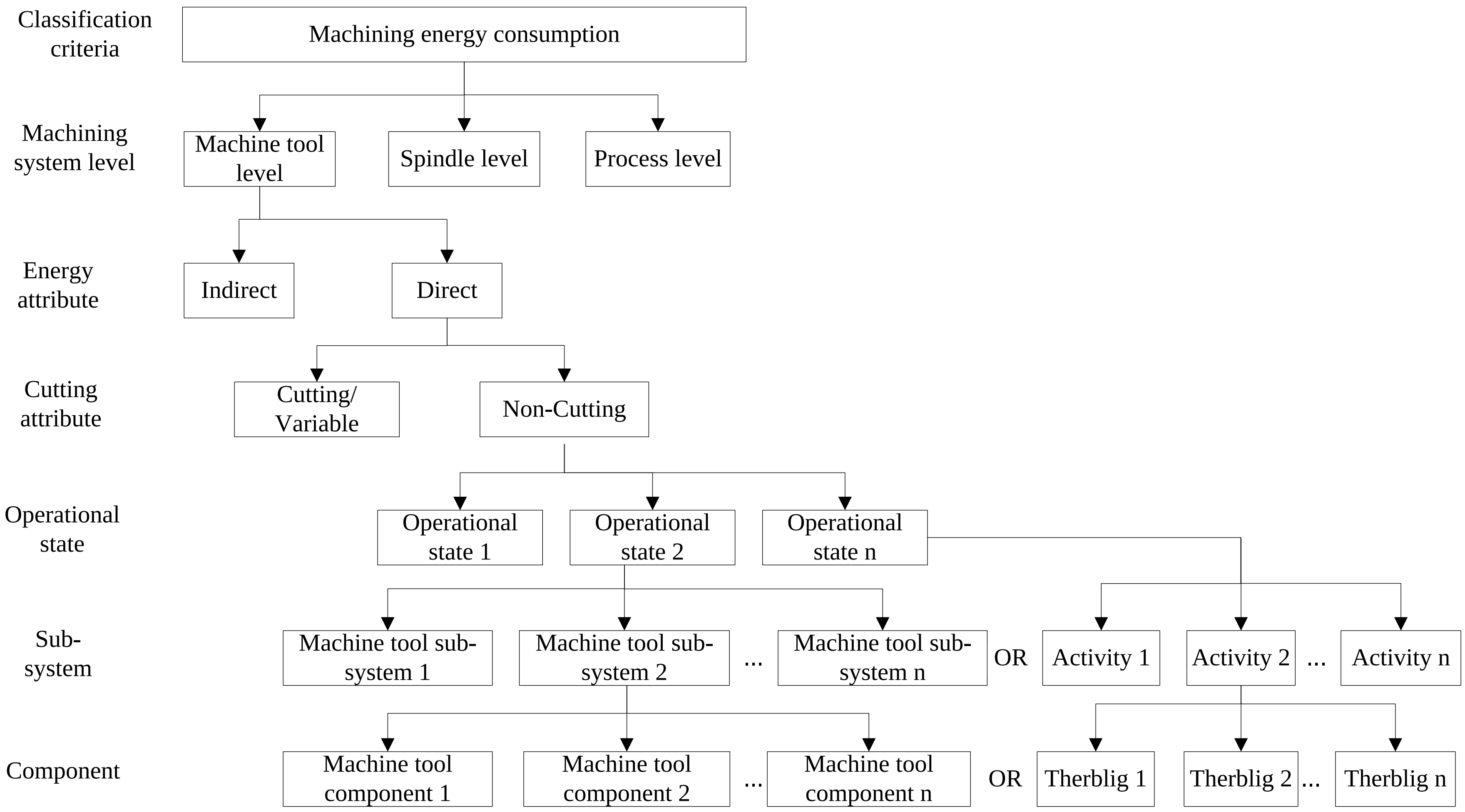

Figure 2.6 Six step hierarchical model for machine tool energy classification

energy models provided in the literature. The energy models are classified into five categories based on their energy expression.

i) Machine tool energy models

ii) Cutting energy models

iii) State based energy models

iv) Component based energy models

v) Therblig based energy models

2.6.1 Machine Tool Energy Models

The specific energy for machining is defined as the energy required for removing a unit volume of material. The energy consumption can be measured at cutting, spindle and machine tool levels. Sealy et al. (2016) analyzed the specific energy at the three levels and studied the variation of these energies with process parameters for sharp and worn out tools under up and down milling conditions.

The pioneering study towards energy analysis of machine tools was presented by Gutowski et al. (2006). The study reported that the energy consumption by machine tools is not constant as assumed by most of the life cycle analysis studies, and the concept of fixed and cutting energy was presented. A theoretical model to predict the SEC was developed as a function of material removal rate based on an exergy framework. However, the coefficients of this theoretical model were not clearly defined and hence energy prediction was difficult to realize.

Li and Kara (2011) undertook this study to develop an empirical model to predict the energy consumption for a turning process. Specific energy consumption, defined as the energy required to remove 1 cm^3 of material, was used as a function unit to compare the energy consumption for different materials under varying process parameters. A mathematical model for SEC was established as

$$SEC = C_0 + \frac{C_1}{MRR}$$

where C_0 and MRR are the coefficient and predictor of the inverse model respectively, C_1 is the coefficient of the predictor. The model coefficients were determined empirically. SEC for three different materials (mild steel 1020, aluminium 2011, and high tensile steel 4140) were experimentally obtained and it was observed that the model was able to predict the SEC for the turning process with an accuracy of more than 90%. The authors further validated the model for multiple milling and turning centers (Kara and Li, 2011).

Li et al. (2013) extended the energy consumption models provided in these studies to provide an improved energy consumption model based on thermal equilibrium and empirical modelling for milling process. The energy consumption by spindle motor is high and constitutes a high portion of total energy consumption for smaller machine tools. Therefore, the variation of spindle energy consumption with process parameters was analyzed and incorporated in the energy consumption model provided by Li and Kara (2011). Experimental investigations were conducted to determine the model coefficients for face milling of medium carbon steel (C45). The prediction accuracy of the proposed model was 96%.

Zhao et al. (2016) considered the unloaded spindle power and coolant pump power along with stand-by and cutting power and developed energy prediction models using empirical modelling and back propagation neural network (BPNN) approach. The proposed models were verified for turning of C45 steel. The energy prediction using empirical and BPNN models had accuracies of 97.29% and 97.70%, respectively.

The above discussed models are based on specific machine tools. Li and Yuan (2013) proposed two energy consumption models for machining processes. First, a generalized energy consumption model was developed for different machine tools with varying efficiency. The generalized model was reported to have high prediction accuracy for highly automated machine tools. But, the accuracy of this model for manual, semi-automated and micro machine tools was limited. Therefore, a second model was proposed for more accurate prediction of energy consumption of a specific machine tool. The total power consumption of a machine tool was modelled as a quadratic function of the MRR. The prediction accuracy of proposed model was compared with the well-known model presented by Gutowski et al. (2006). The accuracy of the proposed model was higher than original model for a wide range of MRR values.

The above discussed models are widely used for specific energy consumption prediction at machine tool level. The model coefficients can be experimentally obtained. However, these models express the SEC as a function of MRR. It implies that SEC for a machining process at same MRR will be same irrespective of the values of cutting parameters. It has been observed that using different combinations of cutting parameters while maintaining the same MRR will result into different SEC. Therefore, energy modelling at parametric level is crucial to improve the prediction accuracy.

Guo et al. (2012) defined the total specific energy consumption (TSE) for turning process as summation of specific process energy and specific constant energy. Experimental investigations were conducted to study the effect of process parameters on the total specific energy consumption for turning of aluminum (AlCuMgPb) and steel (11SMnPb30) workpieces. It was observed that the total specific energy reduces with increase in feed and depth of cut. TSE reduces with increase in cutting speed up to a threshold value and then starts increasing. This was due to dominance of increase in specific process energy over reduction in specific constant energy, after the threshold cutting speed. Zhong et al. (2016b) also modelled the SEC as a function of cutting parameters.

Asrai et al. (2018) modelled the energy consumption of a machining process based on the energy conversion processes in the system. The proposed model was based on fewer assumptions and therefore the prediction accuracy was reported to be higher than the existing models in the literature. The proposed model was illustrated with a steady-state slot milling process and the power input to the machine tool was expressed as a function of cutting speed, feed rate, and material removal rate. The model was statistically tested for uncertainty and accuracy, and it was reported to be more accurate than the existing literature models by Gutowski et al. (2006) and Li and Kara (2011).

Liu et al. (2015) proposed an energy consumption model for milling process using the cutting power at tool tip. The tool tip power was analytically computed using existing cutting force models. The empirical relationship between total power consumption and cutting power was characterized and validated for a slot milling process. The proposed model was compared with the models of Li and Kara (2011) and Li et al. (2013), and it was observed that the proposed model predicted the energy consumption with higher accuracy. The proposed model was also able to explain the variation in power consumption with cutting parameters under constant MRR conditions.

Velchev et al. (2014) conducted experimental investigations to study the dependence of specific energy consumption on process parameters for turning process. A prediction model for direct energy consumption including energy consumption for set up, cutting, tool change for single pass turning process was proposed.

Zhou et al. (2017) considered the effect of spindle rotation speed on the cutting power for a milling process and provided an improved SEC model for milling process. The proposed model was compared with the models of Gutowski (2006) and Li et al. (2013), and better accuracy was reported. The study also reported that the SEC model considering cutting speed, feed, depth of cut as independent variables leads to better accuracy but needs more experimental data. MRR should be considered as an independent variable to predict SEC to achieve higher accuracy with fewer experiments. Xie et al. (2016) modelled SEC for turning process considering the detailed effect of process parameters. The summary of specific energy based models at machine tool level is provided in Table 2.6.

Table 2.6 Summary of specific energy based models at machine tool level

Study	Energy model	Process	Remarks
Gutowski et al. 2006)	$P = P_0 + k\dot{v}$ k is constant (kJ/cm³).	-	Determination of P_0 and k is difficult
W. Li and Kara, (2011)	$SEC = C_0 + \frac{C_1}{MRR}$ C_0 and C_1 are the model coefficients.	turning	It is a machine tool specific empirical model.
Li et al., (2013)	$SEC = k_0 + k_1\frac{n}{MRR} + k_2\frac{1}{MRR}$ k_0, k_1, k_2 are model coefficients.	milling	The variation in spindle energy due to change in cutting speed was considered
Zhao et al., (2016)	$SEC = k_0 + k_1\frac{1}{MRR} + k_2\frac{n}{MRR}$ k_0, k_1, k_2 are model coefficients.	turning	Li (2013) model was extended by considering unloaded spindle power and coolant pump power with stand-by and cutting power.
Li and Yuan, (2013)	$SEC = C_0 * P_{Sp} + C_1\frac{n}{MRR} + C_2\frac{P_{Sp}}{MRR} + C_3$ C_o, C_1, C_2, C_3 are constants.	milling	Generalized model for highly automated machine tools.
	$P = a * MRR^2 + b * MRR + c$ a,b,c are constants for a specific machine tool and cutting tool $SEC = \frac{P}{MRR} = a * MRR + b + \frac{c}{MRR}$		For specific machine tool
Guo et al., (2012)	$SEC = C_0 v_c^{\alpha} f^{\beta} a_p^{\gamma} D^{\phi} + \frac{C_1}{v_c f a_p}$ C_0, C_1 α, β, γ, Φ are model coefficients obtained by least-squares curve fitting method	turning	Parameter based energy modelling for constant specific and process specific energy consumption.
Zhong et al., (2016b)	$SEC = \frac{P_{fixed}}{MRR} + k_2\frac{kn + b}{MRR} + \frac{\lambda v_c^{\alpha} f^{\beta} a_p^{\gamma}}{MRR}$ λ, α, β, γ, are the specific coefficients related to machine tools, work-piece materials, cutting tools, etc.	turning	Cutting energy was modelled in terms of detailed parameters.
N. Liu et al., (2015)	$SEC = \frac{C_0}{MRR} + C_1\frac{\overline{P_{cutting}}}{MRR}$	milling	The variation in power consumption with cutting parameters under constant MRR conditions explained.
Velchev et al., (2014)	$SEC = \frac{P_u}{MRR} + B_0(MRR)^{B_1}$ B_0 and B_1 are specific machine coefficients depending on the workpiece and cutting tool combination.	turning	Energy consumption for set up, cutting, tool change for single pass turning process included.
Zhou et al., (2017)	$SEC = C_1 n^{C_2} + C_3\frac{n}{MRR} + \frac{C_4}{MRR}$	milling	Gutowski (2006) and Li (2013) models were extended by considering the effect of rotational speed on power consumption for milling process
J. Xie et al., (2016)	$SEC = \frac{60 * \int (P_u(t) + P_{ad}(t) + P_c(t))dt}{\int (v_c(t) + f(t) + a_p(t))\, dt}$ $P_u(n) = \{P_u(n_1), P_u(n_2), \ldots P_u(n_n)\}$ $P_c(t) = F_c(t) * \frac{v_c(t)}{60}$; $P_{ad} = a_1 P_c(t) + a_2 P_c^2(t)$	turning	Integrated model for SEC considering detailed process parameters

It is observed here that physics based models have been widely proposed in the literature to predict the energy consumption characteristics of the machine tools. However, these models involve a large number of physical variables, which are difficult to predict. In addition, these models have limited reliability when machine tools and operating conditions are uncertain. Therefore, soft computational techniques such as ANN, SVM, NN have also been used to predict the energy consumption by the machine tools (Ak et al., 2015; Kant and Sangwan, 2015a). Data driven energy prediction models using Gaussian process (GP) – a non-parametric machine learning approach, has also been provided (Bhinge et al., 2016; Park et al., 2015). Borgia et al. (2014) presented an energy prediction model for face milling process using feed forward neural network based on twenty parameters related to machine tool and workpiece specifications, machining features and machining strategies.

2.6.2 Cutting Energy Models

The energy models discussed in the last section focus on SEC at machine tool level and do not directly correspond to the material removal energy at process level. The cutting energy at process level generally accounts less than 20% of the total energy consumption (Gutowski et al., 2006; Jia et al., 2017b; Zhou et al., 2016). However, it is important to analyze the cutting energy since it governs the chip formation and new surface generation (Sealy et al., 2016). It directly impacts the surface characteristics of the machined workpiece. Therefore, a large number of studies focused on cutting energy modelling at process level. The cutting energy consumption models are reviewed and classified based on their characteristics.

2.6.2.1 Models based on cutting force

Indirect method for cutting power modelling based on cutting forces has been used for a long time. The cutting power is calculated as a product of cutting force and cutting speed.

The cutting force is calculated based on analytical models, numerical methods or experimental measurements. For example, Rentsch and Heinzel (2015) provided analytical model to predict the cutting force for milling process. The cutting force and power models were provided as:

$$F_{c_z} = bh_m k_c K_{\gamma 0} K_v K_{ver} K_{lub}$$

$$P_c = \frac{F_{c\_z} * v}{1000 * 60} * z$$

where F_{c_z} is the cutting force per cutting edge, z is the number of cutting edges, $b * h_m$ is the average area of cut, $k_c, K_{\gamma 0}, K_v, K_{ver}, K_{lub}$ are correction coefficients.

Carvalho et al. (2015) used the following model for predicting the cutting force for face milling operation:

$$F_c = a_p C_{s1} f_z^r k^{r-1}(1 - 0{,}0.1 * \alpha) sen\varphi^r$$

where α is the axial rake angle, φ is the rotation angle of the cutting edge, k is the approach angle of the cutter, and r and C_{s1} are coefficients.

Borgia et al. (2017) used cutting torque based models to estimate the cutting energy. The torque required for material removal was modelled as summation of torque due to material removal (T_{MR}) and edge forces on the tool (T_e).

$$T_C = T_{MR} + T_e = \frac{MRR * k_{tc}}{n} + \frac{D}{2} * \sum_{i,k} sgn(n) * \Delta a * \frac{N}{2\pi} k_{te} \{\varphi\}_{\varphi_{st_{ik}}}^{\varphi_{ex_{ik}}}$$

where k_{tc} is the tangential cutting pressure, k_{te} is tangential edge coefficients, N is number of cutting edges, $\varphi_{ex_{ik}}$ and $\varphi_{st_{ik}}$ are the exit and starting angles (rad) for the i_{th} engagement arc of the k_{th} slice.

The analytical models involve a large number of coefficients which are difficult to obtain. To overcome this gap, some researchers used numerical methods to predict the cutting force and cutting energy. For example, Pervaiz et al. (2015) presented finite element modelling based approach to predict the cutting force and energy consumption for turning process. Machining simulations were carried out using DEFORM-3D software. The predicted cutting force was used to compute the cutting energy of the turning process. The non-cutting energy of the machine tool was measured experimentally at the same cutting conditions. The simulated cutting force and energy results were compared with experimental values for dry turning of Ti6Al4V alloy, the results were found to be in good agreement with an error of 1-8%. The proposed methodology can be used to predict the cutting force and energy consumption for machining processes without actually performing the experiments.

Some studies used experimental methods to overcome the complex computation involved with numerical methods. For example, Kant and Sangwan (2014) measured the cutting force for a turning process using dynamometer. The cutting power was calculated as a product of cutting force and cutting speed. The predictive models for cutting power were developed using regression analysis (Kant and Sangwan, 2014), ANN and support vector regression (SVR) (Kant and Sangwan, 2015b).

It is observed from the literature that the cutting force based energy models reflect the theoretical minimum energy required for material removal (Li and Kara, 2011). The actual energy consumption for material removal is higher than the computed values using the cutting force based models.

2.6.2.2 Models based on metal deformation theory

A few studies used metal deformation theory for prediction of cutting power. The material removal energy is decomposed into shear energy (useful) and friction energy (unproductive) (Ma et al., 2014; Park et al., 2016). Chetan et al. (2018) used a mathematical model of SCE for machining of Nimonic 90 under MQL conditions. The

SCE was modelled considering the shearing and frictional energy in primary and secondary shear zones respectively:

$$E_{PSZ} = \frac{\sigma_{PSZ}\bar{\varepsilon}}{n+1}$$

$$E_{SSZ} = \frac{\left(\int_0^{L_{st}} \tau_{st} w dx\right) v_{st} + \left(\int_{L_{st}}^{L_c} \mu_{sl}\sigma_0 \left(1 - \frac{x}{L_c}\right)^{\zeta} w dx\right) v_{sl}}{v f a_p}$$

where E_{PSZ} is the specific energy in the primary shear zone, $\bar{\varepsilon}$ is equivalent shear strain (mm/mm), σ_{PSZ} is flow stress in primary shear zone , n is hardening coefficient, L_{st} is sticking length, L_c is tool chip contact length, τ_{st} is shear stress at sticking zone, μ_{sl} is sliding coefficient of friction, E_{SSZ} is specific energy in the secondary shear zone. σ_0 is nominal normal stress, ζ is exponential parameter, v_{st} and v_{sl} are the velocities in sticking and sliding zones, respectively. It was reported in the study that the SCE required for machining can be reduced by increasing the flow rate and pressure of coolant supply in MQL mode.

Wang et al. (2016) modelled the cutting energy required for orthogonal high speed machining as the summation of friction energy at tool-chip interface, plastic deformation energy in primary shear zone, and kinetic energy of the flowing chip. The proposed model was used to analyze the specific cutting energy consumed for high speed machining of 7075-T7451 aluminum alloy and it was observed that plastic deformation energy had the largest share in total cutting energy consumption followed by friction and chip flow energy. High cutting speed, undeformed chip thickness and positive rake angle were favorable conditions for energy efficient machining.

Meng et al. (2018) proposed a cutting energy model based on plastic deformation and friction theory. The effect of tool geometry and process parameters on the cutting energy was analyzed. The proposed model was experimentally verified for estimation of energy required for linear and circular arc elements and the results were obtained with a maximum error of 17.58%.

2.6.2.3 Models based on detailed parameters

The material removal power has been modelled in terms of detailed parameters by many authors (N. Xie et al., 2016; Lv et al., 2016) as:

$$P_c = kv^a f^b a_p^c a_e^d$$

where a, b, c, and d are fitting coefficients and k is correction coefficient. Here, P_c represents the minimum theoretical power required for material removal by shearing process. The actual power required for material removal is higher and modelled by Zhang et al., (2017b) as:

$$P_{c\_actual} = (1 + \alpha)kv^a f^b a_p^c a_e^d$$

where α is the power loss coefficient.

Liu et al. (2018b, 2015) characterized and evaluated the energy consumed for actual material removal in dry milling of hardened tool steel AISI H13, at machine tool, spindle, and process levels. The empirical models provided by Li and Kara (2011), and Diaz et al. (2011) were discussed in these studies and it was quoted that these models perform well for prediction of specific energy consumption at machine tool and spindle levels. However, at process level, the net cutting specific energy cannot be predicted using these models (R^2=41.7%) and a more detailed and accurate model is required. Regression models for net cutting specific energy considering four process parameters (cutting speed, feed rate, axial and radial depth of cut) were provided as

$$SCE = kv^a f^b a_p^c a_e^d$$

where a, b, c, and d are fitting coefficients. It was also observed that MRR can be used as a unique indicator to predict total and spindle specific energy but for cutting specific energy individual process parameters should be considered.

Balogun and Mativenga (2014) conducted experimental investigations to analyze the cutting power for milling process. The effects of cutting speed, feed per tooth, depth and width of cut on the power consumption were studied and it was observed that cutting speed has highest impact on cutting power. The experimental analysis was used to develop an empirical model between specific cutting energy and uncut chip thickness for three different work materials; aluminum alloy (AW6082-T6), AISI 1045 steel alloy, and titanium 6Al-4V alloy:

$$k_e = K_e h^{-x}$$

$$k_{Al} = 0.071h^{-0.94}\,; \qquad k_S = 0.900h^{-0.33}\,; \qquad k_{Ti} = 0.670h^{-0.51}$$

where k_e represents the specific cutting energy (Ws/mm^3) of the work material and h is the un-deformed chip thickness (mm). It was observed that at lower uncut chip thickness, the SCE is significantly higher as compared to higher uncut chip thickness, generally used for conventional milling. It was recommended to perform rough milling operations at higher feed rates to reduce energy consumption. However, the increased tool wear at higher feed rates was not discussed in the study.

2.6.2.4 Models based on tool wear

The material removal power also depends on tool condition and hence it is complicated to be assessed properly. Yoon et al. (2014) provided an empirical model for material removal energy considering the effect of process parameters and tool wear.

$$P_{material\ removal} = f_1(n, f, a_p) + f_2(n, f, a_p) * \overline{VB}(t)$$

where $\overline{VB}$ is the flank wear. The model was experimentally validated for a 3-axis milling center. It was observed that the material removal power increases with the cutting parameters but the rate of increase in power depends on the tool condition.

Shi et al. (2018) studied the effect of tool wear on the energy consumption for a 3-axis milling process and proposed a model to predict the energy consumption with high accuracy under realistic conditions of tool wear. Initially, the cutting power was modelled based on cutting force analysis and the coefficients were determined experimentally. The power without tool wear was measured experimentally. Subsequently, total power consumption was modelled as a function of tool wear.

$$P = P_0 + f(\overline{VB}) * \overline{P^0_{cutting}}$$

where P and P_0 are the total powers with and without tool wear respectively, $\overline{P^0_{cutting}}$ is the average cutting power during one rotation period without tool wear, and $f(\overline{VB})$ is a polynomial function of flank wear that characterizes the variation the cutting force with tool wear. This model may be used to predict power consumption by measuring the tool wear and vice-versa for the same tool-workpiece combination.

2.6.2.5 Models based on variable MRR

Most of the energy consumption modelling studies consider constant or average MRR neglecting the dynamic energy behavior of variable MRR machining process. End face turning, chamfering and grooving are some examples of variable MRR machining processes. A few studies have considered the effect of variable MRR for machining energy assessment. Jia et al. (2016b) and Diaz et al. (2012) proposed improved energy consumption models for variable MRR machining process. The cutting process was divided into N sub-intervals and the MRR was assumed to be constant within the subintervals. The energy consumption for each sub-interval was summed up to obtain the total energy consumed for machining a feature at variable MRR conditions. The cutting energy for variable MRR was modelled as

$$E_x = N * \Delta t \sum_{i=1}^{N} (k + b * MRR_{avg,i})$$

where E_x is energy consumed for each feature with N sub-intervals. The proposed model was able to explain the variation in cutting energy with cutting parameters. Jia et al. (2016b) illustrated the feasibility of the model with a case study. Diaz et al. (2012) assessed the accuracy of the model based on standard deviation and mean error. The prediction accuracy of the model increased at higher MRR and processing time.

2.6.2.6 Others

Hu et al. (2012) modelled the cutting power based on spindle input power and the losses occurred. The input power for spindle unit was considered as the summation of unloaded spindle power (P_u), cutting power (P_c) and additional losses (P_a). The spindle input energy was measured by installing a power sensor at spindle power supply module. The additional losses were modelled as a quadratic function of the cutting power as:

$$P_a = a_0 P_c + a_1 P_c^2$$

The cutting power model was obtained based on the spindle input power and the unloaded spindle power as

$$P_{in\_sp} = P_u + (1 + a_0)P_c + a_1 P_c^2$$

$$P_c = \frac{-(1 + a_0) + \sqrt{(1 + a_0)^2 + 4a_1(P_{in_{sp}} - P_u)}}{2a_1}$$

where a_0 and a_1 are cutting loss coefficients. The spindle power loss coefficients were determined based on experimental investigation and power balance equation.

Liu and Guo (2018) proposed a prediction model for SCE by integrating machine learning into process mechanics. First, a SCE prediction model was obtained based on the prior knowledge of process mechanics. It was then integrated with tree-based radiant boosting method to reduce the deviation between predicted and measured SCE values. The model was verified by milling H13 tool steel under dry cutting condition and Inconel 718 under dry and wet cutting conditions.

Yang et al. (2016) developed an energy prediction model for face milling process by integrating Gene Expression Programming (GEP) with Greedy Randomized Adaptive Search Procedure (GRASP). The proposed approach overcame the two shortcomings of GEP – passive knowledge mining and premature convergence. The application of proposed model was illustrated for a face milling case study. The proposed model was compared ANN, nonlinear regression, and GEP approaches. It was observed that the accuracy for training and validation for the proposed model was higher than the other models. ANOVA results depicted that cutting speed was the most significant parameter for energy prediction followed by depth of cut and feed rate.

2.6.3 State Based Models

Machine tools undergo a series of operating states to execute a machining process. Researchers have modelled the energy consumption by one or more operating states of the machine tools. ISO 14955-1 (ISO, 2014) defined machine tool operating state as combinations of operating modes of machine tool components. The components can operate in three modes in each operating state - on, off or hold. The machining energy consumption can be obtained as summation of the energy consumed during each operating state. The energy consumption models for each of the operating states are discussed in this section. The distribution of state-based machining energy models on a timeline is presented in Table 2.7.

Table 2.7 Summary of state-based machining energy models across timeline

Reference article	**Contribution**
Mativenga and Rajemi, (2011)	Machine tool set up, tool change, material removal, and embodied energy of the cutting tool was considered for energy modelling.
Behrendt et al. (2012)	Stand-by energy consumption of different machine tools was modelled and compared. It was observed that the stand-by energy consumption for different machine tools is significantly different based on the size and complexity of the machine tools.
Balogun and Mativenga, (2013b)	Basic, ready, tool change, air-cutting, and cutting states were considered and energy was modelled as: $$E_t = E_b + E_r + P_{tc}t_{tc}\left[INT\left(\frac{t_2}{T}\right) + 1\right] + P_{air}t_{air} + (mn + c + P_{cool} + k\dot{v})t_c$$ m is spindle speed coefficient and c is constant.
Arif et al., (2013)	Material removal, idle running, tool replacement states, and embodied energy of the cutting tool were considered for energy modelling.
Li et al., (2014)	Cutting state energy consumption was modelled considering the iron, copper and idling losses.
Wang et al., (2014b)	Idle, cutting and tool change states were considered for modelling of direct machining energy. Embodied energies of cutting tool and coolant were included in the energy model as indirect energy.
Peng et al., (2014)	Start-up, idle, rapid transverse, and cutting states were considered for energy modelling.
Hu et al., (2015)	Air cutting and cutting states, embodied energy of the material were considered for estimation of cutting state energy using a feature based approach.
Guo et al., (2015)	Machining energy was modelled based on rapid transverse, spindle acceleration and material removal states.
Zhang et al., (2016)	Stand-by, cutting, and losses were considered for energy modelling.
Li et al., (2016a)	Developed a comprehensive energy consumption model for machining process considering the energy consumed during stand-by, air cutting, cutting, and tool change operations. $$E_t = P_{st}(t_{st} + t_{air} + t_c + t_{tc}) + P_{auc}(t_{air} + t_c) + \left(P_{s\_motor} + P_{s\_transmission}\right)(t_{air} + t_c) + \sum_i \left(P^i_{f\_motor} + P^i_{f\_transmission}\right)(t_{air} + t_c) + (P_{removal} + P_{ad})t_c$$ where P_{s_motor} and $P_{s\_transmission}$ are power of spindle motor and mechanical transmission of spindle drive, respectively; $P^i_{f\_motor}$ and $P^i_{f\_transmission}$ are power for servo motor and mechanical transmission in the ith feed drive shaft. Temporal features and composition of energy consumption of CNC machining are analyzed.
N. Xie et al., (2016)	The energy consumption of basic, cutting, air cutting, and peak machining states was modelled and then machine tool energy evaluation model was established using Generalized Stochastic Petri Nets (GSPN).

Table 2.7 Summary of state-based machining energy models across timeline (Contd.)

Reference article	**Contribution**
Lu et al., (2016)	Calculated the energy consumption for multi-pass turning considering the energy consumption due to idle running, tool change, cutting, tool wear, and production and disposal of cutting fluid.
Lv et al., (2016)	Performed experimental analysis for energy consumption during cutting and non-cutting states (stand-by, coolant supply, spindle rotation, axis movement, etc.). The study concluded that non-cutting power varies with machine tool for milling machine tools but is independent of machine tools for lathes. The energy consumption is reduced at higher MRR.
Huang et al., (2016)	Provided model for spindle start up energy.
L. Li et al., (2017a)	Modelled the energy consumption based on five operating states: stand-by, workpiece set-up, air cutting, cutting, and tool change. $$E_t = P_{st}t_{st} + P_{st}t_{setup} + (P_{st} + P_{auc} + P_u) * t_{air} + (P_{st} + P_{auc} + P_u) * t_c + (1 + c_0)k * MRV + P_{st}t_{tc}\frac{t_c}{T}$$
Zhang et al., (2017a)	Modelled the energy consumption for multi-pass milling operations considering the energy consumed during machine start up, stand-by, machine ready, cutting, and tool change operating states. $$E_t = E_{start} + \sum_{i=1}^{N} P_0 t_{0i} + \sum_{i=1}^{N}(P_0 + kn_i + b)t_{ri} + \sum_{i=1}^{N}(P_0 + kn_i + b + k_1 v_c^{x_1} f^{x_2} a_p^{x_3} a_e^{x_4})t_{ci} + \sum_{i=1}^{N} t_{ttc} P_0 \frac{t_{ci}}{60T_i}$$
Rief et al., (2017)	Calculated the machining energy as the summation of basic energy, cutting energy, coolant energy, and tool manufacturing energy.
Ma et al., (2017a)	Proposed specific energy estimation model for material removal during milling process considering cutting energy and air-cutting energy.
Lv et al., (2017)	Proposed an energy prediction model for spindle acceleration using moment of inertia of spindle drive system.
Hu et al., (2018a)	The feature based approach developed by Hu et al. (2015) was further used to calculate the energy consumption during tool change and tool path in run-time mode.
Lv et al., (2018)	Divided the cutting state power consumption as stand-by power, operational power, cutting power, and power loss due to cutting load.
Chen et al., (2018)	Considered idle, cutting and tool change states for modelling of direct machining energy and Embodied energies of cutting tool and coolant as indirect energy.
Z. Y. Liu et al., (2018a)	Modelled the machining energy consumption including the direct energy by machine tool and indirect energy due to embodied energy of cutting fluid, cutting tool, and workpiece material.
Jia et al., (2018)	Provided energy consumption model for machine-operator system using the motion study.

2.6.3.1 Basic/standby state

The Cooperative Effort in Process Emission (CO2PE!) considered two operating states: basic and cutting (Balogun and Mativenga, 2013). The basic or stand-by state is defined as the operating state when the machine tool is switched on and the control system, spindle system, servo motors, cooling system, etc. are on hold. The energy consumption in stand-by state is generally experimentally measured. The stand-by power exists for the entire machining operation and therefore its energy consumption is high.

The power drawn by the machine tools during the stand-by state is independent of machining parameters. It fluctuates in certain range due to current and voltage instability. Zhang et al. (2016) modelled stand-by energy consumption using sliding filter to remove the data with large variation.

$$\hat{P}_{BM}(i) = \begin{cases} \dfrac{1}{i}\sum_{k=0}^{i-1} P_b(k) & i \le L \\ \dfrac{1}{L}\sum_{k=0}^{L-1} P_b(1-k) & i > L \end{cases}$$

where $\hat{P}_{BM}(i)$ is the estimated value of $P_b(i)$, L is the length of the sliding filter, i is the sampling point, and k is the counter.

Li et al. (2016a) modelled the stand-by power as summation of the power required by inverter, servo drivers and start-up related auxiliary operations. For multi-pass milling operations, the stand-by energy consumption was modelled as the summation of energy consumed during the stand-by state of each milling pass (Zhang et al., 2017a).

It has been observed in the literature that the stand-by energy consumption varies significantly for different machine tools based on their size, complexity, and degree of automation. Behrendt et al. (2012) developed a standardized procedure for energy monitoring of machine tools, which can be used to compare the energy consumption of various machine tools with different capacities. A standard workpiece was developed based on Japanese Standards Association (JSA) guidelines. The energy consumed to produce the designed workpiece using nine machine tools including four 3-axis VMCs, one 4-axis HMC, two 5- axis VMCs, one turn-mill, and one CNC lathe was measured (Figure 2.7) and it was observed that the stand-by energy consumption varied between 309 W to 4040 W.

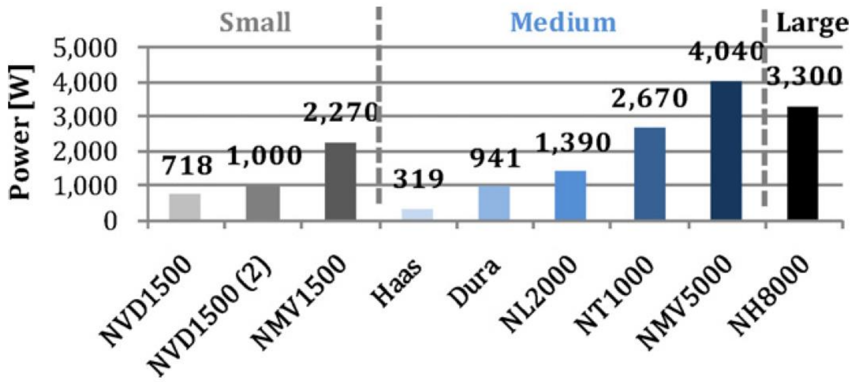

Figure 2.7. Variation of the stand-by power for different machine tools (Behrendt et al., 2012)

2.6.3.2 Cutting state

Cutting state of the machine tool is defined as the state when all the auxiliary components are active and material is being removed. The power consumed during this state consists of the power consumed by basic state, auxiliary components, and material removal by shearing process, and losses in form of friction and heat. The material removal energy has a non-linear relationship with cutting parameters. The summary of specific cutting energy models for machine tools is provided in Table 2.6.

Arif et al. (2013) provided a model for the cutting state energy consumption for a multi-pass turning operation as

$$E_{cutting} = (P_r + k\dot{v})\left[\frac{\pi DL}{1000 v_f f_f} + \sum_{i=1}^{m} \frac{\pi DL}{1000 v_r f_r}\right]$$

where m is the number of roughing passes.

Li et al. (2014) modelled the cutting state energy consumption as the summation of energy consumed for material removal, additional energy loss in electric motor, inertia energy loss of moving components of a machine tool, and idle energy consumed by the auxiliary components.

$$E_t = P_0 t_a + N \left\{ (P_0 + P_m) \frac{60L}{f_u} + \left[P_0 + P_m + (1+b) P_c \frac{60L}{n f_z z} \right] \right\}$$

where N is the number of cutting passes, z is the number of teeth of the milling cutter, f_u is the specified retraction speed, f_z is the feed per tooth (millimeter per tooth), L is cutting length in single pass (mm), b is the coefficient of energy loss in electric motor, P_m is the power consumed for the inertia of the moving component.

Li et al. (2016a) and Chen et al. (2018) modelled the power drawn during cutting state as the summation of power required for basic state, activation of auxiliary components, unloaded spindle rotation, material removal, and additional losses:

$$E_{cutting} = \int_0^{t_c} \left(P_{basic} + P_{auxiliary} + P_u + P_{material\ removal} + P_{additional} \right) dt$$

The cutting time (t_c) was modelled based on the length of the cutting path (L_c) as

$$t_c = \frac{L_c}{n z f_z}$$

Zhang et al. (2016) modelled the summation of cutting energy and additional losses using variable neighborhood search–based gene expression programming. Zhang et al. (2017a) provided energy consumption model for multi-pass milling operations. The energy consumed during cutting state was modelled as

$$E_{cutting} = \sum_{i=1}^{N} \left(P_0 + k n_i + b + k_1 v_c^{x_1} f^{x_2} a_p^{x_3} a_e^{x_4} \right) t_{ci}$$

where *N* is the number of passes ($1 \leq i \leq N$), n_i and t_{ci} are cutting speed and cutting time, respectively during the i^{th} pass, k, b, k_1, x_1, x_2, x_3 *and* x_4 are coefficients that can be determined based on the experimental data.

Ma et al. (2017a) proposed a specific energy estimation model for material removal during milling process considering cutting energy and air-cutting energy. The cutting energy was modelled as:

$$E_c = \int_0^{t_c} (1 + \partial)\big(k + 0.01\partial a_e a_p f_z nz\big)dt$$

where t_c is the material removal time, ∂ is power loss coefficient, k is constant, a_e and a_p are the width and depth of cut (mm), f_z is the chip load (mm/tooth), n is the spindle speed (RPM), and z is the number of teeth. The optimum cutting speed for minimum energy consumption was identified using MATLAB optimization toolbox. It was reported that an increase in MRR resulted into a reduction in energy consumption due to reduction in machining time up to a certain extent. After a threshold, the energy consumption started to increase because the power rise due to increased load dominated over the energy saving due to reduced processing time.

Hu et al. (2015) proposed an energy prediction method to estimate the cutting state energy consumption for machining a part in the design phase based on the features of the part. The design of the part was explained using a binary tree, each node of which represented a feature of the geometry. The machining energy for each feature was classified into three parts, embodied energy of the material (FMEnergy), air cutting energy (FAEnergy), and material removal energy (FTEnergy).

$$\mathrm{FMEnergy} = \mathrm{MRV} * \mathrm{E_v}$$

$$\mathrm{FAEnergy} = \sum_{j=1}^{J}\sum_{k=1}^{K}\left[P_1^{(jk)} P_2^{(jk)} \dots P_{mj-1}^{(jk)} P_{mj}^{(jk)}\right] * \left[s_1^{(jk)} s_2^{(jk)} \dots s_{mj-1}^{(jk)} s_{mj}^{(jk)}\right]^T * \frac{d_{jk}}{v_{jk}}$$

$$\text{FTEnergy} = \sum_{j=1}^{J} WA_j * SEC_j$$

where J is the number of the processes required to machine one feature, K is the number of machining activities for each process, d_{jk} and v_{jk} are the distance and feed in x,y, and z directions respectively during the k^{th} activity of the j^{th} process, and WA_j is the machining allowance (cm^3) for the j^{th} process. The applicability of the proposed method was demonstrated for a shaft component manufacturing by an automotive component manufacturer. The energy consumed for the shaft was calculated with 92% accuracy using the proposed method.

2.6.3.3 Machine ready state

Balogun and Mativenga (2013) introduced a third operating state, machine ready state; which is the transitional state between basic and cutting states. Transitional state consumes additional energy for spindle rotation and axis movement. The power models for spindle rotation and axis movement are generally obtained using regression analysis. Details for these power models are given in sections 2.6.4.1 and 2.6.4.2.

Arif et al. (2013) provided a model for the energy consumption during machine ready state for a multi-pass turning operation as

$$E_0 = P_0[t_P + n(h_1 L_t + h_2) + (h_1 L_t + h_2)]$$

where m is the number of roughing passes, h_1 and h_2 are constants related to tool approach/departure time, and L is the cutting length.

Zhang et al. (2017a) provided a model for the energy consumption during machine ready state for multi-pass milling operations.

$$E_r = \sum_{i=1}^{N} (P_0 + kn_i + b)t_{ri}$$

where N is the number of passes ($1 \leq i \leq N$), t_{ri} is the time spent in the air cutting phase prior to contact with the workpiece during the i^{th} pass.

2.6.3.4 Start-up state

Start-up state refers to the spike during the machine tool start-up. The spike during start-up state is less than the peak power values due to spindle start-up or other rapid changes in the machine tool states. But the instant rise in power drawn may lead to additional energy consumption (Li et al., 2016a). The power consumption during this state is measured as a multiple of stand-by power.

2.6.3.5 Air-cutting state

Air-cutting state is defined as the state where all the components of the machine tool are active but no material is removed. The air cutting energy demand depends on the machine tool features and varies significantly among different machine tools for same cutting operation (Balogun et al., 2013). In this state, the spindle runs the tool path defined by the CNC program but does not remove any material. It is necessary in practical machining operations for safety. Chen et al. (2018) modelled the air cutting energy as

$$E_{air} = \int_0^{t_{air}} \left(P_{basic} + P_{auxiliary} + P_u\right) dt$$

Ma et al. (2017) modelled the air cutting energy as

$$E_{air} = \sum_{i=1}^{N} \int_0^{t_{air}} (x_1\omega^2 + x_2\omega + x_3) dt$$

where t_{air} is air cutting time, ω is the motor angular velocity (rad/s), x_1, x_2, and x_3 are the coefficients; and N is the number of air-cutting sub-intervals. The air-cutting time can be calculated based on the air-cutting length (L_{air}) and feed speed (Li et al., 2016a) as follows:

$$t_{air} = \frac{L_{air}}{nzf_z}$$

2.6.3.6 Spindle acceleration/deceleration state

The spindle acceleration/deceleration power ($P_{acc/dec}$) indicates the power required for accelerating or decelerating the spindle. The spindle is required to reach a specified speed within a short time period during this state (Li et al., 2016a). This causes a sudden peak in the energy consumption. The energy required for spindle start-up is usually considered equal to no-load energy or neglected in energy modelling studies for machine tools. This leads to errors in energy prediction for machining processes. Huang et al. (2016) proposed a methodology to determine the spindle start-up energy consumption. A quadratic mathematical model was established between spindle start-up energy and spindle speed. The feasibility and reliability of the proposed model was verified for 12 machine tools. It was reported in the study that for step speed regulation (SSR) machine tools, the time and energy data can be stored in discrete tables, whereas for step less speed regulation (SLSR) machine tools, the data should be stored as quadratic functions.

Guo et al. (2015) calculated the ($P_{acc/dec}$) based on the acceleration torque as

$$P_{acc/dec} = T_{acc/dec} * \omega = I * \alpha_{acc/dec} * \omega$$

where $T_{acc/dec}$ is the acceleration or deceleration torque (Nm), ω is the angular velocity (rad/s), I is the moment of inertia of the spindle (kg m^2), and $\alpha_{acc/dec}$ is the angular acceleration or angular deceleration (rad/s^2).

Lv et al. (2017) proposed an energy prediction model for spindle acceleration using moment of inertia of spindle drive system.

$$E_{sp\_acc} = \int_0^{t_{sp\_acc}} P_{sp\_acc}\, dt$$

$$P_{sp\_acc} = P_{SR}(n) + T_{sp\_acc} * \omega_m$$

$$t_{sp\_acc} = \frac{2\pi(n_2 - n_1)}{60\alpha_{sp}}$$

where n_1 and n_2 are the initial and final spindle speeds. The proposed model was validated for a CNC turning center and the spindle acceleration energy was predicted with an accuracy of 89.58%.

2.6.3.7 Cutting tool change state

The cutting tool is replaced when the machine tool is in idle state, i.e. the basic modules are turned on but the spindle and feed motors are turned off. The models for cutting tool change energy requirement are summarized in Table 2.8.

Table 2.8 Summary of energy models for cutting tool change state

Reference article	**Energy model**
Balogun and Mativenga (2013)	$E_{tc} = P_{tc}t_{tc}\left[INT\left(\frac{t_c}{T}\right) + 1\right]$
Arif et al. (2013); Li et al. (2016a)	$E_{tc} = P_{basic} * \ t_{tc}$ $t_{tc} = t_{pct}\frac{t_c}{T}$ where t_{pct} is the unit tool changing time
Chen et al. (2018)	$E_{tc} = \int_0^{t_{tc}} P_{basic}\, dt$
Zhang et al. (2017a)	For multi-pass milling operations $E_{tc} = \sum_{i=1}^{N} t_{ttc}\, P_0 \frac{t_{ci}}{60T_i}$ where N is the number of passes ($1 \le i \le N$), T_i is the tool life during the *i-th* pass (min), and t_{ci} is the cutting time during the *i-th* pass, t_{ttc} is the tool changing time.

The feature based approach developed by Hu et al. (2015) was extended to calculate the energy consumption during tool change and tool path in run-time mode (Hu et al., 2018a). This energy depends on the sequence of features to be performed on a workpiece and was termed as the energy consumed during feature transition (EFT). Hu et al. (2018a) studied the correlation between EFT and feature processing sequence and provided energy consumption models for tool change (E_{TC}) and tool path (E_{TP}) for transition from one feature to the next feature. However, the energy calculations for these models were error-prone, cumbersome and time consuming.

2.6.3.8 Additional load loss

Lv el al. (2018) characterized the power loss due to cutting load (PLCL), which accounts for up to 20% of the cutting power, but still got less attention. PLCL consists of two parts, power loss in the mechanical transmission due to cutting load (PLMT) and power loss in the spindle motor (PLSM). It is indicated that PLMT has linear relationship with spindle rotation speed (n) and cutting force (F_c), and can be modelled as:

$$\mathrm{PLMT} = b_m F_c \mathrm{n}$$

where b_m is constant. PLSM is modelled based on the spindle speed as:

When the motor speed is below base speed,

$$PLSM = \frac{900u^2 K_{v1}}{\pi^2}\left(\frac{\pi^2 D^2}{3.6 * 10^9}F_c^2 + b_m^2 F_c^2 + \frac{b_m \pi D}{3 * 10^4}F_c^2 + \frac{P_{um}\pi D}{3 * 10^4 n}F_c + \frac{2P_{um}b_m}{n}F_c\right)$$

When the motor speed is above base speed,

$$PLSM = K_{v2}\left(\frac{\pi^2 D^2 F_c^2 n^2}{3.6 * 10^9} + b_m^2 F_c^2 n^2 + \frac{b_m \pi D}{3 * 10^4}F_c^2 n^2 + \frac{P_{um}\pi D}{3 * 10^4}F_c n + 2P_{um} b_m F_c n\right)$$

where b_m, k_{v1} are constant coefficients, P_{um} is the power of mechanical transmission (W) without load, D is the diameter of the workpiece (mm), and u is the transmission ratio of the spindle shaft to the spindle motor. The proposed models were validated through a turning case study for three different materials on two different lathes. It was observed that cutting force had higher influence on PLCL as compared to cutting power. The energy loss due to cutting load (ELCL) was reduced up to 70.8% by proper selection of cutting parameters and machine tools.

2.6.3.9 Others

Many studies extended the energy consumption models for machine tools by including the embodied energy of cutting tools, cutting fluids, and workpiece materials (Hernández et al., 2017). The embodied energy of the cutting tool (U_{tool}) was modelled as (Arif et al., 2013; Chen et al., 2018; Mativenga and Rajemi, 2011)

$$E_{tool} = U_{tool}\left(\frac{t_c}{T}\right)$$

U_{tool} is calculated based on the energy required to fabricate the cutting tool material ($E_{material}$) (J/cm^3), volume of the cutting inserts (V_{insert}) (cm^3), number of cutting inserts (z), and number of cutting edges per insert (p) (Chen et al., 2018)

$$U_{tool} = \frac{E_{material}V_{insert}z}{N}$$

Wang et al. (2014a) and Chen et al. (2018) further added the embodied energy of the cutting fluids to the indirect energy consumption. It is calculated as the product of the specific embodied energy of the coolant and the coolant consumption rate (Wang et al., 2014a).

$$E_{coolant} = e_{coolant} * v_{coolant} * \rho_{coolant} * t_c$$

where $e_{coolant}$ is the specific embodied energy of the coolant (kJ/kg), $\rho_{coolant}$ is the density of the soluble oil (g/cm^3), $v_{coolant}$is the coolant consumption rate (liters/s).

Chen et al. (2018) calculated the embodied energy of the cutting fluids based on unit embodied energy of the coolant ($U_{coolant}$) and the coolant replacement time ($T_{coolant}$).

$$E_{coolant} = \frac{t_c}{T_{coolant}} * U_{coolant}$$

The unit embodied energy of the coolant is calculated as

$$U_{coolant} = (V_{in}+V_{ad})\eta\rho_{coolant}E_{oil}$$

where η is the concentration of the coolant, $\rho_{coolant}$ is the density of the soluble oil (g/cm^3), E_{oil} is the energy required to produce the soluble oil (J/g).

Liu et al. (2018b) also considered indirect energy consumption due to embodied energy of cutting fluid, cutting tool, and workpiece material. The proposed model was illustrated through a case study of Inconel 718 alloy machining using Tungsten carbide insert with (Ti,Al)N/TiN coating under dry and flood cooling conditions. Machine energy consumption was higher in flood cutting due to the energy intensive coolant pump. However, at high parameter settings, the effect of tool life was significant in cumulative energy demand and hence dry cutting consumed more energy than flood cutting at higher MRR. Carbon emissions and environmental impacts also exhibited similar trends at different parameter settings. However, the model was valid for a specific combination of cutting tool and workpiece material.

Jia et al. (2018) proposed an energy consumption model for machine-operator system considering the energy consumption by operator activities along with machine tool. The energy consumption by the machine tool activities and operator activities were calculated using the motion study. The proposed model was implemented for a case study on a CK6153i CNC Lathe and the total energy consumption (MEC+OEC) was calculated for five machining stages.

2.6.4 Component Based Models

Machine tool components are defined as mechanical, electrical, hydraulic, or pneumatic devices of a machine tool, or their combination such as cooling unit, spindle unit, drive axis, controller, etc. They are considered as the basic energy consumption units of the machine tool and therefore energy modelling at component level provides better transparency.

Many studies have provided analytical or experimental energy models for different machine tool components. These energy models are used to estimate the total energy required for the machining operation. For example, Aramcharoen and Mativenga (2014) calculated the total energy consumption of the milling process as the summation of energy consumed for basic state, tool change, unloaded spindle rotation, feed motion, cutting, and cutting fluid supply. The effectiveness of the proposed model was illustrated through a milling case study. Theoretically calculated energy consumption (181.51Wh) was compared with the experimentally measured value (191.52Wh) for closed pocket milling. The difference of 5.23% in the energy consumption was because of increased energy due to tool wear progression and transition states. The energy models were used to compute the milling energy consumption with different tool paths, and it was reported that contour offset was the most energy efficient tool path for closed pocket milling.

Abele et al. (2015a; 2012) proposed simulation based energy prediction model for a specific machining task. The interactions of the machine tool components and their power models were used as a basis for calculating the energy consumption without performing any experiments. A physical machine controller was connected to the simulator to imitate the real machining environment.

He et al. (2012b) proposed an energy estimation method for machining processes by analyzing the correlation between NC codes and the machine tool components. The energy consumed by individual components was estimated based on their power characteristics and the information extracted from the NC programs. The applicability of the proposed method was illustrated for machining of two workpieces on CNC VMC and CNC lathe.

Hu et al. (2012) analyzed the energy consumption by fixed and variable energy consuming components of the machine tools and proposed an online approach for monitoring the energy efficiency and energy utilization ratio of the machine tools without using force/torque sensors. Energy mapping for machine tools based on the functional requirements and corresponding machine tool components was also presented (Triebe et al., 2018; Um et al., 2015).

Albertelli et al. (2016) proposed an energy evaluation model for a machine tool considering the energy consumed by stand-by mode, functional modules (including axes, tool changer, spindle, chiller, coolant, chip conveyor, and pallet clamp), and cutting operations. The power and operational time for each machine tool component were modelled and used to evaluate the total energy consumption by the machine tool.

Moradnazhad and Unver (2017b) developed a model-based approach to predict energy for a complex turn-mill machine tool. The total energy consumption was estimated as a sum of idle, auxiliary and cutting energies. The turn-mill machine tool can machine more than one features simultaneously. Therefore, cutting energy was computed as sum of energy required by each feature. Auxiliary energy consists of energy demands of various sub-systems such as main spindle, sub-spindle, milling head, turning turret, tool magazine, coolant pump, chip conveyor, chiller, and lubricant pump. The total energy consumption for the turn-mill machine tool was computed as

$$\begin{aligned}
E_t = P_{idle} * \Delta t_1 &+ \int_0^{t_1} P_{main\ spindle}\, dt + \int_0^{t_2} P_{sub\ spindle}\, dt + \int_0^{t_3} P_{milling\ spindle}\, dt \\
&+ \int_0^{t_4} P_{milling\ head\ feed}\, dt + \int_0^{t_5} P_{turret\ feed}\, dt + \int_0^{t_6} P_{tool\ change}\, dt \\
&+ P_{coolant} * \Delta t_7 + P_{conveyor} * \Delta t_8 + P_{chiller} * \Delta t_9 + P_{lubrication} * \Delta t_{10} \\
&+ \sum_{1=1}^{m} E_{Feature_i}
\end{aligned}$$

where m is the number of features. The model effectiveness was tested with two case studies and it was reported that the proposed model can predict energy with 90% accuracy. Further, the energy demand of various auxiliary units was analyzed and it was observed that 61% of the energy was consumed during idle state whereas only 6% of the energy was required for actual material removal process.

Shin et al. (2017) proposed an energy assessment methodology based on component energy modelling and used the model for online energy optimization. Data from NC programs, process planning, and energy measurement was used to develop component energy models. The data stored in repository was extracted, filtered, and synchronized to develop energy models based on second-order regression and ANN approaches. The models were then optimized in real time using divide and conquer methodology.

Mohammadi et al. (2017) proposed an approach for real time visualization of the mechanical, electric, fluidic, and thermal energy flows in a machine tool including its components using 2-D Sankey diagrams. The electrical and thermal energy consumption for machine tool subsystems were obtained by experimental measurements and NC codes. Fluidic power was calculated using the machine tool datasheets. However, the proposed approach was an intrusive load monitoring approach involving large number of sensors. Therefore, the energy measurement was very complex, expensive, and difficult to apply for each machine tool.

Lee et al. (2015) modelled the power consumption for stand-by, coolant system, spindle, feed drive system, and material removal. Stand-by and coolant power was considered to be constant. The spindle, feed movement and cutting power were modelled as linear functions of spindle rotation speed, feed rate and MRR, respectively. A power profile simulator was developed consisting of an NC code analyzer and time wise power profile solver. The proposed model was verified for six machine tools. The proposed model accurately estimated the energy consumption by spindle, feed system and coolant. It was observed that cutting energy was influenced by the process parameters but did not vary significantly with the machine tools. Whereas the spindle and feed systems energies vary significantly with machine tools.

Wei et al. (2018) classified the machine tool components into non-time-varying units (NTVUs) and time-varying units (TVUs) based on their energy characteristics. The energy models were developed based on component state and coupling relationship between different energy units using Business Process Model and Notation (BPMN). BPMN was used over the other energy modelling approaches like Petri nets and Discrete Event System Specifications (DEVS) because it provides a standard specification between design and implementation and assists in process visualization.

Altıntaş et al. (2016) proposed an energy consumption model for feature based milling. The energy consumption for processing of each feature was calculated as sum of basic, auxiliary and cutting energies. The auxiliary energy was defined as the summation of energy consumed by various machine tool components such as spindle, feed axes, coolant pump, ATC, and chip conveyor. The energy consumption models for each component were explained in detail. The cutting energy was calculated as difference in total energy consumption and air cutting energy. The proposed approach was verified for milling of three features on aluminum 6061 workpiece with four different sets of process parameters. Energy consumption for six different tool paths were compared under same operating conditions. It was observed that zigzag tool path consumed least energy.

Lee et al. (2017) developed a simulation approach for modelling and optimization of machining energy using a virtual machine tool (VMT). The VMT was designed consisting models for CNC controller, machine tool components, and cutting process to estimate the machine tool energy demand. The parameters of the proposed simulation models were determined experimentally. The effectiveness and robustness of the proposed model were verified by a milling experimental study. It was reported that the thrust force and energy consumption computed by VMT had accuracy of 96.7% and 99.7%, respectively. The energy consumption was optimized using GA toolbox in MATLAB and the energy consumption was reduced by 13%. Wirtz et al. (2018) presented a simulation based study to predict the power consumption for a milling process considering the fixed, material removal and spindle power. The energy consumption by different components vary significantly with different machine tools and processes. A summary of the energy distribution among machine tool components provided in the reference articles is presented in Table 2.9. The energy models for different components are discussed below:

Table 2.9 Energy distribution among machine tool components for different machine tools

Reference article	Machining process	Energy consumption by machine tool components							
		Coolant pump	Spindle motor	Stand-by	Feed axis motor	Material removal	Tool change	Chip conveyor	Lights
Fujishima et al. (2014)		60%	20-45						
Li et al. (2013)	milling	dry	25-41	35-60	1-2	9-18			
Rahäuser et al. (2013)	machining	50%							
Balogun and Mativenga (2013)	lathe	14.85	24.43	47	16		4.84		
	milling 1		8.29	28	17		7.02		
	milling 2		4.26	50.29	18				
Götze et al. (2012)	milling	33	25					3.7	2
Behrendt et al. (2012)	milling	47	5.2	20	1.9		18.4		
Moradnazhad and Unver (2017b)	turn-mill	-	8	61	1	6	3		
Hu et al. (2017a)	milling	27.15	12.84	48.12	4.7	7.1			
	turning	-	17.56	14.59	1.19				

2.6.4.1 Spindle energy (E_{sp})

Spindle energy refers to the energy required by the spindle transmission module for rotating the spindle. It is calculated based on the power required by the spindle motor. The power consumed by the spindle motor at no load condition is termed as unloaded spindle power (P_u). The unloaded spindle power varies with rotational speed of the spindle motor, and can be acquired using simple statistical measurement approach. Many studies have modelled the P_u as linear function of spindle speed (Lee et al., 2015; Lv et al., 2016; Pavanaskar and Mcmains, 2015; N. Xie et al., 2016; Zhang et al., 2017b; Zhou et al., 2018)

Altıntaş et al. (2016) modelled the spindle energy consumption as piecewise linear function of spindle speed. Machine tools consist of complex transmission system. Therefore, Luan et al. (2018a) suggested to model the unloaded spindle power as a piecewise quadratic function as:

$$P_u = \begin{cases} A_1 n + B_1 n^2 + C_1 & (0 < n \leq n_1) \\ A_2 n + B_2 n^2 + C_2 & (n_1 < n \leq n_2) \\ \cdots & \cdots \\ A_n n + B_n n^2 + C_n & n_{n-1} < n \leq n_n \end{cases}$$

where A, B and C are the coefficients which can be calculated from the experimental results. The proposed model was explained theoretically based on the working principle of the motor. The effectiveness of proposed model was verified experimentally for a milling process. It was evident from the accuracy analysis that the models were in good agreement with the experimental data.

Moradnazhad and Unver (2017b) provided piecewise polynomial functions for power consumption by spindle units of a turn-mill center as:

For main spindle: $$P_{main\_sp} = \begin{cases} A_1 n + B_1 n^2 + C_1 & n < n_1 \\ A_2 n + B_2 n^2 + C_2 n^3 + D_2 & n \geq n_1 \end{cases}$$

For sub spindle:

$$P_{sub\_sp} = \begin{cases} A_1 n + B_1 n^2 + C_1 n^3 + D_1 & n < n_1 \\ A_2 n + B_2 n^2 + C_2 n^3 + D_2 & n \geq n_1 \end{cases}$$

For milling spindle:

$$P_{mill\_sp} = \begin{cases} A_1 n + B_1 n^2 + C_1 n^3 + D_1 n^4 + E_1 & n < n_1 \\ A_2 n + B_2 n^2 + C_2 n^3 + D_2 n^4 + E_2 & n \geq n_1 \end{cases}$$

Some studies provided spindle energy models based on the electrical characteristics of the motor. For example, Wójcicki et al. (2018) modelled the spindle energy consumption as the summation of mechanical power output and electrical power losses:

$$P_{sp} = K_T i_q(\tau)\omega + 3R(i_q^2 + i_d^2)$$

where K_T is the torque constant (Nm/A), i_q is the quadrature current (A), ω is the motor speed (rad/s), R is the winding resistance (Ω), and i_d is the direct current (A).

Borgia et al. (2017) modelled the power for spindle system as summation of mechanical power output (P_{M_sp}) and power loss due to motor resistances (P_{R_sp}).

$$P_u = P_{M\_sp} + P_{R\_sp} = T_{M\_sp} * \omega_{sp} + R_s * i_q^2$$

where T_{M_sp} is the resistant torque (Nm) on the spindle motor, R_s is the phase resistance (Ω), and i_q is the quadrature current (A).

Mohammadi et al. (2017) modelled the spindle energy consumption as

$$P_{sp} = 3I^2 \frac{L_h^2 R_r \omega}{R_r^2 + L_r^2 \omega}$$

where *I* is the current, L_h is the mutual inductance, L_r is the rotor inductance, and R_r is the rotor resistance.

Avram and Xirouchakis (2011) presented a mechanistic model for energy consumption assessment for a machine tool system considering the dynamic power characteristics of spindle and axes feed systems. Three important aspects for spindle energy evaluation were identified as: (i) the transient phases and energy recovery possibilities, (ii) the unloaded power consumption and (iii) the power fluctuations due to dynamic cutting loads.

Liu et al. (2015a) proposed an energy prediction model for the main driving system (MDS) of a machine tool considering the power loss of the motor, friction loss of mechanical transmission system, cutting power, magnetic field energy of the motor, and the kinetic energy of the mechanical transmission system and the motor rotor. The energy consumption of the MDS was divided into three states of start-up, idle and cutting. The energy consumption by the spindle motor and transmission system (main driving system) in each of the three states was modelled. The energy consumption in start-up (E_{s_MDS}) and idle state (E_{s_MDS}) was obtained as functions of spindle speed, and cutting energy (E_{s_MDS}) was estimated based on cutting power (P_c) and load loss coefficients (α_1 and α_2) as:

$$E_{s\_MDS} = x_1 n^2 + x_2 n + x_3$$

$$E_{u\_MDS} = P_u * t_u \,, \qquad P_u = g(n)$$

$$E_{c\_MDS} = \int_0^{t_c} (\alpha_2 P_c^2 + (1+\alpha_1)P_c + P_u)\, dt = \alpha_2 \int_0^{t_c} P_c^2 dt + (1+\alpha_1)\int_0^{t_c} P_c dt + t_c * P_u$$

The predicted results were compared with the experimental values and the error was analyzed. The proposed methodology was illustrated with a case study of CNC lathe and 7.73% deviation was obtained between actual and predicted energy values.

2.6.4.2 Feed axis motor energy (E_{feed})

Feed axis motor energy (E_{feed}) is the energy required by the axis motor to move the machine tool table or cutting tool in x, y and z directions at the specified feed. The feed energy is calculated by adding the energy required by each feed axis motor as:

$$E_{feed} = \sum_{i=1}^{m} \int_{t_{i_{start}}}^{t_{i_{end}}} P_{feed_i} * dt$$

where P_{feed_i} is the power required by the feed motor for movement in i^{th} direction, m is the number of axis motors in the machine tool. The energy required for rapid traverse can also be calculated similarly.

Many studies have modelled the P_{feed} as linear function of feed rate (Altıntaş et al., 2016; Lee et al., 2015; Moradnazhad and Unver, 2017b; Pavanaskar and Mcmains, 2015; N. Xie et al., 2016; Zhang et al., 2017b). Some studies modelled the P_{feed} as quadratic function of feed rate (Lv et al., 2016; Zhou et al., 2018).

Campatelli et al. (2015) presented an energy consumption model for machine tool axes involving the equivalent mass and friction of the axes.

$$E_{axis} = \int_0^S \left[(Mx * a_x(s) + \mu_x * Mx * g) + \left(My * a_y(s) + \mu_y * My * g\right)\right] ds$$

where Mx and My are the equivalent masses of *x* and *y* axes respectively, $a_x(s)$ and $a_y(s)$ are the instantaneous accelerations, $\mu_x$and μ_y are the equivalent friction coefficients, s is the tool path length, and g is the gravity acceleration. Different axes have different equivalent mass and friction, therefore, the energy consumption is also different. The proposed approach was experimentally verified for a milling case study.

Edem and Mativenga (2016) proposed a predictive model for energy consumption by feed axes motors of a machine tool considering weight of machine tool axes, workpiece and feed force acting on the axes.

$$P_f = P_0 + (aWf + bW)$$

where a and b are constants and W is the summation of weight of machine tool axes, vice and workpiece. The proposed model was validated for a CNC milling center. The authors used this model to refine the energy consumption models for the machine tools and developed an energy estimation software to predict the energy consumption using the proposed energy model with NC codes (Edem and Mativenga, 2017b).

The workpiece setting and orientation also affect the feed motion and hence feed energy. Sato et al. (2017) investigated the effect of workpiece setting on the energy consumption by feed drive systems. The energy consumed by the feed drive system was measured for a five-axis machining center. Further, a mathematical model was proposed to estimate the feed system energy consumption (P_{IA}) considering losses due to friction (P_{LF}), motor (P_{LM}) and amplifier (P_{LA}) as:

$$P_{IA}(\omega) = P_{LF}(\omega) + P_{LM}(\omega) + P_{LA}(\omega) + T_d\omega$$

where T_d is the disturbance torque and ω is the angular velocity of the motor. The model was verified for motion accuracy evaluation of five-axis machining center using cone-frustum cutting model.

Further, the feed motion can be divided into horizontal and vertical movements. Luan et al. (2018a) provided the energy models for feed motion in horizontal (x and y) and vertical (z) directions for a machining center as:.

$$\begin{cases} P_{xf} = C_x + b_{1x}f + b_{2x}f^2 + \cdots\cdots + b_{nx}f^n \\ P_{yf} = C_y + b_{1y}f + b_{2y}f^2 + \cdots\cdots + b_{ny}f^n \end{cases}$$

$$\begin{cases} P_{z\_up} = C_{z\_up} + b_{1z\_up}f + b_{2z\_up}f^2 + \cdots\cdots + b_{nz_{up}}f^n \\ P_{z\_down} = C_{z\_down} + b_{1z\_down}f_{z\_down} + b_{2z\_down}f_{z\_down}^2 + \cdots\cdots + b_{nz\_down}f_{z\_down}^n \end{cases}$$

where P_{z_up} and P_{z_down} are the power of feed motion power along Z-up axis and Z-down axis, respectively, f_{z_up} and f_{z_down} are the feed upwards and downwards respectively, C_{z_up}, C_{z_down}, b_{1z_up}, b_{2z_up}, ……, b_{nz_up}, b_{1z_down}, b_{2z_down}, ……, and b_{nz_down} are the coefficients which can be calculated from experimental data.

The rapid feed power model was given as

$$\begin{cases} P_{FDA} = P_{FD}(v_{fa}) + T_{fa} * \omega_f \\ P_{FDC} = P_{FD}(v_{fmax}) \\ P_{FDD} = P_{FD}(v_{fd}) \end{cases}$$

where P_{FDA}, P_{FDC} and P_{FDD} are the power consumption during acceleration, steady and deceleration states; v_{fa}, v_{fmax} and v_{fd} are the feed rates during acceleration, steady and deceleration states; T_{fa} and ω_f are the accelerating torque and angular velocity of the servo motor, respectively.

Calvanese et al. (2013) proposed power models for axes motors and axes chiller as:

$$P_{axes} = F_m(t) * v(t) + R * 2 * \left(\frac{F_m(t)}{K_t}\right)^2$$

where F_m is the force of motor (N), R is the phase resistance (Ω), K_t is the force constant of the motor (N/A_{rms}), and v is the axis velocity (m/s).

$$P_{axes\ chiller} = P_{sby} + \theta * P_r(t)$$

where P_{sby} and P_r are the constant and variable components of axes chiller power, respectively and θ is a model coefficient.

Yoon et al. (2018) analyzed the effect of gravitational force on the power consumption of feed drive units of a machine tool and proposed an improved power model for the machine tool rotational axes.

$$P_{axes} = [\{C_{STO-P} * f + C_{STI-P}(X)\}\{C_{STO-N} * f + C_{STI-N}(X)\}] * \begin{bmatrix} P_P \\ P_N \end{bmatrix}$$

where X is the position of the table, C_{STO-P}, C_{STI-P}, C_{STO-N}, C_{STO-N} are power coefficients, and P_P & P_N are the indicators of feed direction. The proposed model was experimentally verified for a 5-axis machining center and it was observed that the power consumed by the rotational axis was significantly influenced by the position of center of mass and the direction of movement.

Borgia et al. (2017) modelled the power for feed system as summation of mechanical power output (P_{M_axis}) and power loss due to motor resistances (P_{R_axis}).

$$P_{axis} = P_{M\_axis} + P_{R\_axis} = k_t * i_{q_{rms}} * \omega + R_s * i_q^2$$

where $i_{q_{rms}}$ is the axis motor quadrature current (rms value) ($\mathrm{A_{rms}}$), i_q is the axis motor quadrature current (A), ω is the axis motor velocity (rad/s), k_t is the axis motor torque constant (Nm/$\mathrm{A_{rms}}$) , R_s is the axis motor stator resistance (Ω). The application of proposed model was shown for a milling case study and it was observed that the proposed simulator can predict the energy consumption with an accuracy of more than 90%.

Mohammadi et al. (2017) modelled the energy consumption by servo motors as

$$P_{servo} = 3I\omega k_i + 3I^2 R_a$$

where I is the current, k_i is the back electromotive force constant and R_a is the armature resistance.

2.6.4.3 Coolant pump energy ($E_{coolant}$)

Coolant pump energy ($E_{coolant}$) refers to the energy required by the coolant pump motor to supply the cutting fluid to the cutting area. The coolant power is generally constant for a machine tool. It can be either obtained from machine tool technical specification data or measured experimentally.

2.6.4.4 Automatic tool changer energy (E_{atc})

The energy consumed by the automatic tool changer includes the energy required for the movement of tool turret for changing the tools, and the loading and unloading of the cutting tools. The turret is rotated to a specific position to pick the tool specified by the NC code. The energy required by the ATC can be calculated as

$$E_{atc} = P_{atc} n_{tc} \frac{t_c}{T}$$

where P_{atc} is the power required by ATC motor, n_{tc} is the number of cutting tools used for one machining operation. P_{atc} is constant for a specific machine tool and can be either obtained from the machine tool technical specification data or measured experimentally.

2.6.4.5 Chip conveyor energy (E_{cc})

Chip conveyor energy (E_{cc}) refers to the energy required by the chip conveyor motor to remove the metal chips from the machine tool. The chip conveyor power is generally constant for a machine tool. It can be either obtained from machine tool technical specification data or measured experimentally.

2.6.4.6 Fixed energy consuming components

A few components of the machine tools such as fan motors, servo systems, control panel, relays, lights, lubrication system, etc. are always activated when the machine tool is switched on and these components consume a fixed amount of energy. ISO/WD14955-1 defined the fixed energy state as the state when the mains, machine control, peripheral units are on and machine processing unit and machine motion unit are ON HOLD (Hu et al., 2012). ON HOLD is the condition when the unit is on but not operational and no processing or movements are carried out. The fixed energy can be computed as a product of fixed power and total machining time. The fixed power is constant for a machine tool and therefore can be experimentally measured and stored in the database.

Modern CNC machine tools have a centralized lubrication system with periodically changing operational status. The activation of lubrication system is based on the oil pressure and temperature. Therefore, the fixed energy consumption can be modelled as a piecewise function based on lubrication system activation (Zhou et al., 2018) as:

$$P_{fixed} = \begin{cases} C_0 & 0 < t \le \tau_0 \\ C_1 & t \in (\tau_{oil} * n_{cyci}), n_{cyci} = 1,2,3 \ldots \\ C_2 & t \in (\tau_{uoil} * n_{cyci}) \end{cases}$$

where τ_0 is the pre-heat time of machine, τ_{oil} is the amount of time oil is needed for one work cycle of the lubrication system, τ_{uoil} is the non-oil supply time during one work cycle of lubrication system, n_{cyci} is the ith lubrication work cycle, C_0 is the stand-by power consumption in pre-heat time, C_1 is the stand-by power consumption in oil supply time, and C_2 is the stand-by power consumption when oil is not supplied.

2.6.5 Therblig Based Energy Models

Another energy consumption modelling approach is based on the micro motion of the machine tool. The machining tasks are completed through execution of a series of energy consuming machine tool motions, and energy characteristics of CNC machine tools can be determined based on their motion control. Therblig based energy modelling has emerged as a powerful tool for energy analysis of the fundamental motions of the machine tools. Therblig is considered as the basic energy demand unit. Therbligs are defined as a set of fundamental motions which are executed by machine tool to complete a machining operation (Lv et al., 2014). The Therblig based energy demand modelling divides the machining processes into a series of activities, and activities into Therbligs; and Therbligs are linked with the machining state. Lv et al. (2014) provided models for calculation of power consumption by different Therbligs. Jia et al. (2016a) provided a methodology to divide a machining process into activities using Therblig activation information. Jia et al. (2017a) extended the study to predict the non-value added energy based on Therblig based power models for turning process. Jia et al. (2017b) proposed, for the first time, a Therblig embedded value stream mapping (TVSM) method to map the energy consumption by the machining process at micro level. The proposed approach provided better energy transparency and clearly showed the energy waste during machining. The proposed TVSM enables the users to improve time and energy efficiencies in machining without decreasing the machining quality. The above papers (Jia et al. 2017b; 2016a; 2014; Lv et al. 2014) validated the proposed models for turning processes. Therblig based analysis provided a deep insight into the motion and energy demand of a machining process.

2.7 MACHINING ENERGY SAVING STRATEGIES

The need for improving energy and resource efficiencies has led to analyses of energy saving potentials and strategies for machine tools. The common energy losses occurring at machine tool levels have been studied in the literature, and measures to reduce these losses are briefly explained (Schmitt et al., 2011). Long operating time, inefficient loading of electric drives, inefficient components, and poor process design may lead to significant energy waste in machine tools. A large number of energy saving measures for machining operations have been proposed in the literature.

Zein et al. (2011) presented a structured approach to categorize the energy saving measures based on energy reduction, reuse and recovery. The functional requirements and corresponding design parameters to fulfill the requirements were defined and mapped in a structured way to provide clarity towards selection of suitable sequence of improvement measures. Duflou et al. (2012) divided the energy saving measures at five levels: unit process, multi-machine system, factory, multi-factory, and supply chain levels. A review of energy saving approaches for each level was provided.

Since the number of studies reporting energy saving measures for machine tools are large, a careful classification and simplified discussion is important for clear understanding. In the present study, the energy saving strategies are classified based on three phases: design, macro process planning and micro process planning. In this section, the strategies to reduce fixed and variable components of machining energy are discussed for each phase.

2.7.1 Design Phase

It is well evident in literature that the energy efficiency of the machine tools can be improved by incorporating improvements such as design of light weight components, reduction of stand-by energy consumption, use of intelligent control loops, and improvement in structural aspects of machine tools during machine tool design. Reduction in weight of moving parts of the machine tool will reduce the inertia and lesser power will be required. The use of light-weight materials such as aluminum alloy, fiber reinforced plastic (FRP) and fine ceramics can be used for machine tool structure (Fujishima et al., 2014).

Kroll et al. (2011) studied the energy saving potential of machine tools by reducing the weight of the machine tool components and its direct and indirect impacts on the energy efficiency. Maximum possible mass reduction for different strategies and subsequent energy reduction were studied.

Another important strategy is to improve the energy efficiency of machine tool components (Duflou et al., 2012; Lv et al., 2016). Abele et al. (2011) analyzed the energy saving potentials for machine tool spindle units. The study reported that the spindle energy can be reduced by reducing the consumption of compressed air, hydraulics and stand-by power.

Albertelli (2017) proposed a systematic approach for comprehensive evaluation of energy consumption by two alternative spindle systems using a combination of empirical modelling and experimental analysis. A direct drive spindle system was developed and the energy consumption was compared with a traditional spindle system consisting motor-transmission. The model was tested for a milling case study under a set of operating conditions and it was observed that the new spindle system consumed considerably less energy as compared to the traditional system due to absence of gear box and other auxiliary components.

Brecher et al. (2013) analyzed the energy consumption and energy saving measures by the hydraulic units of the machine tools. The study was extended and a novel design for an energy efficient hydraulic unit was proposed based on a variable displacement pump with a hydraulic booster and a variable speed control unit (Brecher et al., 2017).

Edem and Mativenga (2016) reported that the power consumed by machine tool axes can be reduced by reducing the weight of the axes. Okwudire and Rodgers (2013) presented design of a new feed drive system for energy efficient machining. The feed drive was actuated and configured based on the machine tool operating state. The experimental investigations reported that the proposed feed drive consumed lesser energy while the accuracy and speed were improved.

Brecher et al. (2012) presented an optimal cooling system with tunable compressor, pressure controlled circulation pump, optimized chiller, and controlled EC-fan. The study reported that the coolant energy can be reduced between 30 to 60% using the optimal coolant pump. Rahäuser et al. (2013) discussed the application of demand based control strategy for coolant pump. The energy consumption of the coolant system was reduced by 73% by using demand based control for a case study. A dust and chip vacuum system was introduced to replace the coolant pump for machining of carbon FRPs and a significant reduction in power consumption was reported (Fujishima et al., 2014).

Neugebauer et al. (2011) reported that the machine tool structure should be incorporated with robustness, mobility, miniaturization, adaptability, mutability, multi-functionality, and energetic networking to improve the energy efficiency. Gontarz et al. (2015) focused on consideration of energy efficiency for configuration of customized machine tools. Over dimensioning of machine tools often leads to high energy and resource consumption. Therefore, it is important to assess the machine tool usage such as manufacturing environment, operational information, machine functionality, and component dimensions in advance. The machine tool should be designed and configured based on customer usage to improve the energy and resource efficiencies. Eisele et al. (2011) presented a simulation based approach for energy modelling of machine tool components in the design phase and also reported that the energy efficiency can be improved by designing energy efficient machine tools and avoiding oversizing of the machine tool components. Li et al. (2011) also quoted component design improvement as an effective measure to reduce the fixed energy consumption of the machine tools.

Other approaches to improve the energy efficiency of the machine tools are waste recovery within a machine tool (e.g. kinetic energy recovery system) and design of integrated or central peripheral components (Duflou et al., 2012). However, improving design of the existing machine tools requires heavy investment and industries are more interested in reducing the energy consumption in the use phase.

2.7.2 Macro Process Planning Phase

The energy efficient strategies at the macro process planning phase are:

2.7.2.1 Machine tool selection optimization

Energy is the primary input for metal working machine tools and the energy saving efforts start right from the procurement phase of the machine tools. It is observed that the initial investment for energy efficient equipment is generally higher than the less efficient alternatives but the energy saving from the efficient machine tools is also desirable. The cost of energy consumed by a machine tool in its life time accounts for a major percentage of its life cycle cost and the investment into energy efficient machine tools is reported to be financially viable (Bharambe et al., 2015).

Machining of a feature can be realized by many alternate machine tools, cutting tools and cutting strategies. Selection of an appropriate machining system is important for energy efficient machining (Balogun et al. 2015; Avram and Xirouchakis 2011). Wang et al. (2018a) proposed a hybrid approach to select the optimal machine tool by using a combination of STEP-NC, ontology and ant colony optimization techniques. The energy consumption for a milling process was modelled based on key influencing factors identified in STEP-NC. Ontology was used to identify preliminary machining systems based on feasibility of operations, machine tool capacity, cutting parameters, and cutting strategies. The best machining system was identified using ant colony optimization.

2.7.2.2 Machine tool maintenance

After selecting the best suited machine tool, it is important to maintain and operate the machine tools optimally to minimize the energy waste. Product-Service systems (PSS) provide services along with products for the better use of products in the use phase from financial and environmental perspectives. Mert et al. (2015) investigated the effect of services like maintenance, operator training and process consulting on the energy efficiency of machine tools. The study reported that the energy efficiency of machine tool components can be significantly improved by maintenance and retrofitting of the components. Operator training helps to reduce the operating time and select optimum process parameters and energy saving up to 20% can be achieved. Process consulting supports the customer in procurement phase to select the optimal machine tool for energy efficient machining.

2.7.2.3 Energy efficient scheduling and process planning

Energy efficient scheduling, management and task scheduling are also important energy saving measures for machining processes. The energy efficiency can be improved by integrating the energy efficiency measures at machine tool and production facility levels (Salonitis and Ball, 2013).

2.7.3 Micro Process Planning Phase

The energy efficient strategies at micro process planning phase are:

2.7.3.1 Cutting parameter optimization

Cutting parameters have a direct influence on the performance of the machine tools in terms of various performance measures including productivity, tool life, surface roughness, energy efficiency, etc. Effect of cutting parameters on different process responses has been analyzed in a large number of studies and it has been reported that selection of optimum parameters improves the machining performance significantly. The optimum parameters should be carefully selected to improve the machining performance while satisfying the constraints related to tool life, machine tool capacity, vibrations, etc. For example, if the cutting speed is close to the natural frequency of the cutting tool, vibration in the machine tool increases resulting in higher cutting power consumption and poor surface finish.

Carvalho et al. (2015). Machining is a complex system consisting large number of variables and multiple contradictory objectives. Improvement in one process response often demands sacrifice in some other response. Multi-objective optimization is an effective technique to identify trade-off among multiple process responses. The commonly used optimization techniques are ANN, GA, desirability analysis, RSM, Taguchi approach, GRA, etc. Summary of the key optimization studies for milling and turning processes has been provided in Table 2.10.

Table 2.10 Summary of cutting parameter optimization studies

Article	**Process**	**Material**	**Coolant condition**	**Optimization method**	**Process variables**					**Process responses**									
					v_c	**a_p**	**f**	**a_e**	**Other**	**Cutting energy**	**SCE**	**Total energy**	**Production time**	**R_a**	**Tool wear**	**SEC**	**CE**	**EE**	**Other**
Paul et al. (2018)	Turning	AISI 1060 steel	dry			x	x		Tool geometry		x								Back force
Luan et al. (2018b)	Face Milling	HTCuCrSn-250 alloy cast iron	dry						Tool path		x			x					Cutting time
Cui and Guo (2018)	Turning	AISI 1045 steel	dry	FEM, Contour plots	x		x				x			x	x				
Warsi et al. (2018a)	Turning	Al 6061-T6	dry	Energy mapping	x	x					x								
Warsi et al. (2018b)	Turning	Al 6061-T6	dry	Energy mapping	x		x				x								
Chen et al. (2018)	Milling (R_a is constraint)	S45C carbon steel	wet	PSO	x	x	x									x			Cost, SPT
Zhang et al. (2018)	Turning (R_a is constraint)			NSGA-II	x	x	x									x			Noise, cost
Bagaber and Yusoff (2018a)	Turning	AISI 316 steel	dry	Desirability approach	x	x	x			x				x					

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	**Process**	**Material**	**Coolant condition**	**Optimization method**	**Process variables**					**Process responses**									
					v_c	**a_p**	**f**	**a_e**	**Other**	**Cutting energy**	**SCE**	**Total energy**	**Production time**	**R_a**	**Tool wear**	**SEC**	**CE**	**EE**	**Other**
Wang et al. (2018b)	Face milling	Medium carbon steel (150NHB)	dry	Evolutionary strategy	x	x	x									x			Cost
Luan et al. (2018c)	Face milling	HTCuCrSn-250 alloy cast iron	dry	GRA & 3-D surface plots	x		x			x				x	x				
Li et al. (2018a)	Free form surface milling	Al-6061	dry	Adaptive dynamic GA													x		Cutting + air cut energy
Xie et al. (2018)	Turning	Carbon steel C45	dry	NSGAIII	x	x	x		Tool wear		x			x				x	
Zhou et al. (2018)	Milling (R_a, tool life, are constraints)	AISI 1045	dry	GA	x	x	x	x					x			x			
Zhao et al. (2018)	Milling	Carbon steel C45	dry	GRA	x	x	x	x						x		x			
Zhang et al. (2017b)	Milling (Tool life, R_a, are constraints)	Steel 16 Mn	dry	GA	x	x	x	x					x						CSEC

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	Process	Material	Coolant condition	Optimization method	Process variables					Process responses									
					v_c	a_p	f	a_e	Other	Cutting energy	SCE	Total energy	Production time	R_a	Tool wear	SEC	CE	EE	Other
Kumar et al. (2017)	Turning	EN 353 alloy steel	wet	Taguchi-TOPSIS	x	x	x		Nose radius					x				x	AECM, APCM, MRR, PF
Shin et al. (2017)	Milling	Mild steel 1018	wet	Online optimization	x	x	x	x				x							
Lee et al. (2017)	Milling	stainless steel SUS	dry	GA	x		x					x	x						
Zhang et al. (2017a)	Milling	Carbon steel C45	dry	GA	x	x	x	x				x	x				x		
He et al. (2017)	Milling and turning	Carbon steel C45	dry	GA, pareto plot	x	x	x	x				x	x						Back force
Arriaza et al. (2017)	Milling	Aluminum 7075	dry	RSM, DA	x	x	x	x		x							x		Cutting time
Wang et al. (2017)	Milling	Ti–6Al–4V alloy		Pareto plot	x	x	x	x		x			x						Tool life
Sangwan and Kant (2017)	Turning	AISI 1045 steel	dry	RSM, GA		x	x	x											Cutting power
Liu et al. (2017a)	Milling	Al6061-T6	dry	Response surface			x	x		x									Machining accuracy

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	Process	Material	Coolant condition	Optimization method	Process variables					Process responses									
					v_c	a_p	f	a_e	Other	Cutting energy	SCE	Total energy	Production time	R_a	Tool wear	SEC	CE	EE	Other
Li et al. (2017a)	Multi pass milling	Carbon steel C45	dry	AMOPSO	x	x	x		No of passes							x			Cost
Zhong et al. (2016b)	Turning	Carbon steel , ductile iron	dry		x	x	x									x			
Park et al. (2016)	Milling	AISI 4140 steel	dry	NSGA-II	x		x		Tool geometry		x							x	
Lu et al. (2016)	Multi pass turning	Carbon steel C45	wet	MOBSA	x	x	x		No of passes			x							Machining precision
Bilga et al. (2016)	Turning	EN 353 alloy steel		Taguchi, ANOVA	x	x	x		Nose radius									x	AECM, PF
Albertelli et al. (2016)	Milling	High alloy steel	wet	Exhaustive enumeration method	x	x		x				x	x						
Li et al. (2016b)	Milling	AISI 1045 steel	dry	Taguchi, MOPSO	x	x	x	x			x		x						
Altıntaş et al. (2016)	Milling	AISI 304 SS	wet	RSM	x	x	x					x							
Li et al. (2016a)	Milling	Carbon steel C45	dry	Tabu search	x	x	x	x					x			x			

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	**Process**	**Material**	**Coolant condition**	**Optimization method**	**Process variables**					**Process responses**									
					v_c	**a_p**	**f**	**a_e**	**Other**	**Cutting energy**	**SCE**	**Total energy**	**Production time**	**R_a**	**Tool wear**	**SEC**	**CE**	**EE**	**Other**
(Camposeco -Negrete et al., 2016, 2013)	Turning	AISI 1018 steel	dry and wet	MEP	x	x	x					x							
Jang et al. (2016)	Milling	SM45C steel	dry, wet, MQL	PSO	x	x	x									x			
Tapoglou et al. (2016)	Milling			DMOEA	x	x	x												Cutting power, time
Iqbal et al. (2015)	Grooving	AISI 4340	dry	Fuzzy methodology	x	x	x		Material hardness	x					x				MRR
Camposeco-Negrete (2015)	Turning	AISI 6061 T6 aluminum	wet	RSM, DA	x	x	x							x		x			
Warsi et al., (2015)	Turning	AISI 6061 T6	dry	Contour plots	x		x				x								
Garg et al. (2015)	Milling	Cast ZG35	dry	Com-MGGP	x	x	x					x							
Velchev et al. (2014)	Turning	Steel	dry	Differenti-ation	x	x	x					x							

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	Process	Material	Coolant condition	Optimization method	Process variables					Process responses									
					v_c	a_p	f	a_e	Other	Cutting energy	SCE	Total energy	Production time	R_a	Tool wear	SEC	CE	EE	Other
Wang et al. (2014a)	Turning	Carbon steel C45	wet	NSGA-II	x	x	x					x		x					Cost
Li et al. (2014)	Rough milling	Aluminum alloy	dry	GA	x		x						x			x			
	Finish milling				x		x							x		x			
Arif et al. (2013)	MP Turning (R_a, F_c, tool life, are constraints)	Alloy steel	dry	NLP	x	x	x		No of passes			x							
Camposeco-Negrete (2013)	Turning (No MOO)	AISI 6061 T6 aluminum	dry	Taguchi S/N, MEP	x	x	x					x		x					
Yan and Li (2013)	Milling	Carbon steel C45	dry	SQP	x	x	x	x		x				x					MRR
Calvanese et al. (2013)	Milling (R_a is constraint)	Aluminum alloy	wet	Surface plot	x		x					x							PT
Newman et al. (2012)	Milling	Aluminum alloy 6042	dry			x	x												Power, MRR

Table 2.10 Summary of cutting parameter optimization studies (Contd.)

Article	**Process**	**Material**	**Coolant condition**	**Optimization method**	**Process variables**					**Process responses**									
					v_c	**a_p**	**f**	**a_e**	**Other**	**Cutting energy**	**SCE**	**Total energy**	**Production time**	**R_a**	**Tool wear**	**SEC**	**CE**	**EE**	**Other**
Guo et al. (2012)	Turning	steel	dry		x	x	x							x		x			
Mativenga and Rajemi (2011)	Turning	Medium carbon steel	dry		x	x	x									x			
Kant and Sangwan (2014)	Turning	AISI 1045Steel	dry	GRA	x	x	x							x					Cutting power
Bagaber and Yusoff (2017)	Turning	Stainless steel 316	dry	DA	x	x	x			x				x	x				
Campatelli et al. (2014)	Milling	AISI 1050 carbon steel	dry	RSM	x	x	x	x			x					x			
Bhushan (2013)	Turning	Al-SiC composite	dry	RSM, DA	x	x	x		Nose radius										Power, tool life
Hanafi et al. (2012)	Turning	PEEK-CF30	dry	GRA, MEP	x	x	x							x					Cutting power
Bagaber and Yusoff (2018b)	Turning	AISI 316 steel	dry	NSGA II	x	x	x					x							Machining cost

2.7.3.2 Stand-by energy optimization

Machine tools consume a significant portion of energy as stand-by energy or fixed energy. Lanz et al. (2010) reported that the financial benefits due to reduction of cutting energy by parameter optimization are less significant. The energy efficiency can be achieved by reducing the non-productive and non-value adding times for a machining process by better process planning and switching off the machine during long idle times (Li et al. 2011; Hu et al. 2012).

Utilizing on-off strategy to switch off the machine tool during setting up periods is considered as an efficient way to reduce the stand-by energy consumption (Camposeco-Negrete, 2013; Fujishima et al., 2014; Lenz et al., 2017; Lv et al., 2016; Peng and Xu, 2013). For example, Mori Seiki machine tools are equipped with electromagnetic brakes which are applied to gravity axes to turn off the equipment if the machine tool does not perform any operation for five minutes. Energy saving potential using this strategy depends on the type of machine tool and its operational status.

Lenz et al. (2017) reported that up to 28% of the machining energy can be saved by implementing energy saving strategies such as improving the component design, component start-stop, setting some components to sleep mode in stand-by state, and retrofitting with a regulatory control. However, unnecessary start-stop of components may lead to higher energy consumption (Lv et al., 2017) and the component activation should be optimized to reduce the energy consumption during non-cutting operations.

Eberspächer and Verl (2013) proposed a graph based approach to find whether the energy saving mode should be activated or not. The authors analyzed the time and energy required for state transition and machine tool warm up for production readiness. The consumption graph for a machining process was developed and optimized using A*-algorithm. The optimization results indicated that if the gap between two production states was more than 123 seconds, the energy saving mode should be activated. The proposed approach was applied to a milling machine tool and the energy consumption was reduced by 5% in two continuous production shifts of 8 hours each. The study was further extended to automate energy efficient switching-off of machine tool components to reduce energy consumption during nonproductive operating states (Eberspächer et al., 2016). The time required to return to production state was considered as one of the constraints to ensure high productivity. Schlechtendahl et al. (2016) designed a machine independent energy optimizer based on real time machining information to manipulate the operating states of the machine tool components for energy saving. The application of the optimizer was illustrated for a 5-axis milling machine tool.

2.7.3.3 Reduce spindle acceleration time

Lv et al. (2017) proposed strategies for reducing the energy consumption for spindle acceleration (ESA) at machine tool level and system level. At machine tool level, the ESA can be reduced by avoiding unnecessary spindle start-stop, reducing the acceleration time and incorporating lightweight design. At system level, ESA can be reduced by selecting suitable machine tools. The energy saving between 10 to 50% can be achieved by using these strategies.

Mori et al. (2011) proposed a novel spindle acceleration/deceleration control for reducing the energy consumption during spindle acceleration/deceleration and observed that the power consumption was reduced by synchronizing the spindle acceleration/deceleration with rapid transverse.

2.7.3.4 Reactive power compensation and braking energy storage

Götze et al. (2012) presented a study to analyze the energy and cost effectiveness of the machine tools for the adoption of two energy saving measures – reactive power compensation and braking energy storage. The drive system energy consumption was simulated to identify the energy flow and saving potentials. The proposed approach was implemented for a milling case study and it was reported that both the measures had technical and ecological advantages, but only reactive power compensation was economically viable.

2.7.3.5 Feature sequence optimization

The sequence of the features performed on a workpiece also affects the energy consumption of the machine tools during different operating states. Hu et al. (2017b) studied the effect of feature processing sequence on the cutting energy and observed that up to 14% energy saving and 20% machining time reduction can be achieved by optimizing the feature processing sequence. The feature processing sequence also affects the energy consumption of tool change and tool path during run-time. Hu et al. (2018a) studied the correlation between the energy consumed during feature transition (EFT) and feature processing sequence; and provided models for tool change energy (TCE) and tool path energy (TPE) for transition from one feature to the next feature. The EFT was reduced by 28.6% with optimum sequencing of the features. Further, the model was extended for multiple machine tools and bi-objective optimization considering feature transition time (TFT) as the second objective. The TFT was reduced by 27.95% with bi-objective optimization.

The energy model was improved by including the energy consumption due to spindle acceleration/deceleration for calculation of non-cutting energy (NCE) of machine tools (Hu et al., 2017a). The spindle acceleration/deceleration energy can be up to 14% to the total NCE of machine tools and hence the energy saving potential is significant. The optimum feature sequence to minimize the NCE was identified using ant colony optimization (ACO) approach. The effectiveness of the proposed model was illustrated with two case studies with 12 and 15 features, respectively. It was reported that the optimum sequence identified by the proposed approach reduced the NCE by 8.70% and 30.42%, respectively as compared to bottom-to-top sequence of features. The performance of various deterministic and meta-heuristics optimization approaches was compared with ACO and it was reported that the performance of ACO was best for this case study in terms of solution quality and processing time.

The authors extended their analysis to a multi-objective optimization study considering machining time and deviation as process responses along with machining energy (Hu et al., 2018b). The sequence related machining time (S-MT), deviation (S-MD) and energy consumption (S-MEC) were modelled and analyzed in the study. The activities which were not related to the sequence and were common in all possible sequences were ignored. The multi-objective problem was solved using the evolutionary approach of Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the deterministic approach of Non-dominated Inserting Enumeration Algorithm (NIEA). It was observed in the study that NIEA always returned the global optimum whereas NSGA-II returned near optimal solution. However, the computation time for NIEA was high and intolerable for large number of features. Therefore, a new optimization approach, Genetic-based Non-dominated Enumeration Algorithm (GNEA), was proposed for large number of features to obtain better quality solution in a reasonable time. The proposed model was illustrated through a case study of three parts with different features and the results showed that S-MEC, S-MD and S-MT can be reduced by 16.66%, 5.29% and 20.51%, respectively with optimum feature sequencing.

Li et al. (2018b) proposed an optimization approach for NC program at two different levels – setup level (a group of NC codes for a setup) and NC program level (a group of features in the same NC program). At the setup level, processing sequence of different NC programs for machining of different features on a part was analyzed. At this level, energy required for tool change between different NC programs was optimized. Whereas, on the NC program level, the processing sequence of different features in the same NC code was optimized to reduce the energy consumption due to cutting tool movement and travelling time of the cutting tools. The optimum NC code sequence at setup level and feature sequence at NC program level was obtained using honey-bee mating optimization (HBMO)-simulated annealing (SA) algorithm. The proposed approach was verified with simulation experiments for two case studies and the energy efficiency was reported to be improved by 10% and 15.9%.

Wu et al. (2017) presented a tool selection optimization study for CNC milling of 2.5D pocket for minimization of machining cost and energy consumption. The effect of tool sequence on the machining cost and energy consumption was analyzed in the study and optimum tool sequence was obtained using graph algorithm.

2.7.3.6 Workpiece setting optimization

The machine tool axes have different equivalent mass and friction and the energy consumption for movement along each axis is different. The orientation of workpiece affects the axial movement along each axis and hence the energy consumption for machining process. A few studies analyzed the effect of workpiece setting on the machining energy consumption and investigated the possibilities to reduce the energy consumption by optimizing the orientation of the workpiece. The optimization of workpiece orientation is advantageous over the other techniques such as MQL, energy efficient design of components, or parameter optimization, as it does not require extra investment or parametric adjustments.

Campatelli et al. (2015) presented an energy consumption model for machine tool axes involving the equivalent mass and friction of the axes and reported 23% reduction in the machine tool axes energy consumption for a milling case study using optimal workpiece orientation.

Edem and Mativenga (2017a) studied the effect of workpiece orientation on energy consumption and surface roughness for a milling process. The surface roughness and electric energy consumption for milling of AISI 1045 steel were measured for different orientations of workpiece. It was reported in the study that the surface roughness and energy consumption can be reduced by 29% and 50% respectively when the workpiece was oriented in the direction of axis carrying least weight.

Sato et al. (2017) studied the effect of workpiece setting on the energy consumption by feed drive systems. The feed drive energy for a five-axis machining center was analyzed for 25 different workpiece settings and it was observed that an energy saving of 20% can be achieved using optimum workpiece setting.

Xu and Tang (2016) analyzed the effect of workpiece set-up on the energy consumption for a free form milling process. An energy consumption model was proposed for free form milling based on kinematic configuration of the machine tool. The proposed model was optimized, and it was observed that the energy consumption can be reduced up to 50% by optimizing the workpiece set up without changing the tool path.

2.7.3.7 Tool path optimization

The effect of different tool path strategies on the machining energy consumption has been analyzed by many researchers and it has been observed that the energy consumption varies significantly for different tool paths (Aramcharoen and Mativenga 2014; Guo et al. 2015). For example, Aramcharoen and Mativenga (2014) analyzed the energy consumption with different tool paths for a milling process and observed that contour offset was the most energy efficient tool path for closed pocket milling.

Pavanaskar and McMains (2015) developed an energy prediction model for CNC machine tools considering the tool path aspects and used the model to analyze the effect of variation in cutting parameters and tool path on the machining energy consumption. A software interface was developed for energy analysis of CNC machine tools and the energy consumption for different tool paths was analyzed and compared. Xu et al. (2016) studied the effect of tool path on the energy consumption for free form surface milling process using a five-axis milling machine tool. It was observed that the proposed tool path was 25% more efficient in terms of energy consumption as compared to the traditionally used tool path.

Edem and Mativenga (2017a) studied the effect of three tool paths – zag, zigzag and rectangular contour – on energy consumption for a milling operation. It was observed that rectangular contour resulted in least energy consumption. In another study by Edem et al. (2017), the electric energy demand for pocket milling of AISI 1018 steel for two different machine tools was measured using three different tool path strategies of zag, zigzag and rectangular contour. It was reported that the optimum tool path for minimum energy was different for both the machine tools and depends on the axis configuration of the machine tool. It was also observed in their study that tool path with more number of tool retracts results into longer processing time and higher energy consumption.

Luan et al. (2018b) investigated the effect of tool paths on energy consumption, machining time and surface integrity of the workpiece for face milling of alloy cast iron under dry cutting conditions. The cutting energy, cutting time and surface roughness were measured for six different tool paths: up milling, down milling, zag-X, zag-Y (up milling), morph spiral, and parallel spiral. The zigzag tool path was favored for low energy consumption and high processing efficiency.

Li et al. (2018a) analyzed the effect of tool path on machining time, carbon emissions and energy consumption for free form surface milling and established a trade-off among the three process objectives. A tool path was defined as a set of cutter contact points (CCPs) and both number and sequence of CCPs were optimized to improve the production efficiency, energy saving and environmental performance of machining process. Cutting and air-cutting tool paths were considered as two process variables and the process objectives were modelled as a function of tool path length. Multiple objectives were converted into a single-objective using linear weighted summation method and the tool path was optimized using adaptive dynamic GA. The proposed model was verified with a case study of free form surface machining of Al06061 alloy under dry cutting conditions. It was reported that with optimum tool path selection, the total tool length can be reduced by 13.37% and 18.25%, respectively as compared to parallel and streamline milling, respectively.

2.7.3.8 Improvement in coolant conditions

The coolant conditions have significant impact on energy consumption for machining processes as the coolant pump is a significant energy consumer. The impact of coolant conditions on the energy consumption has been studied by various researchers and alternative cooling strategies have been proposed with higher energy efficiency such as minimum quantity lubrication (MQL) (Lv et al., 2016). Many researchers have explored the conditions to replace wet machining with environment friendly, dry or MQL machining (Zhang et al. 2015; Shokrani et al. 2018). It has been observed that the SCE for dry cutting is higher than cryogenic machining due to limitations on MRR. For flood cooling, energy consumption is significantly higher than dry and cryogenic machining due to high power consumption by coolant pump. Cryogenic cutting condition facilitates the use of higher cutting speed without compromising the tool life. Hence, cryogenic machining can result into minimum energy consumption with acceptable tool life.

Denkana et al. (2015) investigated the effect of coolant flow rate on the power consumption of the machine tool while considering the tool wear constraints. Minimum amount of coolant flow rate required to remove the heat generated by spindle unit was investigated. It was observed that at higher spindle process power, more heat is generated. Therefore, higher coolant flow rate was required to impair the tool wear. It was also observed that the mean power consumption of spindle motor was not increased by reducing the coolant flow rate.

2.8 MACHINING ENERGY EFFICIENCY EVALUATION MEASURES

In the previous sections, the energy consumption models and energy saving strategies for machine tools have been discussed under various classifications. The quantification of energy efficiency is important to analyze that how the implementation of energy saving strategies impacts the energy performance of the machine tools. It is evident that only a small percentage of the total energy consumption is used for material removal, whereas a significant portion is either consumed for auxiliary operations or wasted. Energy efficiency of a machining process can be improved by reducing the energy waste and increasing the percentage of material removal energy.

Energy efficiency of machine tools is affected by factors related to both machine tool components (Schudeleit et al., 2016) and manufacturing task (Draganescu et al., 2003). Liu et al. (2018a) proposed a potential energy method for evaluation of machine tool energy efficiency considering the effect of both machine tool components and machining tasks. The factors related to machine tools were modelled by acquiring information from the machine tool manufacturers. The workpiece related factors were modelled by acquiring production information such as workpiece diversity, cutting parameters and process uncertainty. An energy efficiency evaluation model was proposed by combining both factors, and the proposed model was illustrated for a gear hobbing machine. In design and procurement phases, the energy performance evaluation of machine tools is an important pre-requisite for development and selection of energy efficient machine tools. As the buyers cannot perform cutting test for different machine tools at procurement stage, an energy efficiency model is required which can evaluate and compare the energy efficiency of various machine tools without requiring experimental data.

It is evident from the literature that the researchers have widely used four measures for energy efficiency of the machine tools: energy utilization ratio, real time energy efficiency, specific energy consumption, and relative energy efficiency.

2.8.1 Energy Utilization Ratio (U)

Energy utilization ratio is defined as the ratio of energy required for material removal to the total energy consumed by the machine tool. Energy utilization ratio is a widely used measure for energy efficiency of the machine tools (Hu et al., 2012; Kumar et al., 2017; L. Li et al., 2017; Z. Y. Liu et al., 2015; Lv et al., 2016; Ma et al., 2017; Sealy et al., 2016; Tuo et al., 2018b; Zhao et al., 2016). It signifies the proportion of cutting energy to the total energy consumption by the machine tools. Hence, the energy efficiency is higher if larger proportion of the machine tool energy consumption is utilized for material removal and lesser energy is required for auxiliary operations.

Some researchers (Ma et al., 2014; Park et al., 2016) studied the energy consumption for machining process at material removal level. The cutting energy was decomposed into shear energy (useful) and friction energy (unproductive). The energy efficiency or energy utilization ratio at material removal level was defined as the ratio of shear energy to cutting energy.

2.8.2 Real Time or Instantaneous Energy Efficiency (η_t)

Real time or instantaneous energy efficiency is defined as the ratio of material removal power to the total power drawn by the machine tool (Y. Cai et al., 2018c, 2018b; Cai and Shao, 2017; Draganescu et al., 2003; Guo et al., 2012; Hacksteiner et al., 2017; Hu et al., 2012; L. Li et al., 2017; N. Liu et al., 2015; P. Liu et al., 2017; Xie et al., 2018). It should be noted that real time or instantaneous energy efficiency is a transient value defined for a time instant, whereas the energy utilization ratio is a process value.

2.8.3 Specific Energy Consumption (SEC)

Specific energy consumption is defined as the ratio of total machining energy to the effective output of a machining process. SEC can be defined at three levels – process, spindle and machine tool levels wherein the energy required for material removal, the energy consumed by spindle unit and the total energy consumed by the machine tool are considered, respectively. The SEC definitions provided in the literature are summarized in Table 2.6. The effective output can be measured in terms of material removal rate (Lv et al., 2016; Warsi et al., 2015), volume of removed material (Chen et al., 2018; C. Li et al., 2017; Li et al., 2016a, 2016b) or number of parts processed (L. Li et al., 2017). Sometimes the efficiency of spindle or chiller unit is also considered for calculation of SEC at spindle level (Draganescu et al., 2003; Hacksteiner et al., 2017; Wójcicki et al., 2018) and the SEC is measured as:

$$SEC = \frac{P_c}{60\eta_{sp}MRR}$$

where η_{sp} is energy efficiency of the main spindle.

2.8.4 Relative Energy Efficiency (EE_{rel})

Relative energy efficiency is defined as the ratio of minimum energy required to the actual energy consumption for a unit operation.

$$\mathrm{EE}_{rel} = \frac{minimum\ energy\ requirement}{actual\ energy\ consumption}$$

Kreitlein et al. (2017) evaluated the least energy demand to perform a unit operation on the machine tools based on the energetic interrelations without considering a specific machine tool or production process. Least energy demand was defined as the minimum energy required for shearing the material in the form of chips.

The least energy demand is also used for benchmarking the energy consumption for machining processes. Energy benchmarking is reported to be an efficient strategy for energy efficiency management and improvement. The complexity of machining systems makes the development and use of energy benchmarking system for machine tools a challenging issue. Cai et al. (2017a) identified the drivers for energy benchmarking of machining systems and analyzed their characteristics. An energy benchmarking framework was then proposed at motion, application and objective levels covering the static and dynamic, product and process based, single and multiple objective dimensions of energy benchmarking, respectively. In another study by Cai et al. (2017b), a dynamic energy benchmarking system was proposed for mass production processes to assess the energy efficiency of machining systems. Dynamic energy benchmark can assess the energy consumption of different machining systems for the production of same products. Further, Cai et al. (2018a) presented two energy benchmarking rules for energy efficiency improvements of machine tools. First rule facilitated the energy benchmarking for a group of products and the second rule provided an evaluation measure for energy benchmarking termed as benchmarking rating.

The above stated measures have been widely used for energy efficiency evaluation using different methods. Each evaluation method has its own pros and cons; and a standard test procedure for energy efficiency evaluation of machine tools is still missing.

2.8.5 Others

Karpov (2015) introduced 'energy efficiency of the cutting operation (K)' as an integral measure of machining effectiveness considering multiple power cycles.

$$K = \frac{\Delta w * V}{n_c * A_c} = \frac{\Delta w * V}{n_c * \int_0^{\tau_c} N(\tau) d\tau}$$

where Δw is the specific energy intensity of processed material, V is the volume of processed material, n_c is the number of cutting power cycles $N(\tau)$ during the tool travel, A_c is the work done for cutting, and τ_c is the cycle time for power change.

Schudeleit et al. (2015) evaluated and compared four energy efficiency test approaches: reference part method, reference process method, specific energy consumption method, and component benchmark method using analytic hierarchy process (AHP). The four alternatives were compared against seven performance criteria: evaluation time, simplicity, machine tool comparison, dependence on workpiece and tool, real time use, implementation phase, and operating states evaluation. The reference process method (36.1%) was ranked as the most suitable method for energy efficiency evaluation of machine tools followed by the component benchmark (26.2%), specific energy consumption (20.9%), and reference part (16.8%) methods. However, the reference process method had limited application in the design phase.

Tuo et al. (2018b) proposed an energy efficiency evaluation system for machine tools using a virtual part method. Two energy efficiency evaluation indexes were defined and evaluated, namely comprehensive energy consumption (CEC) and comprehensive energy utilization (CEU). Reference process, reference part, specific energy consumption, and component benchmark methods were critically analyzed in their study. A new virtual part based evaluation method was proposed to overcome the shortcomings of these existing methods, such as material wastage, cutting parameters, workpiece material and geometry, features, and machining cost.

The studies on energy performance evaluation of machine tools generally focus on specific energy consumption for a reference workpiece while consideration of process controls in use phase (state of auxiliary components, rotational speed of spindle, feed rate, etc.) is scarce. Tuo et al. (2018a) assessed the inherent energy performance (IEP) of the machine tools with consideration of various process controls in use phase. The IEP indexes were divided into two categories: energy consumption function indexes and equivalent energy consumption indexes. The former was used for known operational processes while the latter was used for unknown operational processes. The proposed indexes were more comprehensive and systematic as these consider process control in use phase and the distribution of process controls. The proposed methodologies can be utilized to develop energy labels for machine tools, estimation of energy demand during use phase, and selection of more efficient machine tools during process planning and procurement phases.

Hu et al. (2012) proposed an online approach for monitoring the energy efficiency and energy utilization ratio of the machine tools without using force/torque sensors. A software for real time energy efficiency monitoring was developed to display the power consumption and energy efficiency in real time, energy utilization ratio for two consecutive shifts.

Hacksteiner et al. (2017) used specific energy consumption and overall equipment efficiency as energy efficiency indicators and proposed an interface to determine energy efficiency and productivity indicators in real time using sensor data and machine control data. SCADA software was used for recording, processing, and storing the data.

Kianinejad et al. (2015) conducted an experimental study to compare the energy consumption of old machine tools with the modern machine tools. The energy efficiency study of old machine tools may provide insights for reuse, reconditioning, upgrading, life cycle, and end of life assessment studies. Two milling machine tools representing old and new scenario were selected and energy consumption was measured for different operations/components and processing conditions. It was observed that the energy efficiency of newer machine tool was 40% higher than that of old one. However, the old machine tool can perform more efficiently for the materials which can be processed only at lower cutting speeds such as nickel alloys as compared to aluminum alloys.

2.9 SUMMARY

The energy efficiency analysis for the machine tools has emerged as a key research focus for both industry and academia since the last decade. The thesis presents the first systematic literature review of 226 reference articles, from 1994 to 2018, focusing on energy aspects of the machining processes. It was found that the first paper on machining energy was published in 1994 as per the search criteria of the study. There are seven review articles in the list of 226 articles and it was observed that the existing review articles focused on limited aspects of machining energy; whether energy classification or modelling or saving strategies or efficiency evaluation. The number of articles reviewed in these studies were also limited. Descriptive analysis of the reference articles shows that most of the research in energy aspects of machining has been conducted during the last decade. It has also shown that most of the research is being conducted in China followed by USA, UK and Germany. But, it also shows that the research on the topic is going on in many countries. Broadly, the research on the topic can be classified in four categories, viz.

(i) machining energy classification, (ii) machining energy modelling, (iii) machining energy saving strategies, and (iv) machining energy efficiency evaluation measures.

Based on the different energy classification approaches used by the researchers, the research can be divided into six hierarchies; from machining system level to component/Therblig level. The researchers have used analytical, numerical and experimental modelling techniques for estimation of machining energy at different levels. Based on the expression of energy and the level of assessment, the energy models can be divided into five groups: machine tool energy models, cutting energy models, operational state based models, component based models, and Therblig based energy models. It was observed that Therblig based models provide higher level of classification and help to develop precise and accurate energy models. It was found that the machining energy saving strategies have been researched at design, macro process planning, and micro process planning phases. Some important energy saving strategies in design phase include replacing long and bulky mechanical drives with light and direct drives, incorporating electrical actuators, integrating safety controller for moving parts, reducing transformer losses, and use of lighter and efficient machine tool components. The energy saving strategies at macro process planning include selection of machine tool and energy efficient scheduling of machining operations. At micro process planning phase, the energy can be reduced by benchmarking the energy consumption of machine tool components, using modular programs, optimizing the tool path and machining parameters, efficient loading of the electric drives, and retrofitting the machine/components. The strategies at design level are difficult and expensive to implement. The four major energy efficiency evaluation measures used by the researchers are: energy utilization ratio, real time energy efficiency, specific energy consumption, and relative energy efficiency. Based on the systematic literature review of 226 articles, following research gaps are identified:

Development of energy consumption index:

The energy performance of the machine tools should be an important aspect in the design phase. An energy consumption index should be developed and added to the machine tool technical specification data for comparison of energy performance of the different machine tools. Also more research is needed to benchmark the energy consumption for standard machining processes for better energy management and process planning.

Configuration of customized machine tools:

The machine tools should be configured for customized machine tools. More research is required to understand the customer requirements and demand side management. This will help to avoid overdesigning of machine tools and waste during non-productive times.

Energy modelling upto micro level:

It is observed in the review study that quantification of energy flow upto micro level improves the energy transparency for the production process. Therblig based energy modeling helps to envision the machining energy flow at micro level and provides better insights about the energy hotspots. In future studies, improved value stream maps should be developed to visualize energy consumption and carbon emissions at a micro level, more process objective should be added to the value stream maps, and it should be extended to other manufacturing processes.

Selection of optimization objectives from energy and environment perspective:

It is observed that the selection of process objectives and constraints is not standardized. For instance, surface roughness is often considered as a process objective. However, in reality, a pre-defined value of surface roughness for a product is acceptable and any efforts made to further reduce the surface roughness will result into undesired energy and resource consumption. The future studies should work towards providing more practical approach for the selection of optimization objectives including energy and environmental perspectives.

Real time energy data analytics:

The machine tool performance changes with time, progression of tool wear and deviation in process parameters. Real time data monitoring is facilitated by use of sensors and data analytics. The use of such technologies is a challenge for industries, especially SMEs, due to high investment cost and complexity. Therefore, future research should focus of development and deployment of low cost sensors, using off the shelf technologies for data acquisition and real time monitoring.

Use of energy data for condition monitoring and predictive maintenance:

Electrical power data involves diverse characteristics related to technical specification and operational status of machine tools. Abrupt changes in energy profile indicates anomaly in the machine tool performance. The real time energy data can serve as a basis for online condition monitoring of machine tools. It will help to detect the downtime before it occurs, create strategic maintenance timelines that can be performed when needed. This will result into better-planned maintenance processes and significant cost saving by reducing equipment failure and increasing machine lifetime.

Integration with industry 4.0 applications:

The integration of energy data analysis with industry 4.0 application can help to track the operational state of the machine tool in real time from a remote location and send the status or alert to the right personnel. Further, the future research should explore the opportunity of machine-to-machine communication to coordinate the production process. For example, in case of a breakdown or error in production process, the communication in machine tools can alert the production line about the breakdowns/bottlenecks. This facilitates to intensify the pace of production and may automate it entirely in future.