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Intelligent energy based status identification as a platform for improvement of machine tool efficiency and effectiveness

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ABSTRACT

The combination of increasing energy costs, corporate image concerns, and environmental legislation is driving a transition towards energy and resource efficiency within the manufacturing sector. Developing a more comprehensive understanding of how energy is consumed within manufacturing facilities is now a core component of research efforts aiming to advance industrial energy efficiency. A variety of different research teams have proposed approaches and methodologies that attempt to quantify the energy consumed at a unit process level however, the application of intelligent energy sensors that aim to support this goal is a topic that has received very little attention within the literature. This paper presents a novel nonintrusive intelligent energy sensor that can infer the operational status of a machine tool from information contained within the power signals recorded at the machine tools main incomer. Researchers within the literature agree that obtaining transparency on the status of a machine tool during machining will motivate improvements that can reduce the energetic impacts of machining and therefore improve the overall energy efficiency of manufacturing. The research work presented in this article reveals that the information available at the machine tools electrical service entry is capable of identifying individual component activations in addition to the overall operational status.

1. Introduction

The economic, political, and environmental climates currently facing governments worldwide are unprecedented. The need to ensure a secure energy supply is now more urgent than ever. The past decade has brought almost unparalleled uncertainty to the energy industry characterised by the recent turmoil in the Middle East and North Africa, a global recession, and the catastrophic earthquake and tsunami which triggered the Fukushima nuclear disaster in Japan (IEA, 2010). The global recession has provided an unexpected, and relatively narrow, window of opportunity to take action to concentrate investment on low carbon technologies (WEC, 2010). A combination of the rate at which economies and populations within the developing world grow, energy efficiency trends, environmental legislation, and the development and deployment of new technologies will all play a role in reducing the projected gap between the supply and demand of energy.

The precise quantity of each energy source that will be used to fulfil global energy demand remains unknown. There can be no doubt that the worldwide energy landscape will continue to change and adapt as existing technologies improve and new technologies develop however, it is still a certainty that fossil fuels have a pivotal role to play up to 2035 (IEA, 2012). Nuclear power will also have a significant role to play in the future of global energy with generation IV, generation V, and nuclear fusion reactors potentially commercially viable within this century. Although the demand for coal, oil, and gas is predicted to grow in absolute terms between 2012 and 2035, their combined share of the global energy mix will decrease from 81% to 75% during the same period (IEA, 2012). Renewable energy resources currently supply 14% of the total world energy demand and this share is expected to increase significantly to between 30% and 80% before 2100 (Manzano-Agugliaro et al., 2013; Dovi et al., 2009). According to the IEA, this increase will be driven by incentives, falling costs, technological advancements, and rising fossil fuel prices (IEA, 2012). The dramatically increased availability of natural gas, primarily from unconventional sources, has significantly impacted on the economic effectiveness of certain renewable sources, particularly wind energy. It is predicted that

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hydroelectric power, responsible for 16% of global electricity generation and 88% of the electricity generated by renewables, will remain the most significant renewable energy source moving forward (IEA, 2012).

Globally, the industrial sector is the largest consumer of energy (Saidur, 2010). The manufacturing sector, which is a subset of the industrial sector covering the mining and quarrying of raw materials, construction, and also the manufacture of finished goods and products is responsible for over one third of global energy use and CO_2 emissions (IEA, 2010). According to Duflou et al. (2012), manufacturing is responsible for 84% of the industrial sectors energy related CO_2 emissions and 90% of the industrial sectors energy consumption. Hesselbach et al. (2009) noted that as a consequence of the high levels of energy consumed during manufacturing, companies have an economic motivation to consciously consider energy issues alongside traditional production objectives including cost, quality, and time. In order to increase the efficiency of electrical energy consumption and reduce energy waste, Kopac and Pusavec (2009) suggested that manufacturing companies must follow the resource flow, quantify it, and analyse the data in order to identify opportunities for improvement. As part of this analysis, it is essential to take a holistic approach that considers the electrical energy requirements of equipment required directly and indirectly during production (Hesselbach et al., 2009; Naughton, 2006).

Another aspect of this approach that allows a structured analysis of manufacturing facilities involves decomposing the system hierarchically. Researchers agree that the potential for energy savings in the manufacturing sector lies not only in improving the energy efficiency of production processes and products life cycles, but also in developing novel energy monitoring and management approaches (Weinert et al., 2011; Herrmann and Thiede, 2009; Kleměs et al., 2012; Thollander and Ottosson, 2010). The hierarchical approach to energy consumption represents one such novel approach. A complete description of this hierarchical approach can be found in O'Driscoll et al. (2013a). A critical component of any attempt to develop novel energy efficiency and management approaches is the energy measurement equipment used to quantify consumption. Vikhorev et al. (2013) described how energy data is collected at all levels of the hierarchy from the sub-process level to the global manufacturing sector at a variety of different temporal resolutions depending on the nature of the analysis to be performed. According to Herrmann et al. (2011), energy metering facilitates one of the critical components of sustainable manufacturing; the availability of adequate and prompt information on energy demands and consumption patterns at all hierarchical levels. The challenges associated with implementing facility wide energy metering systems are complex, considering issues such as meter selection, meter location, meter quantity and the interpretation of the measured data; these technical issues are addressed in O'Driscoll and O'Donnell (2013), O'Driscoll et al. (2012, 2013b). The paper has been structured as follows: in Section 2, we report the theoretical background of the research, highlighting previous literature and open issues within the subject area. Section 3 describes the intelligent energy sensor presented in this study. In Section 4, we present a case study before closing with concluding statements in Section 5.

2. Background

The importance of understanding the energy requirements at each level of the manufacturing hierarchy – from the enterprise level to the machining state level – was discussed by Rahimifard et al. (2010). Within their research study, the authors claim that significant improvements can only be made through a “Design for Energy Minimisation” approach that is only achievable with a complete understanding of each hierarchical level. The focus of the research work presented here is at the process level, where the scale of energy savings is minimal in comparison to enterprise level improvements. The literature includes various studies that focus on system level optimisations, for example the work of Zhu et al. (2014) describes a linear programming approach for industrial energy optimisation that aims to identify the most efficient way to meet an automotive assembly plant's total energy (i.e. electricity, steam, CA, etc.,) requirements.

According to Mekid et al. (2007), the future of manufacturing will see an increased proliferation of intelligent devices and sensors supporting the enhancement of manufacturing systems. Cannata et al. (2008) predict that future manufacturing systems will be composed of autonomous entities provided with intelligent perception, reasoning, learning, and the ability to seamlessly interact with other system units. Developing an understanding of the duration of time a machine tool spends in each operational state during processing has been identified as an important research area that can be progressed via the implementation of intelligent sensor technology (Vijayaraghavan and Dornfeld, 2010; Dahmus and Gutowski, 2004).

Within the literature, researchers have presented a variety of different perspectives and interpretations on the definition of machining states. Kalla et al. (2009) and Dahmus and Gutowski (2004) presented similar methodologies that separate a machine tools power profile into three components; basic energy, idle energy, and processing energy. The study reported by Vijayaraghavan and Dornfeld (2010) described a similar interpretation of operational modes however, Vijayaraghavan and Dornfeld (2010) proposed a fourth mode of operation reserved for machine tool start up and shut down. The research of Weinert et al. (2011) progressed some of the ideas proposed in the research studies described previously with the development of the EnergyBlocks methodology. This methodology segregates a production process into individual operations that can be considered independently and operates by matching energy consumption to operational state and time.

Deshpande et al. (2011) presented a study that aimed to quantify the duration of time a machine tool spent in different operational modes. The Deshpande et al. (2011) study required the user to input threshold values that allowed the smart energy sensor to identify off, idle, and in-cycle machine states. The study also relied on information obtained directly from the machine tool controller in order to infer status information. A fixed energy rate of 10 cents per kilowatt-hour was included in order to allow the sensor to calculate the financial cost of the measured energy consumption. The Deshpande et al. (2011) study reported strong results however, the inference of machine tool status was only achievable by using a combination of sensory inputs.

The application developed by Chiotellis and Grismajer (2012) used only power information in order to identify the operational status of a 3-axis CNC milling machine. The application is based on a combination of status-specific power value thresholds and the dynamic time warping similarity metric. The approach proposed by Chiotellis and Grismajer (2012) uses low resolution data, 250 ms to 1 s, to identify the operating state and high resolution data, 1–250 ms, to perform basic process monitoring. Vikhorev et al. (2013) built on the work of Chiotellis and Grismajer (2012) with a study that attempted to identify the operational status of a series of machine tools in a major European automotive manufacturing facility. The study required the input of energy status threshold values, based on expert knowledge of the process, in order to infer state information. The threshold values defined for the test machine tool described in the Vikhorev et al. (2013) study are: idling (0.6–1 kW), waiting (3–8 kW), and producing (8–30 kW). The system reported positive results but was unable to accurately