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Automated energy monitoring of machine tools

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ABSTRACT

Reducing the energy consumption of machine tools can significantly improve the environmental performance of manufacturing systems. To achieve this, monitoring of energy consumption patterns in the systems is required. It is vital in these studies to correlate energy usage with the operations being performed in the manufacturing system. However, this can be challenging due to complexity of manufacturing systems and the vast number of data sources. Event stream processing techniques are applied to automate the monitoring and analysis of energy consumption in manufacturing systems. Methods to reduce usage based on the specific patterns discerned are discussed.

1. Introduction

Manufacturing and the processes involved consume substantial amounts of energy and other resources and, as a result, have a measurable impact on the environment [1,2]. Reducing the energy consumption of machine tools can significantly improve the environmental performance of manufacturing processes and systems. Furthermore, given that machining processes are used in manufacturing the tooling for many consumer products, improving the energy efficiency of machining-based manufacturing systems could yield significant reduction in the environmental impact of consumer products.

The first step towards reducing energy consumption in machine tools and manufacturing systems is to devise methods to understand and characterize their energy consumption [3]. In this endeavor, it is important to first do a comprehensive analysis of energy consumption in machining and to note, specially, that the energy consumed by machine tools during machining is significantly greater than the theoretical energy required in chip formation. Past work has characterized machining energy usage solely based on the specific cutting energy [4]; while this approach is useful in understanding the fundamentals of chip formation, it may exclude important elements of machine operation in characterizing the total energy consumed by a machine tool during machining. Dahmus and Gutowski [5] showed, for instance, that the specific cutting energy accounts for less than 15% of the total energy consumed by a modern automatic machine tool during machining. Although other machining processes may differ from this value, machine "tare" consumption (that is, energy consumed by the machine outside of chip formation) is significant [6]. Other approaches offer more promise but still exclude many of the machine systems aspects [7]. Hence it is vital to go well beyond the tool–chip interface to fully understand machine tool energy consumption.

Studying the energy consumption of machine tools provides valuable data that can be applied in the life cycle analysis (LCA) of the use phase of machine tools, as well as the manufacturing phase of the products that are made by them. This data can also be used to derive the embedded energy in consumer products. As manufacturing supply chains span the globe and intra-country carbon accounting becomes increasingly important, accurate manufacturing energy data serves a vital need. Environmental reporting standards such as those of the World Research Institute (WRI) are also including supply chain effects when determining an enterprise's carbon footprint [8]. Given that most complex machined parts (for example: medical devices, aerospace turbines) require multiple machining processes, a system level approach is essential in characterizing – and reducing – the embedded energy of these parts.

This paper is motivated by the need to understand the energy consumption of metalworking and machining-based manufacturing systems. These systems can be studied at different levels of analysis, ranging from that of the entire enterprise to the tool–chip interface. Each of these levels of analysis also has a corresponding temporal scale of decision making, which ranges from several days at the enterprise level to micro-seconds at the tool–chip level. Fig. 1 illustrates the range of variation in the analysis and temporal scales, along with the types of decisions that are made at each level. The paper discusses the development of tools to automate the monitoring and analysis of machine tool energy consumption in complex manufacturing systems. Automation is a vital step in characterizing the energy consumption of complex systems; the next section discusses the motivation behind such an approach, and lays out the challenges in pursuing it.

2. Motivation

Automated monitoring can significantly decrease the complexity of working with large systems. While manual approaches are available for energy measurement (such as with hand-held power meters), they can be cumbersome for simple systems, and

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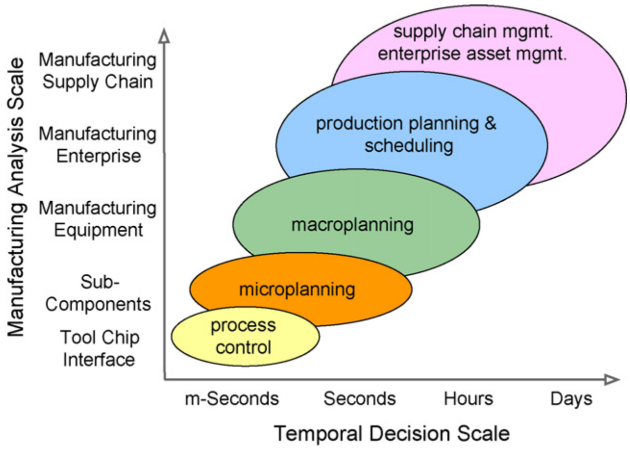

Fig. 1. Level of analysis of manufacturing with temporal decision scales.

impossible for more complex systems. A more important consideration is the need to analyze the temporal aspects of the energy data. In order to decrease energy consumption, energy data has to be placed in context of the manufacturing activities. Automated monitoring systems can help attach contextual process-related information to the raw energy data.

Another motivator is the growth of smart grid technologies for energy generation, transmission, and delivery [9]. The goal of these technologies is to save energy, reduce cost, and increase reliability. Smart energy delivery technology includes demand response, where demand requirements are driven based on energy pricing and availability. While demand response technologies are taking hold in consumer energy markets, their growth has been much slower in industrial markets. A main reason for this has been the lack of detailed demand data from the manufacturing facilities that can be used to drive grid requirements. Moving towards automated monitoring systems will allow better communication of manufacturing system demand data to the grid, enabling smart grid technologies in manufacturing systems.

3. Related work

Energy consumption in manufacturing systems has been primarily studied from the perspective of accounting for it as an environmental flow of the system for LCA and other characterizations. Dahmus and Gutowski [5] tracked energy flows when characterizing the environmental impact of machining, making a distinction between the energy required for chip formation and operating the manufacturing equipment.

Srinivasan and Sheng [10] developed an approach for macro- and microplanning of feature-based machining. Microplanning looked at selecting process parameters, tooling, and cutting fluid based on process energy use, waste streams, process quality, and machining time. While this work developed a very thorough approach for process planning, process energy usage was characterized solely by the chip removal energy. Toenissen [11] characterized in detail the power consumption of a precision machine tool during various types of manufacturing activity. The power consumption of various machine tool components was estimated using empirical analysis. Devoldere et al. [12] discussed the improvement potential in two types of manufacturing equipment for discrete part production. Power requirements for activities in a machine tool was investigated and classified into productive and non-productive periods. This type of analysis is the starting point in designing machines that have lower tare (or fixed) energy loads, and higher variable (or per-part) energy loads.

4. Approach

Past efforts in energy monitoring and analysis of manufacturing systems have been performed either as an accounting exercise, or by using theoretical estimates of the energy required for the various tasks and sub-tasks involved in manufacturing a part. The former approach is not granular enough to support decision making at the different levels outlined in Fig. 1, and the latter approach is not accurate enough, especially in complex systems.

This paper presents a software-based approach for automated energy reasoning, which can support decision making across the multiple temporal levels shown in Fig. 1; Fig. 2 shows examples of the types of analysis required across some of these levels. Based on the analytical complexity of manufacturing processes and systems, the software tools need to have the following capabilities:

- Concurrent monitoring of energy use with process data
- Standardized data sources
- Scalable architecture for large data volumes
- Modular architecture to support analysis across different manufacturing scales

Based on these requirements, the automated energy monitoring system is developed using two key components: an interoperability standard for manufacturing data that can normalize data exchange in the manufacturing system, and a rules engine and complex event processing (CEP) system to handle data reasoning and information processing.

4.1. Data standards: MTConnect^{SM}

The MTConnect^{SM} standard for data exchange is selected for data collection from the manufacturing equipment. MTConnect^{SM} defines a common language and structure for communication in manufacturing equipment, and enables interoperability by allowing access to manufacturing data using standardized interfaces [13]. It is an XML-based standard, and describes the structure of manufacturing equipment along with the near-real-time data

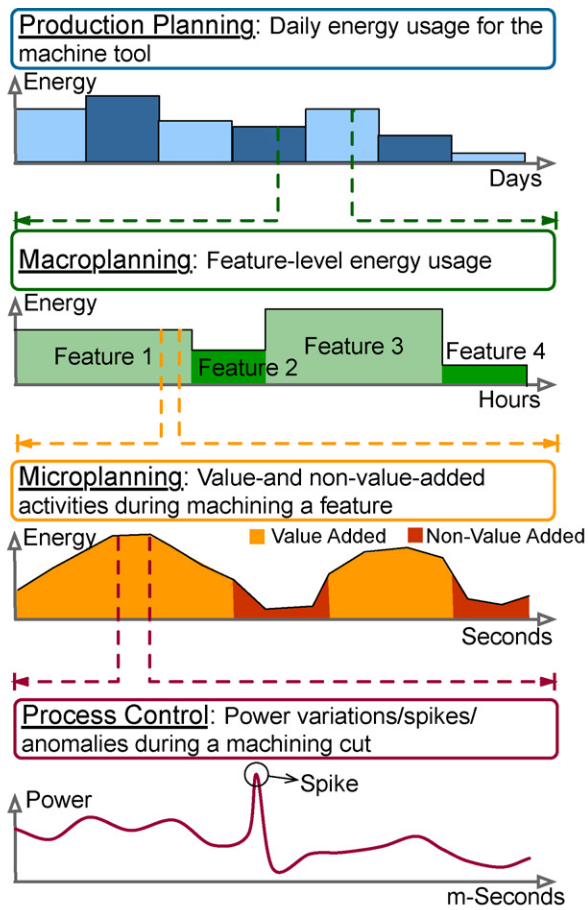

Fig. 2. Examples of analysis across temporal scales.

occurring in the equipment. It allows a way for logically organizing data from equipments, without being constrained by physical data interfaces. Previous work by researchers has used the MTConnect^{SM} standard in monitoring the energy consumption of machine tools [11]. With MTConnect^{SM}, the operational data of the machine tool can be monitored in context with the energy consumption data.

4.2. Reasoning: event stream processing

Events can be understood as something that occurred either at a point in time or over a range of time. In manufacturing systems, events can be a numerical value (for example, the instantaneous power consumption at a point in time) or can be a type of annotation (for example, the alarm state of the machine tool over an interval). Complex events are abstractions of events that are created by combining simple events. For example, based on simple events pertaining to the tool position, the instantaneous power consumption, and the machine tool's alarm state, a complex event indicating that the machine tool's spindle has crashed can be created. Event streams are linearly ordered sequences of events and, in our context, correspond primarily to time series events.

Events stream processing techniques include rules engines (RE) and complex event processing (CEP). These techniques can be used to create higher level abstract events and reason on them by pattern matching and identification. A common algorithm implemented in RE/CEP systems is the Rete algorithm. The Rete algorithm provides a very efficient way of matching patterns by "comparing a large collection of patterns to a large collection of objects" [14]. Naive approaches to pattern matching involves testing each rule against each event (or set of events) in the stream, and iterating over the rules and the events; this can quickly become inefficient in systems with large number of rules and events. Instead, the Rete algorithm uses a tree-structured sorting network to index and match patterns, avoiding computationally expensive iterations. Event stream processing techniques bring in additional capabilities for time series events. This includes temporal reasoning over sliding and static time windows, temporal causality, correlation, and abstractions.

4.3. Architecture

A software architecture is developed for energy monitoring and analysis based on MTConnect^{SM} and complex event processing techniques. Standardized data is streamed from the various sources in the manufacturing system, including process equipment, ancillary equipment, and embedded sensors. This data populates the event cloud, against which a near-real-time rules engine operates. The rules engine operates on the events and creates complex events at higher levels of abstraction, which in turn also populate the event cloud. In addition to this, a specialized "timeline" module is used to handle high frequency time series data, and a "metrics" module is used to perform mathematical operations on the time series data. The objects created by these modules are also populated into the event cloud, and are operated on by the rules engine. Timelines and metrics are made available for visualization in an online or offline UI, and for export into further analysis and processing systems, such as life cycle analysis (LCA) tools and environmental databases. This architecture is shown in Fig. 3. It is fully modular and can be easily extended to support different manufacturing data standards such as OPC and frameworks such as AutomationML. Scalability can be achieved by implementing the architecture using parallel processing and distributed computing.

This architecture effectively combines the flexibility of using an open standard for data exchange with the capabilities of event stream and complex event processing. The architecture enables accurate characterization of process and equipment energy usage, which can be applied in life cycle analysis as well as in environmentally conscious optimization of machining processes.

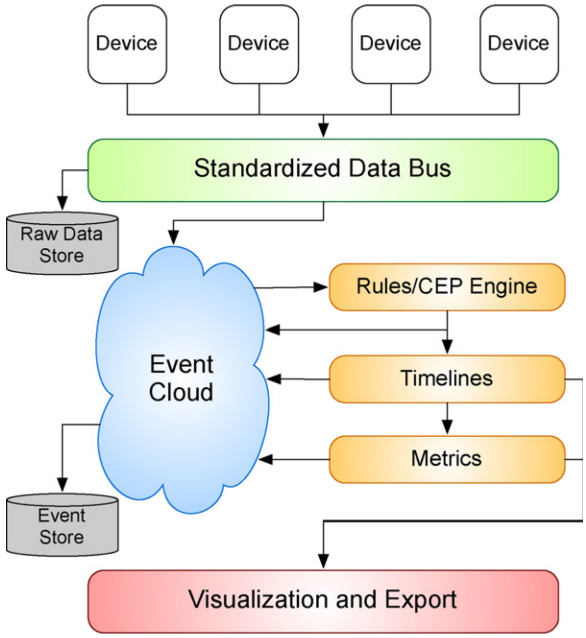

Fig. 3. Software architecture for temporal analysis.

CEP systems are very flexible, and rules can be designed to identify diverse patterns in the system, supporting a wide array of processes, systems, and activities therein. This approach makes reasoning across the different levels of a manufacturing system very efficient. The use of standardized data also removes limitations imposed by custom standards, and makes available data from a large number of devices for analysis. The processing capabilities of CEP systems also enables near real-time communication and decision based on the reasoning.

5. Case study

In this case study demonstrate the application of the energy monitoring and analysis framework using energy consumption and process parameter profiles from machining experiments is demonstrated. A simulated energy profile is developed based on actual measured data from Toenissen [11] and Diaz et al. [6], from the end-milling of aluminum using a 2-flute carbide cutter in a 3-axis precision milling machine. The simulated profile extrapolates the laboratory measurements to a more representative industrial case, with multiple parts/cycles, machine tool events, and a longer operational time. The profile also corresponds broadly with the research presented by Hermann [15]. The spindle occupies three states during this profile: idle (0 rpm), low (8000 rpm) and high (16,000 rpm). The operational states of the machine tool include startup, shutdown, idle, and in-cycle (machining a part). The machine tool demonstrates "spikes" in the energy consumption during a spindle speed change. The power consumption increases when the spindle is engaged at a higher rpm, and when there is material removal (that is, when the machine is in-cycle).

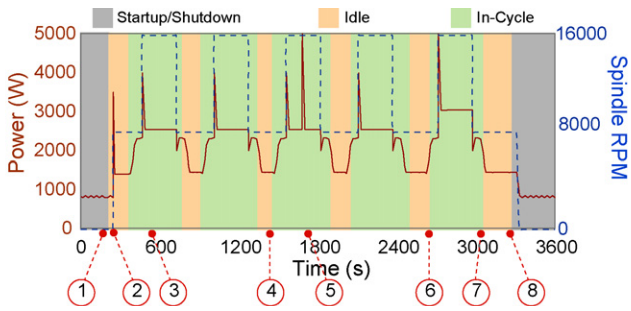

Fig. 4. Energy consumption and spindle rpm profile for case study.

Table 1
Event reasoning case study.

Event	Time	Reasoning
1. Machine idle	242 s	Average energy use < idle threshold; spindle speed = 0
2. Expected energy spike	243 s	Spike due to spindle startup (0–8000 rpm)
3. Expected energy spike	464 s	Spike due to spindle speed increase (8000–16,000 rpm)
4. Idle energy constant	1457 s	Previous two idle periods energy use constant at 124 kJ
5. Anomalous spike	1679 s	Energy spike unaccompanied by shift in spindle RPM. Potential failure in spindle
6. Idle energy increase	2612 s	Current idle period energy use (211 kJ) > past idle period average energy use (124 kJ)
7. Part energy higher	3074 s	Current part energy (1218 kJ) > previous parts average energy (1087 kJ)
8. Idle energy trend	3309 s	Idle energy increasing monotonically over past two periods (342 kJ > 211 kJ > 124 kJ)

The temporal analysis framework is applied in automatically detecting phenomenon pertaining to relationships between energy usage and operational performance of the machine tool across various temporal ranges. The software framework was implemented using the open source rules engine package Drools [16]. The specific events identified by the analysis framework, along with the energy and spindle profiles are shown in Fig. 4. The events are discussed in more detail in Table 1.

This automated temporal analysis supports decision making to improve the operational and environmental performance of the machine tool. Some scenarios supported by this analysis include:

- Reduce total energy use for the machine tool based on the usage during idle and non-value-added periods
- Identify disruptions in smooth part production based on anomalous power usage spikes
- Track maintenance state of the machine tool using historical power usage profiles
- Enable environmental reporting on a per-part basis by accurately accounting for the energy use of the part as it is being manufactured
- Notice emerging trends in the energy usage, such as increased total consumption for successive parts, which may indicate process plan deviations and inconsistencies.

6. Conclusions

This paper introduced a framework based on event stream processing to temporally analyze the energy consumption and operational data of machine tools and other manufacturing equipment. This can be expanded to analyze other types of environmentally pertinent data streams in manufacturing systems, enabling decision making to improve the environmental performance of machine tools. As demonstrated, the event stream processing technology enables reasoning of vast data streams, over the events that occur in the streams, as well as complex, abstracted events. This capability simplifies environmental analysis and optimization for complex manufacturing systems, where decision making is required across multiple levels of abstraction. Future work in this research includes a real-time implementation of this reasoning engine in an actual factory production line environment, using its MTConnect^{SM} data sources. This includes the machine tools in the factory as well as associated energy meters and embedded process sensors. This demonstration will further validate the effectiveness of these techniques. Finally, application to a wider range of in-processing monitoring applications that would benefit from standardized data exchange and complex event processing is envisioned.

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