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Estimating manufacturing electricity costs by simulating dependence between production parameters

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ABSTRACT

The electricity costs associated with manufacturing generally consist of an energy charge and a demand charge, which are calculated by total kWh × $/kWh and peak kW × $/kW, respectively. While these two charges have been extensively studied with production scheduling, dependence between production parameters has not been thoroughly investigated for production energy costs when the production parameters are assumed to be independent. Such dependence, however, can significantly affect the peak kW and resulting energy costs. Therefore, industrial practitioners need a tool to simulate the production power demand and cost to evaluate energy costs for each production plan and for any dependence in the parameters. In this paper, we propose a method for simulating the power demand at the machine and facility levels, focusing on the dependence in milling machine parameters. Using probabilistic techniques with copulas, we quantify the degree of dependence between two milling parameters (processing times and processing amounts) and build a power demand simulator combining discrete event simulation and numerical simulation models. From 35 illustrative examples, we show that a production strategy to adjust dependence can reduce the peak kW and energy costs by more than 15% and 4%, respectively. In addition to dependence, less variability in processing times results in less peak kW and energy costs. Other factors such as a marginal probability distribution and copula types having the same degree of variability have been found to have limited effects on reducing energy costs.

1. Introduction

As industrial structures are becoming more and more sophisticated, individuals possess extremely diverse preferences in terms of high-tech products, thereby increasing manufacturing complexity to satisfy these various needs and requiring changes in manufacturing activities at all levels. In such a complex production environment, a complete connection between low (that is, machine) and high (that is, supply chain) levels needs to be pursued, so that management can build and apply more smart and flexible manufacturing strategies based on data collected from all supply chain levels and make an immediate response based on the collected data. Sustainable manufacturing is one of the important areas in smart production strategies and operations, since more production energy data can be collected from the smart manufacturing environment [1]. Reduction in excessive energy consumption and greenhouse gas emissions also is a necessary condition required by most of today's manufacturing companies, and such an energy-saving and environmentally friendly manufacturing strategy should be integrated with complex production to achieve the maximum operational and energy efficiency simultaneously. Specifically, energy consumption in manufacturing systems is a key element of building an energy-efficient control mechanism. As the most important component that enables sustainable production systems, an understanding of production activities with different energy profiles is crucial to establish energy-aware manufacturing strategies. In particular, a comprehensive understanding of impacts of production variations on energy consumption and production performance plays a significant role in effectively designing products and required production processes, controlling manufacturing capacities, and building long-term green production strategies.

The industrial sector in the U.S. accounts for 27% of electricity usage among four sectors (residential, commercial, industrial, and

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transportation). In particular, more than half of the electricity consumed in manufacturing is spent powering motor systems, including manufacturing machines and equipment [2,3]. This suggests that machining energy analysis can provide opportunities for reduction in energy consumption and costs. Industrial electricity costs for manufacturers mainly consist of two parts: energy charge and demand charge [4]. Electrical energy consumed is calculated in kilowatt-hours (kWh), and customers are responsible for the amount of energy they use each billing period (energy charge). Electrical demand is denoted by the kilowatt (kW), and customers should pay the peak demand × demand rate ($/kW) as the demand charge. Thus, a clear understanding of energy and demand charges can help manufacturers reduce utility costs.

The extensive studies on manufacturing energy consumption have been conducted in order to spend less amounts of energy in manufacturing processes. These studies include approaches to optimizing manufacturing parameters [5,6] and scheduling production [7,8]. Studies on the peak demand and demand charges, however, have been less well studied. While some sustainable manufacturing optimization studies for production parameters and for production scheduling are currently available, a close relationship between peak demand and manufacturing parameters needs to be investigated further [9,10]. Thus, a study examining the relationships among manufacturing parameters, peak demand, and demand charge is urgently needed, since it can show how manufacturing parameters affect peak demand and offer ways to reduce demand charge in manufacturing facilities. Furthermore, power suppliers must invest a great deal of capital into building and maintaining a power system to meet the peak demand required by various manufacturing customers [11,12]. Thus, detailed studies on the relationship between peak demand and manufacturing parameters can help manufacturers as well as power suppliers and offer benefits to society as a whole. While production parameters can stand for a broad range of factors in manufacturing systems, in this study we narrowly define and use production parameters as machining parameters or machine-relevant parameters.

2. Background

A general introduction to the structure of electricity costs can be found in [4]. The report explains how demand charge is evaluated from the peak demand for a billing period and how utility costs are calculated from the demand charge and energy consumption. From the report, the real rate plan of utility providers such as [13] can be readily understood. Applying this framework, the study in [14] provides an extensive survey on utility costs for $/kWh and $/kW in the U.S. In particular, the study focuses on time-of-use (TOU) pricing, in which the values for $/kWh and $/kW vary depending on the time of day.

Considerable efforts have been made to effectively manage both energy consumption and power demand in various systems, such as buildings. For approaches studying an integrated objective function of both energy consumption and power demand to be improved, one can find several studies especially in smart building applications, since both energy and demand charges are principal components for the calculation of the total energy costs in building management systems. For example, the study in [15] proposed the model predictive control (MPC) approach to building energy systems based on balanced model reduction that aimed at removing the impacts of large singular values on the input-output system behaviors. Vaghefi et al. analyzed daily load profiles of nonresidential buildings and developed a classifier for predicting the classes of the future load profile [16]. Cai et al. also considered building energy systems; the optimal zone temperature setpoint trajectories were determined by minimizing daily energy costs regarding both demand and energy charges under TOU pricing [17].

There are a few studies on manufacturing systems with energy and demand charges; one study compared the production energy costs between a TOU based electricity demand response rate and a flat rate [14]. In most studies, however, those energy components are considered as decision criteria in an isolated manner because of limited analysis on the dynamic relationship between energy consumption and power demand in specific systems. In particular, sustainable manufacturing studies mainly investigated production scheduling problems rather than the relationship between production parameters and electricity costs. The two surveys on sustainable manufacturing provide an extensive list of relevant scheduling studies [7,8]. Most of them focus on optimizing production scheduling for two decision criteria: energy and conventional scheduling performance measures (e.g., makespan, tardiness, throughput, and product quality). For the energy criterion, most studies use energy consumption rather than power demand, and a few papers pay attention to TOU pricing based on time-varying electricity prices. Since TOU pricing is applied to $/kWh as well as to $/kW, those studies present relevant analyses about energy charge and demand charge based on demand response [14,18]. As a different application area, the workload scheduling problem in data centers was investigated regarding peak power demand and electricity consumption costs [19]. The idea of partial execution for energy efficient management was incorporated into the discrete time model in which service level agreements are considered for response quality to customers, and finally optimal workloads were determined to minimize the expected demand and energy costs. The study in [20] also solved the operations scheduling problem for a battery energy storage system of wind turbine generators with the objective function of minimizing both energy and demand charge. The author proposed a heuristic method, called multipass iteration particle swarm optimization (PSO), borrowing the concepts of multipass dynamic programming and PSO, and applied it to an energy storage system considering TOU electricity pricing. One recent study investigated the energy-aware production scheduling problem aiming at smartly balancing energy consumption levels of both nominal and idle machine processes and production performance under the TOU pricing policy [21]. The authors developed continuous-time variable control models and algorithm, which produced better energy and operational performance than PSO.

As seen in the studies above, power demand and energy consumption are utilized as decision criteria for various energy-critical systems. Studies on the dynamic relationships among production parameters, energy, and power demand or impacts on manufacturing system performance are very limited due to the sophisticated structures of real systems. For example, papers characterizing average power demand in machine states [22,23], estimating energy in production lines by discrete event simulation [24], and developing an energy consumption prediction model based on machine states and energy consumption have been conducted as fragmentary energy-related analysis [25]. From the manufacturing system performance point of view, the relationship between energy consumption levels of individual machine operations, which are possibly changed by machine capacity (that is, machining speed), and resulting production performance was explained by the control theoretic approach [26]. Also, some studies investigated optimal cutting parameters to reduce production costs. For example, production rates, production quality, and operation costs have been optimized in relevant studies by applying a genetic algorithm (GA) and artificial neural network (ANN) [27,28] or by controlling a feed rate [29].

When we study the dynamics between energy costs and production parameters, the dependence between production parameters needs to be carefully investigated. For example, the amount to be processed (A) and production time (T) may be dependent on each other; for a larger amount to be processed, a longer processing time is likely to be used. This observation has a significant implication in material cutting processes such as milling and turning, since power (kW) $\approx b_1 \times$ (processing rate) + $b_2 = b_1 \times$ (processing amount) / (time) + b_2, where b_1 and b_2 are constants [10,22,30,31]. More specifically, given the correlation between the milling amount and time, milling power (kW) can be significantly different from other milling power with independent processing time and amounts. The correlation between production