Real Time Machine Coordination for Instantaneous Load Smoothing and Photovoltaic Intermittency Mitigation

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Abstract
With industrial equipment causing large and variable power loads, the industrial sector has a significant impact on the power quality in the United States. Also impacting power quality is the large growth of distributed intermittent renewable energy resources such as photovoltaics and windmills. Coupling factories' high demand variability with intermittent energy resources' high generation variability creates large unpredictable swings in net demand for the utility. While we cannot control the weather driven intermittency of renewable resources, in this paper we show it may be possible to control the power demands of industrial processes in order to reduce the variability in net demand observed by the utility. This research looks at a new alternative way to alleviate some of the burden imposed by renewable energy sources on the grid by coordinating a fleet of industrial machines. By smoothing a machine fleet’s power demands over time we demonstrate a significant reduction in the variability of net power draws on the power grid of photovoltaic equipped factories. We demonstrate the impact of net demand variability reduction in both a stochastic and deterministic production setting using 10 months of 1 Hz solar irradiance data. When floor shop variability is high as in the stochastic system, net demand variability can be reduced by 7% while maintaining throughput with minimal impact to total energy consumed and part time in system. When shop floor variability can be highly controlled, such as in the deterministic system presented, the net demand variability can be reduced by 35%. By reducing the net demand variability of renewable energy equipped factories, the application of instantaneous load smoothing strategies provides a new alternative solution to mitigating the impact of renewable energy source intermittency on the grid, and could provide improved power quality to facilities with integrated renewables.

Keywords
peak load reduction, production scheduling, photovoltaic intermittency mitigation

1 Introduction
In 2015, 26% of the electricity produced in the United States was used by the industrial sector, indicating that gains in efficiency and novel methods of power management applied to the industrial sector can have significant environmental, economic and power quality impacts (U.S. Department of Energy, 2016). Additionally, large rapid swings in power demand which are often seen in industrial settings, make it challenging for utilities to maintain power quality. Compounding the problem, the U.S. Energy Information Administration believes that solar capacity...
in the United States will grow by 60% and 25% in the years 2016 and 2017 respectively (EIA, 2016). As industrial companies continually try to become more environmentally friendly, many of these solar installations could find homes as distributed energy resources on factory roofs. Unfortunately, the highly intermittent nature of photovoltaics coupled with the high power demand variability of factory floors, creates a highly volatile net demand situation for a utility. High variations in power demand can cause voltage sags and harmonic distortions, both of which can damage expensive commercial equipment and impact the stability of the grid.

Many commercial and industrial customers incur two charges associated with their electricity use: a consumption charge for total energy (kWh) used, and a demand charge related to the maximum average power load (kW) observed over a period of time. The separate demand charge is imposed to cover the utilities’ costs of maintaining infrastructure and reserve demand in order to meet the variable high demands of large customers at any point in time. Currently, peak demand is measured over a sliding window that ranges between utilities from 30 minutes down to as low as 5 minutes. With such large peak demand windows, the instantaneous power demands of factories have been largely ignored, in favor of work that improves the overall energy efficiency of factories and the minimization of time of use energy costs. This paper explores manufacturing floor control strategies to smooth the instantaneous power demand profile of factory floors. Here we refer to instantaneous power demands as those observed over a one second interval. We show that by smoothing the power demand profile of factory floors equipped with photovoltaic generation, the net demand variability observed by the utility can be significantly reduced.

Smoothing instantaneous power demands of a factory floor necessitates a mechanism to reduce the peak instantaneous electricity demand created by commercial and industrial processes while simultaneously not affecting quality of service measures, such as factory throughput and cycle time. While there has been research addressing macro level production scheduling to minimize electricity costs (Fang et. al, 2016; Sharma et al., 2015) these methods have focused mainly on macro level scheduling decisions such as machine assignments and job start times. There has been very little investigation into coordinating the micro-level activities of a fleet of machines, so as to smooth the instantaneous electricity demand across the fleet once jobs have begun processing. By targeting the coordination of micro-level activities of machines, such as spindle start, motor speed changes, and cutting operations, future industries could help combat the intermittency of renewable generation resources by smoothing the variability in net demand observed by the utility.

In this work two investigations were conducted to evaluate both a stochastic and an idealistic deterministic production system. Firstly, a discrete event simulation was developed to analyze the potential benefit of using real time machine coordination strategies for smoothing power load under a system with operator and energy demand variability. The simulation model was used to verify the existence of an opportunity to smooth instantaneous demand, and to evaluate the impact of demand smoothing strategies on net demand variability of photovoltaic equipped factories. A second approach to scheduling was also evaluated using an integer programming model to find the optimal part production pattern to deploy for a more controllable factory setting. Both approaches show significant net demand variability reduction potential. The value of the work is demonstrated with a case study of a fleet of Computer Numerical Control (CNC) machines coupled with 10 months of solar irradiance data. The paper begins by reviewing relevant literature in the area of energy management of Computer Numerical Control (CNC) machining facilities, is followed by a description of the simulation model and characterization of photovoltaic equipped factory net demand. Results are then presented for the stochastic model. Finally, the integer programming formulation for the deterministic setting is introduced followed by a presentation and discussion of related results. The paper is concluded with suggestions for future work.
Literature Review

This literature review first covers research related to energy management for manufacturing and CNC machining operations followed by a review of renewable energy intermittency mitigation strategies. Research related to energy management and CNC machining operation efficiency has so far taken three main avenues: (1) modeling power consumption of machine tools, (2) optimizing toolpaths given power models, and (3) macro level scheduling algorithms that take into consideration energy costs. Prior to the implementation of energy cost reduction strategies, significant research had taken place to estimate machine tool energy use given machining parameters. Zhou et al. (2016) provides a comprehensive review of different approaches to estimating power demands of machining operations. Once power demands of machining tools were investigated and modeled, the first strategy used to minimize energy costs with respect to manufacturing CNC parts was to optimize the toolpath used to create the required part. By evaluating various cutting parameters such as tool speeds, cutting angles, and tool paths the amount of energy required to produce a single part can be minimized. The second approach to managing energy costs and improving energy efficiency has been to look at a macro level scheduling view of part production, where a production schedule is devised that attempts to meet customer demand at minimal cost while incorporating energy costs into the production decisions. The macro level scheduling approach determines which part should run on which machine at what time. In many cases, the macro level scheduling algorithms can influence the toolpath decisions by recommending cutting speeds for certain parts produced during specific timeframes. The macro level scheduling decisions take place on a scale of minutes to hours. This work picks up after these three initial components have been completed in order to smooth the power demand observed in the facility as machines are running according to a predefined schedule using a predetermined optimal toolpath. The relationship between all three energy management strategies can be seen in Figure 1. The third process of real time machine coordination is seen in Figure 1 labeled with a (3), indicating that we will be coordinating the production of a set of parts that have been optimally scheduled to run across several machines. To date, no known research has looked at coordinating the activities of individual machines to smooth demand curves once machines have started processing according to predetermined optimal schedules and optimal toolpaths.

Figure 1: Levels of Energy Management in Machine Shop Environments: (1) - Optimal tool path determination for a single part, (2) Optimal production scheduling across machines, and (3) Real time machine coordination across operating machines. Each box represents a part assigned to a specific machine for a certain amount of processing time.

The remainder of this section looks first at energy management strategies from a scheduling perspective, then summarizes work related to modeling machine power requirements and optimal toolpath determination, and concludes with research related to alleviating the intermittency of renewable generation sources.

2.1 Production Scheduling Including Energy Costs
With the utilities’ introduction of time of use pricing, real time pricing, and peak demand charges research has attempted to address the situation through the design of optimal production schedules that take into account energy costs. Even in the absence of time of use pricing schemes, energy costs can be reduced by minimizing machine idle times, and thereby reducing energy waste. Due to the combinatorial nature of scheduling problems, integer programming formulations leading to NP-Hard problems, the approaches have often been minimal in scale. For example (Mouzon and Yildirim, 2008) and (Shrouf et al., 2014) create models to minimize total energy consumption, but only look at a single machine. A ten machine, 4 stage process is evaluated in a case study by (Sharma et al., 2015), but again the process is simplified by only looking at the optimal production schedule of a maximum of 13 parts per 8 hour shift. While some approaches have relatively short solve times, for example the genetic algorithm approach proposed by Shrouf et al. (2014) can solve a single machine problem with 60 jobs in 12 seconds, the approaches used for scheduling jobs before production starts may be too computationally complex to use for decision making when jobs are in the middle of processing, and split second decisions need to be made. In contrast to traditional scheduling approaches which optimally schedule parts before production starts, the algorithms proposed in this work need to work in real time to coordinate the machining operations across a fleet of machine tools. This work does not replace scheduling algorithms for macro level planning operations, but builds off of them by further smoothing instantaneous demand for machines that have been scheduled to run at the same time.

Various goals have been addressed for energy management strategies including: reducing total electricity costs, minimizing ecological impact, responding to demand response events, minimizing peak power, and minimizing electricity costs across several factories under real time pricing. Some research has focused on reducing total energy consumption for a certain production schedule when taking into consideration time of use pricing (Shrouf et al., 2014; Mouzon and Yildirim, 2008; Sharma et al., 2015). Zhang et al. (2015) evaluated flow shop coordination strategies under real time pricing scenarios, where factories could work together to minimize their energy costs. Other research has focused on reducing total energy consumption from the perspective of identifying opportunities to turn down machine production in the wake of machine break downs and maintenance requirements (Lin et al., 2012; Sun and Li, 2013). He et al. (2015) created a model to minimize energy costs and makespan in a job shop including the condition that different machine tools use different amounts of energy to perform the same operations. A multi-objective optimization model was developed by Fang et al. (2011) for a flexible flow shop that looked to minimize makespan, peak power consumption, and total energy consumption. Their model proved exceedingly difficult to solve and highlighted the challenges involved in considering energy in industrial sized problems. Zhang et al. (2014) evaluated the tradeoff between minimizing electricity costs in a time of use pricing scheme versus environmental impact. Their model showed that as more electricity use is shifted to off peak hours, the environmental impact of the system is actually increased as more load is met by high carbon footprint coal power plants. Finally, other approaches have looked at using buffer inventory to allow for machine shutdown during periods of peak electricity pricing (Fernandez et al., 2013; Sun et al., 2014) and methods to respond to demand response events required by the utility (Sun and Li, 2014). Fang et al. (2013) evaluated minimizing peak power load in a flow shop. Their work is similar to the work proposed here except that Fang et al. assumed that the production of a single part required a constant amount of energy for the whole entire production process, and this energy was related to the speed of the machine. Our work extends this research to further smooth load profiles by looking at the coordination of the individual machining operations across machines. To the authors’ knowledge, no-one has yet addressed near real time load smoothing. The smallest window observed was a one minute window used in (Sharma et al., 2015).

Various production parameters have been explored with research addressing energy goals including: changing machine energy states, tool speed changes, machine assignments, shutting down or idling machines, and reducing throughput requirements. Sharma et al. (2015) explore machine speed changes as part of their production model. In their model each machine is allowed a maximum number of speed changes per day. As machine speeds are lowered energy consumption decreases along with throughput. Each machine’s speed can be changed independently. The work of Fang et al. (2011) also allowed for speed tool changes, and his worked demonstrated that relaxing the
discrete nature of speed changes, to allow for continuous speed changes allowed the problems to be significantly more tractable. He et al. (2015) explore machine assignment combined with scheduling in a flexible machine shop to minimize total energy costs. Sun and Li (2014) use a Markov decision process model to determine when to lower the energy state of a machine during a demand response event based on the current state of the manufacturing system. Sun and Li (2013), Fernandez et al. (2013) and Li et al. (2012) consider shutting down or lowering the power states of machines to improve energy efficiency or meet demand response goals. On a 5 machine, 4 buffer system Sun et al. (2014) were able to show a 22.5% decrease in electricity consumption with only a 0.2% throughput reduction for a demand response event. Similarly, Shrouf et al. (2013) consider the impact of changing a single machine’s processing state between off, idle and processing to minimize total electricity costs with time of use pricing. They show by strategically scheduling idle times electricity costs could be reduced by as much as 32% depending on the specific scenario looked at. While many works focus on maintaining system throughput, Sun et al. (2014) considers the tradeoff between system throughput reductions and reduced energy costs. In this work the air cutting, or time between cutting operations, is allowed to vary in order to coordinate high energy machining operations.

Modeling approaches vary across the research as well. Sharma et al. (2015) use a multi-criterion “ecological” mathematical model which they solve using a hybridized search mechanism combining aggregate indexing and simulated annealing. Even with their metaheuristic the problem could be time prohibitive to solve for large cases. Similarly Shrouf et al. (2014) employed a genetic algorithm to solve an integer programming model for the optimization of a single machine’s production schedule. Sun et al. (2014) employ a Non-linear Integer Program to model their “Just-For-Peak” optimization strategy, an off the shelf solver was used to solve the model. Sun and Li (2014) employ a Markov Decision Process with a forward method to avoid the curse of dimensionality seen in dynamic programming. Discrete event simulation has been used to evaluate multi-machine systems with respect to turning off or down machines during blockages (Li et al. 2012, Sun and Li 2013). He et al. (2015) demonstrate that a Nested Partitioning approach can be effective for solving flexible job shop scheduling problems with machine tool energy considerations. In this work we will use both discrete event simulation and integer programming to evaluate the impact of instantaneous demand smoothing strategies.

2.2 Energy Measurement and Optimization

The ability to predict a part’s energy profile is a prerequisite to implementing the strategies suggested in this paper. Fortunately, there has been a significant amount of research dedicated to accurately estimating the power and total energy requirements for parts made on machine tools; see (Zhou et al., 2016) for a detailed literature review on such models. The energy requirements for machining processes can largely be split into three categories: the energy required for the auxiliary support systems of the machine, the energy required for run time operations, and the energy required for machining (Kordonowy, 2003). The auxiliary support systems of a machine consume a constant amount of energy and include the power for the computers, cooling fans, coolant pump system, and unloaded motors. Kordonowy found for a 3-axis CNC milling machine that minimally 13.2% of the machine’s energy was used for auxiliary support. Since these auxiliary systems do not contribute to demand variability, they will not be considered in this work. This paper, however, focuses on the power required for run time and machining operations.

Run time operations include those operations that require constant energy regardless of the cutting parameters employed. Run time operations include starting the spindle, tool changes, and part movements, and account for at least 20.2% of the total energy consumed in machining operations. Finally, up to 65.8% of the energy used for machining a part comes from the machining or cutting process itself. The energy required for machining is dependent on cutting parameters such as cutting speed, feed rate, depth and angle of cut. Of interest in this work is only the energy required for run time operations and machining energy, as the flow shop environment investigated has high enough utilization to prevent the machines from ever needing to shut down.

Since the machining energy is dependent on cutting characteristics, estimating the machining energy has garnered significant attention. Several models have been able to accurately predict machining energy requirements as a
function of material removal rate, see Gutowski et al. (2009) and Li et al. (2013) for two examples. While models based on material removal rate are arguably the most simplistic, other models become increasingly more complex and detailed including those based on metal deformation theory, models based on tool wear, models based on cutting force and models based on the main cutting parameters of feed rate, cutting speed, and cutting depth. See Zhou et al. (2016) for a complete review of each of these types of models. The case study parts used in this model were based on the energy requirements research completed by Peng and Xu (2013).

While many of the energy models developed require painstaking experiments and expensive equipment to derive machine specific model coefficients, Hu et al. (2012) demonstrated that power profiles of parts could be accurately obtained using a simple $55 power sensor and power balance equations. Their model was able to accurately determine power consumption of cutting operations to within 3% of estimates that were made using the traditional approach of employing an often prohibitively expensive dynamometer. While their system was designed with cutting parameter optimization in mind, a similar system could be employed to measure the energy consumption of a part with very little investment. Finally, Vijayaraghavan and Dornfeld (2010) have suggested an online framework that utilizes the MTConnect™ messaging to obtain real time machine tool parameters, a complex event processing system to identify events in real time, and real time energy data to learn energy characteristics of a fleet of operating machines. A simulation based case study of their architecture demonstrated that the framework allowed for the detection of 7 different machine states including idle, spindle start up, spindle speed change, anomalous spikes, and increasing periods of idle energy. This type of system provides another option for determining part power profiles in future Internet of Things enabled factories.

A natural progression from models that estimate energy requirements to machine a part was the optimization of cutting parameters to produce the part with minimal energy. Complementing scheduling based approaches to energy efficiency and electricity cost reduction are approaches to optimize the cutting pattern and parameters of machined parts. Much research has been completed on optimizing the tool path coupled with choosing optimal machining parameters such as cutting speed, feed rate and depth of cut in order to manufacture a part using the least energy possible. Pavanaskar (2015) was able to demonstrate a 20% energy savings through choosing an optimal toolpath. Garg et al. (2015) looked at milling operations, and were able to derive closed form non-linear relationships between cutting speed, feed rate and depth of cut in order to predict energy consumption. Similarly, Ma et al. (2014) looked at the effects of rake angle and edge radius on energy efficiency, and found both need to be decreased for optimal energy usage.

This work assumes that the optimal tool path and cutting parameters have already been identified for the parts that are produced, and that the power profile of the part is known. Additionally, an optimal macro level production schedule has also been defined. From this point, this work explores approaches to coordinate several machines that have all been assigned jobs, such that their instantaneous demand stays as smooth as possible without impacting throughput and total energy consumption.

2.3 Mitigating Renewable Energy Generation Intermittency
Mitigating the intermittency of renewable energy generation systems, in particular photovoltaic and wind power systems has been a recently increasing area of research focus. Of closest relevance to the work presented here is the work by Mammoli et al. (2012) that investigated to use of HVAC systems to smooth cloud-driven intermittency in photovoltaic generation. By introducing variation in the fan operation of HVAC systems, Mammoli et al. demonstrated that the fan could absorb a large percentage of the photovoltaic dips in power supply. A more commonly evaluated method to mitigate photovoltaic intermittency is the use of battery systems. Essakiappan et al. (2015) provide an example of a utility scale battery system that requires only 10% of the power rating of the solar array to mitigate intermittency. A drawback of such battery systems is their high cost, limited life time, and severe end of life environmental impact. Traube et al. (2013) simulate a system that mitigates intermittency by using electric-vehicle-to-grid technology. Their work showed the feasibility of such a system to reduce the rate of change.
of photovoltaic power output to less than 10% per minute, with limited impact to battery life. Finally, integrated hydro-photovoltaic power systems have been explored to minimize photovoltaic intermittency. Li and Qu (2016) created an optimization model to optimally dispatch hydro and photovoltaic generation, but their model only accounted for intermittency at the daily level, not for intermittency at a second by second level. This work complements existing work to reduce the impact of solar power intermittency. By smoothing the power demands of a factory floor, the variability of net power demands observed by the utility will not be as extreme as those experienced without smoothed power demands.

3 Motivation
Two parallel approaches were used to address the objective of smoothing the power demand for machining activities. The first approach was to evaluate real time control strategies using a discrete event simulation with programmable control logic. This approach was used to understand the energy characteristics of a set of CNC machines, such as a set of vertical milling machines, as they performed operations on a continuous stream of parts with variability introduced with respect to machine energy consumption and operator response time. The blue line in Figure 2 (a) illustrates the variable power demand pattern of a simulated group of 10 CNC machines producing Part A (described in section 4.3) with operator induced start time variability. With average system peaks around 12,000 W and valleys around 4000 W there is considerable room to smooth the load profile over the course of production. All power demand data represented in the graph was drawn from the discrete-event simulation described later in section 4.1. Figure 2 also illustrates the power generation of a 12000 W solar array. The solar power generation data was generated using the 1 Hz frequency solar irradiance data from the National Renewable Energy Laboratory: Oahu Solar Measurement Grid project (Sengupta and Andreas, 2010), and represents data for March 18th, 2010 from 11:00am to 3:00pm. The irradiance data was converted into DC power generation using a simplified version of the PVWatts Model (Dobos, 2014), where no temperature correction was included, see equation (1). Where $I_{tr}$ was the global horizontal irradiance as reported in (Sengupta and Andreas, 2010) and $P_{dec}$ was the base capacity of our solar unit of 12000W

$$P_{dc} = \frac{I_{tr}}{1000} * P_{dec}$$

(1)

Figure 2 illustrates that both the demand pattern for a set of machine tools (2a) as well as photovoltaic power production (2b) can exhibit significant variability. Figure 2 (c) illustrates the net demand that would be observed by a utility in the case where the factory has solar generation. In the case where the factory has no solar generation, the fluctuations in net demand are the same as those required for the machining process in (2a). However, in the case of a factory with solar panels, Figure 2 (c) illustrates the compounding effect that production variability and solar panel power generation variability have on net demand observed by the utility. In the four hour time period pictured, the net demand ranges from 800 W to 11650 W for the no photovoltaics (PV) scenario, while for the PV scenario the net demand range almost doubles to -8397 W to 10064 W.

This work looks at the feasibility and benefit of coordinating the activities of a fleet of machine tools on reducing the variability in net demand observed by the utility for machine shops with integrated PV generation. To perform the analysis two situations were evaluated: firstly, a stochastic system with operator and machining induced variability, and secondly an idealistic deterministic system to understand the bounds of the potential benefits.

After verifying that there could exist considerable real time variations on power demand in a stochastic system both with and without PV integration, a real time control strategy was implemented to attempt to smooth the load profile while maintaining system throughput. The simulation model and corresponding real time control strategy for systems with operator and energy demand variability are discussed in Section 4. The impact of load smoothing on peak load, throughput, load factor, and total energy (kWh) were evaluated through a series of case studies.
In many CNC machine shops the machines are fed by an automated means, such as with bar stock feeders for lathes, or newer automation systems such as the SV-2 (Simons Design Innovation) for vertical milling machines, thereby removing the operator induced cycle time variability, and mimicking a more deterministic process. In Section 5 an integer programming formulation is discussed that was used to identify the optimal configuration to run several parts at the same time, in order to maximize the machining load factor while maintaining system throughput. The impact of time between parts on peak load and overall load factor are discussed. Finally, in Section 6, results of power smoothing strategies will be related back to net power demands to evaluate the reduction in variability these strategies may provide to facilities with integrated PV systems.

Figure 2: (a) Simulated power demands of a stochastic production process (Part A - 90% Utilization, 10 Machines)(b) simulated PV power generation for a 12000 W array for the hours of 11:00am to 3:00pm on March 18th, 2010 in Oahu, Hawaii (c) The net machining power demands of machining operations with PV generation

4 Smoothing Power Demands in a Stochastic Production Process
This section provides details on the evaluation of strategies for real time power demand smoothing in a stochastic system. A discrete event simulation approach was used to model a high volume CNC machine shop. The model allowed the user to manipulate real time control logic, the energy profile of parts in the system, the number of machines in the system, and utilization rates. While there are many sources of variability that could be included in a discrete event simulation model, the model produced for this work has accounted only for the variability induced by the operator response times and the variability in power demand used in each processing step of a part. Each processing step was modelled as requiring a constant power demand throughout the step, but the exact power required for each step was chosen from a normal distribution whose parameters for mean (µ) and standard deviation (σ) are specified in Table 1. This section first describes the simulation model developed including a description of the real time control logic evaluated. The model description is followed by details of the case study and experimental design. Finally, Section 4.4 concludes with a presentation and discussion of results.
4.1 Simulation Model Details

A discrete event simulation model was created to model a CNC machine shop. The model allowed for a variable number of machines where parts flow through the machines with specific energy consumption patterns, and a variety of load smoothing strategies could be programmed. The parameters in this simulation model included number of machines, part energy profile, utilization of machines, and product mix. The performance measures tracked were peak load (W), load factor, total parts completed, and total energy consumed (kWh). The utilization rate of the machines was controlled by increasing or decreasing the mean time for an operator to remove a part and start a new one. The operator service time was exponentially distributed while the machine processing step times were deterministic.

The operations or machine states considered in the model included: idle, starting the spindle, cutting, and air cutting. Air cutting occurs when a cutting tool is spinning, but is not actively removing material, such as when a tool is being repositioned for the next cutting operation. The energy profile of parts provided only accounts for the machining power demands, the auxiliary power used while a machine was not actively machining a part was not modelled as that power remains constant throughout the time the machine is on, and does not contribute to demand variability.

A real time control logic was designed to test the effects of limiting peak load as a strategy for smoothing demand. In the logic, parts were only allowed to start on their next step if the total power demand in the facility after starting the next step was expected to be lower than a predefined limit or peak load restriction. If the current restriction would be exceeded by starting the next cutting or spindle start operation, the machine would remain in the air cutting or idle stage until the overall power load in the system was lowered and the part could proceed. The overall logic of the system can be seen in Figure 3.

![Figure 3: Simulation Model Components and Real Time Machine Control Logic](image)
In this system machines are assumed to communicate with a central system that is monitoring total power load in the facility. Machine requests to proceed to the next cutting operation are processed in a first-in-first-out manner.

### 4.2 Case Study Specifics

The electricity profiles of the parts in the model were based on existing research that looked into energy consumption in machine tools, specifically part A is modeled after (Peng and Xu, 2013). In Table 1 are the details of part’s energy profiles that were used for the model, keep in mind that these power demands are only for the machining energy and do not include auxiliary power used by the machine. As these parts are processed by the machines, the cutting times are fixed, but the control strategy may choose to extend air cutting and idle operations.

<table>
<thead>
<tr>
<th>Action</th>
<th>Time (s)</th>
<th>Power (W) N(µ, σ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Idle</td>
<td>15</td>
<td>(400,50)</td>
</tr>
<tr>
<td>Spindle Start</td>
<td>5</td>
<td>(1,000,50)</td>
</tr>
<tr>
<td>Air Cutting</td>
<td>10</td>
<td>(800,50)</td>
</tr>
<tr>
<td>Cutting</td>
<td>15</td>
<td>(1,200,50)</td>
</tr>
<tr>
<td>Air Cutting</td>
<td>15</td>
<td>(850,50)</td>
</tr>
<tr>
<td>Cutting</td>
<td>15</td>
<td>(1,200,50)</td>
</tr>
<tr>
<td>Remove Part</td>
<td>End</td>
<td>0</td>
</tr>
</tbody>
</table>

### 4.3 Simulation Experiment to Identify Minimum Power Restriction

A set of experiments were run to identify the minimum peak load restriction allowable before total parts produced significantly differed from the case of no power restriction. For each run four measurements were recorded: instantaneous peak load (W), total parts made in the 72 hour run, load factor, and total energy used (kWh). Load factor was calculated as the (average power utilization)/instantaneous peak load. A total of 30 replications were run for each restriction level, where each run consisted of 80 hours, with an 8 hour warm up period and 72 hours of data collection. The power restriction was decreased from 12,000 W down to 10,000 W in increments of 100 W. At each restriction level, a Tukey test was completed to identify if the total parts produced differed in a statistically significant manner from the model with no implemented power restriction.

The utilization rates of the system were manipulated by adjusting the time it took for operators to respond to a completed part. The utilization rate for this set of experiments was set to 90%, which corresponded to a mean operator response time of 6.9 seconds.

### 4.4 Minimum Power Restriction Results

Figure 4 illustrates the impact of load restriction on the performance measures of interest. Highlighted in red is the data corresponding to the minimum load restriction allowable before total parts produced is impacted. In this experiment, the minimum load restriction was found to be 11,100 W. Figure 4 highlights that as the power restriction is lowered, the observed peak demand also lowers as expected. As the power restriction is lowered, the load factor of the facility increases. The load factor in the facility with no power restriction was 0.65, and with the optimal power restriction improved to 0.74. Further decreasing the power restriction continues to increase the load factor, but has a significant trade off with part production. As the power restriction is lowered, the total parts produced does not begin to steeply decrease until a peak restriction of 11,000 W is reached, with 11,100 W
identified as the lowest restriction that can still produce the same number of parts as the no restriction case. As the power restriction is lowered, the total energy used to produce the parts does appear to slightly increase as the peak load restriction is introduced, but the effect is minimal and tapers off after a restriction of 10,300 W is imposed.

Figure 5 compares the box plot of power demand of the 11,100 W restricted power profile to the no restriction power profile. As can be seen in the figure, and summarized in Table 2, the 11,100 W restricted profile has significantly less variability than the no restriction level. An ANOVA test indicated the means and standard deviation of both load profiles were significantly different from one another with a p-value of less than 0.001.

Figure 4: Part A - 90% Utilization Power Restrictions versus Performance Measures: (Top Left) Peak power observed, (Top Right) Load Factor, (Bottom Left) total energy consumed in production of all parts, (Bottom Right) total parts produced

Figure 5: Boxplot of power demand distribution for stochastic system with no restriction vs a stochastic system with an optimal power restriction of 11,100 W.
Table 2: Load Profile Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Mean Power (W)</th>
<th>Standard Deviation (W)</th>
<th>Load Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Restriction</td>
<td>7025</td>
<td>1952</td>
<td>0.65</td>
</tr>
<tr>
<td>11,100 W Restriction</td>
<td>8305</td>
<td>1472</td>
<td>0.74</td>
</tr>
</tbody>
</table>

5 Load Profile Smoothing in a Deterministic System

In high volume CNC machine shops, machines can be fed in an automated manner, which can effectively remove the variability between the start of jobs caused by human operators. In such a situation, where the same parts are made one after the other with limited start time variability between parts, smoothing the power demand becomes a question of how best to stagger the start times of parts such that the load factor in the system is maximized.

A mathematical model is presented in Section 5.1 that can be used to identify an optimal set of start times for a set of machines processing similar parts in order to minimize the factory peak load. The minimization of peak load, naturally increases the facility load factor. The model could easily be extended for minimizing the peak load of a set of different parts.

5.1 Mathematical Model

A mathematical model was developed in the form of an integer program to model the peak load of a series of parts being processed on a set of CNC machines fed in an automated manner. The model is presented here:

Sets
- $T = \text{set of all time increments}$
- $M = \text{set of all machines processing jobs}$
- $S = \text{set of all possible start times}$

Parameters
- $\rho_{tk} = \text{the power required at time } t \in T \text{ for a start time of } k \in S$

Decision Variables
- $\alpha_{mk} = \begin{cases} 
1 & \text{if machine } M \text{ starts at start time } k \\
0 & \text{otherwise} 
\end{cases} \quad \forall m \in M, k \in S$
- $\omega \geq 0 \text{ the peak demand}$

The integer programming model’s objective function (2) is looking to minimize the peak demand observed over the course of manufacturing a set of parts. The first constraint (3) ensures that each machine is assigned exactly one start time, while the second constraint (4) calculates the maximum observed peak load over all time instances in the model horizon.

The integer program was used to identify the optimal start times for processing part A on 10 machines. In addition to identifying the optimal machine start times, a question remained as to what was the optimal time between parts to use in order to maximize the load factor. In this model energy the expected value of power requirements were used...
as indicated by the means from Table 1. The model was run several times with different specified time between parts. The peak load, total parts produced and load factor were recorded for each configuration.

5.2 Deterministic System Results

This section presents the results of using the integer programming model to identify the optimal start time of jobs and time between parts. Table 3 shows the impact to peak load, parts produced and load factor of increasing the time between parts. The baseline provided in Table 3 is the system where all parts are started at the exact same time across all 10 machines. Figure 6 represents the results of Table 3 graphically, where one can easily see that using a time between parts of 10 seconds produces the highest load factor and a competitive peak load.

Figure 7 illustrates with a red solid line the power curve associated with the optimal start times for a time between parts of 10 seconds. This graphic clearly illustrates the benefit that coordinating machines could have on smoothing power demand and increasing load factor.

<table>
<thead>
<tr>
<th>Time Between Parts (s)</th>
<th>Peak Load (W)</th>
<th>Parts Produced in 72 Hours</th>
<th>Load Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>12000</td>
<td>24686</td>
<td>0.71</td>
</tr>
<tr>
<td>0</td>
<td>9950</td>
<td>24686</td>
<td>0.90</td>
</tr>
<tr>
<td>5</td>
<td>9700</td>
<td>23564</td>
<td>0.88</td>
</tr>
<tr>
<td>10</td>
<td>8950</td>
<td>22539</td>
<td>0.92</td>
</tr>
<tr>
<td>15</td>
<td>8750</td>
<td>21600</td>
<td>0.89</td>
</tr>
<tr>
<td>20</td>
<td>8650</td>
<td>20736</td>
<td>0.87</td>
</tr>
</tbody>
</table>

5.3 Deterministic System Discussion

The results of the deterministic optimization indicate a significant potential to reduce peak load and increase the facility load factor, thereby smoothing demand. For part A with 10 seconds between parts, using an optimal set of start times, the peak load can be reduced from 12000 W to 8950 W, a reduction of over 25%. This reduction coincides with an increase in load factor from 0.71 to 0.92, making the energy use of the facility more uniform and predictable for a utility. The results show that as the time between parts is increased, there is a point of diminishing returns. For example, with 10 seconds between parts the system observes the highest load factor of 0.92 and a peak load of 8950 W; increasing the time between parts to 15 seconds only nets an additional 200 W of peak load savings,
but decreases the load factor to 0.89 while simultaneously losing almost 1000 parts over the 3 day production period.

Comparing the deterministic results to the stochastic production of part A, a dramatic improvement in load profile smoothing can be seen with the integer programming approach versus the real time threshold based control logic. For example, the stochastic process was only able to obtain a load factor of 0.74 while the deterministic system was able to achieve a load factor of 0.92. This suggests reducing variability in the production system could provide a significant benefit for load smoothing, this would include measures such as installing automated feeding systems, so that an optimization approach can be used to schedule part production.

6 Effects of Smoothed Load Profiles on Net Demand and Power Fluctuations for PV Integrated Systems

This section quantifies the benefits of smoothing load profiles towards reducing net demand variability and minimizing net demand fluctuations in a PV integrated system. First the experimental design is described, followed by a presentation and discussion of results.

6.1 Experiment Description

To evaluate the effects of load profile smoothing on net demand variability and net demand fluctuations of PV enabled systems, a set of experiments were designed using 593 days of 1 second interval solar irradiation data made available from the National Renewable Energy Laboratory (Sengupta and Andreas, 2010). For each of the 593 days of available data, the net demand and demand fluctuations were evaluated for the hours of peak solar irradiation between 11:00am to 3:00pm. The solar irradiance was converted to PV power using the modified PVWatts formula discussed in equation (1). Ten randomly sampled load profiles were generated for each of the load profile conditions: stochastic no restriction, stochastic 11100 W restriction, discrete all same start time, and discrete optimal staggered starts. For each of these 10 samples, the net demand profile was calculated for the four hour period of maximum irradiance for each of the 593 days. The mean and standard deviation of each net power demand profile were recorded, along with the maximum net demand observed. Finally, for each profile an evaluation of the second by second fluctuations was performed. For this, statistics of interest included the largest second by second power change observed, and a characterization of the number of power fluctuations over 1000W.

6.2 Results

The mean and standard deviation for each of ten runs for each of 593 days were recorded for each of the four load profile conditions. T-tests were performed on the ten samples each day to determine if the means and standard deviations significantly differed from one another between the non-smoothed and smoothed load profiles. The t-tests indicated that all 593 days showed a statistically significant difference between the mean and standard deviations of the smoothed and non-smoothed load profile conditions. Table 4 summarizes the mean and standard deviation values across all 593 days, and provides the average p-value for the daily differences in performance measures.

<table>
<thead>
<tr>
<th>Table 4: Net Demand Results Characterization for all 593 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean Net Demand (W)</strong></td>
</tr>
<tr>
<td>Stochastic No Restriction</td>
</tr>
<tr>
<td>Stochastic 11000 W Restriction</td>
</tr>
<tr>
<td>Deterministic All Same Start Time</td>
</tr>
<tr>
<td>Deterministic Optimal Start</td>
</tr>
</tbody>
</table>
A second measure of performance is the ability of the smoothed load profiles to decrease the number of high net demand fluctuations. For this, the second by second differences in net demand were calculated for each of the ten runs for each of the 593 days. The largest single observed difference was recorded, as well as the number of differences over 500 W, 1000 W, 2000 W and 5000 W. Results are captured in Table 5. The total percentage of net demand fluctuations below each level are captured in Figure 8.

Table 5: Characterization of Net Demand Fluctuations

<table>
<thead>
<tr>
<th></th>
<th>Max Difference (W)</th>
<th>Percent of Net Demand 1 Hz Fluctuations (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>&gt; 500W</td>
</tr>
<tr>
<td>Stochastic No Restriction</td>
<td>14927</td>
<td>23.2</td>
</tr>
<tr>
<td>Stochastic 11000 W Restriction</td>
<td>14077</td>
<td>25.6</td>
</tr>
<tr>
<td>Deterministic All Same Start Time</td>
<td>21386</td>
<td>14.6</td>
</tr>
<tr>
<td>Deterministic Optimal Start</td>
<td>14926</td>
<td>18.7</td>
</tr>
</tbody>
</table>

Figure 8: Percentage of all fluctuations below the defined level in Watts for the stochastic and deterministic net demand load profiles

6.3 Discussion
Both the stochastic and the deterministic smoothed load profiles demonstrated an ability to reduce the standard deviation of the PV integrated net demand profiles. This means that over the course of a day, a facility will have a less variable second by second net demand profile if the load profile of the manufacturing equipment has been smoothed. The standard deviation of net demand was more significantly reduced in the deterministic smoothed load, reducing standard deviation of net demand by 1748 W or nearly 35%. The standard deviation was less pronounced in the stochastic framework, producing only a 271 W reduction in net demand standard deviation, or a 7% standard deviation reduction.

With regards to the performance related to minimizing net demand fluctuations the results were mixed. Both the stochastic and deterministic smoothed load profiles successfully reduced the maximum observed second by second fluctuation. The stochastic smoothed load reduced the maximum observed fluctuation by 850 W, while the deterministic smoothed load profile reduced the maximum observed demand by 6460 W. When looking at the number of observed fluctuations above certain wattage thresholds, the deterministic smoothed load profile performed significantly better than the smoothed stochastic load profile. The smoothed stochastic profile actually showed a higher percentage of larger readings than its non-smoothed counterpart, for all ranges checked, although the differences were of small magnitude, typically less than 2 percent. In contrast, the smoothed deterministic load profile...
significantly reduced the number of high wattage demand fluctuations (>1000W or higher) over the worst case deterministic scenario. Two important observations can be gathered from these results: firstly, the high load factor (0.92) of the deterministic smoothed load could be playing a significant role in reducing the number of occurrences of high demand fluctuations. Secondly, it’s important to notice that while the standard deviation of net demand may be decreased, this does not directly translate into a decrease in the number of large fluctuations observed, so both performance measures are important to track.

7 Conclusions
This work developed two strategies for smoothing machine tool power load, and evaluated the impact of smoothing the machine tool power load on combating the intermittency of PV arrays. A real time dispatching rule that limits peak load demonstrated the ability to improve machining load factor by 14%, while a mathematical model for a deterministic system demonstrated the ability to improve load factor by 29%. These smoothed load profiles, when coupled with a PV array, reduced the variability in the net demand load profile significantly. Additionally, the deterministic smoothed load showed an ability to reduce the frequency of high intensity power fluctuations when coupled with a PV system. Both the stochastic and deterministic models reduced the magnitude of the largest observed demand fluctuation of an integrated PV system. These results demonstrate the potential for using factory load profile smoothing to mitigate the intermittency of PV arrays, which could help reduce the impact of factory PV array installation on power quality.

Future work could be done to expand on both the stochastic and deterministic approaches developed in this paper. More complex power profiles could be introduced. In reality the amount of power required to perform the different machining operations could vary within the operation itself instead of the constant power modeled in this paper. Additionally, a larger variety of parts and operations could be added to the model. Future work could evaluate additional real time control strategies that could further improve the load factor of a stochastic system. One example would be to incorporate the results of the integer programming model into the real time dispatching rule of a stochastic system. Similarly, the real time control logic of extending air cutting time could be incorporated into the integer programming approach such that increasing the air cutting steps could be a factor in the model, potentially increasing the load factor even further. Future work could also be done to evaluate the effectiveness of the load smoothing strategies on various types of production systems, beyond CNC machine shops, or to increase the array of product types in the production system. Finally, extensions could be made to allow the factory machine fleet react to solar intermittency further reducing the size and variability of net demand fluctuations.

Acknowledgements
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References


Li, L., Yan, J., Xing, Z., 2013. Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modeling. Journal of Cleaner Production, 52, 113-121.


Website References:
Highlights

- The instantaneous power profile of a set of machines can be smoothed.
- Power demand profiles can be smoothed without impact to production throughput.
- Smoothing power profiles can reduce the variability in net power demand.
- Photovoltaic equipped facilities will see less severe power fluctuations.
- Smoothed load profiles could also improve power quality.