Applied Energy 174 (2016) 88–100

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

# Energy-Performance as a driver for optimal production planning

Niloofar Salahi *, Mohsen A. Jafari

*Department of Industrial and Systems Engineering, Rutgers the State University of New Jersey, Piscataway, NJ 08854, USA*

## HIGHLIGHTS

- A 2-dimensional Energy-Performance measure is proposed for energy aware production.
- This is a novel approach integrates energy efficiency with production requirements.
- This approach simultaneously incorporates machine and process related specifications.
- The problem is solved as stochastic MILP with constraints addressing risk averseness.
- The optimization is illustrated for 2 cases of single and serial machining operation.
- Impact of various electricity pricing schemes on proposed production plan is analyzed.

## ARTICLE INFO

*Article history:*
Received 9 November 2015
Received in revised form 3 April 2016
Accepted 16 April 2016
Available online 26 April 2016

*Keywords:*
Energy efficiency
Manufacturing
Stochastic optimization
Production planning
Energy-Performance
Electricity price uncertainty

## ABSTRACT

In this paper, we present energy-aware production planning using a two-dimensional "Energy-Performance" measure. With this measure, the production plan explicitly takes into account machine-level requirements, process control strategies, product types and demand patterns. The "Energy-Performance" measure is developed based on an existing concept, namely, "Specific Energy" at machine level. It is further expanded to an "Energy-Performance" profile for a production line. A production planning problem is formulated as a stochastic MILP with risk-averse constraints to account for manufacturer's risk averseness. The objective is to attain an optimal production plan that minimizes the total loss distribution subject to system throughput targets, probabilistic risk constraints and constraints imposed by the underlying "Energy-Performance" pattern. Electricity price and demand per unit time are assumed to be stochastic. Conditional Value at Risk (CVaR) of loss distributions is used as the manufacturer's risk measure. Both single-machine and production lines are studied for different profiles and electricity pricing schemes. It is shown that the shape of "Energy-Performance" profile can change optimal plans.



## 1. Introduction

The industrial sector in the U.S. currently accounts for 24.5 quadrillion Btu in 2013, representing approximately 34% of total energy consumption and the consumption of energy by the sector has almost doubled over the last 60 years. Furthermore, industrial energy consumption is expected to increase at an annual rate of 1.3% from 2013 to 2025 [1]. Production processes and manufacturing activities play a major role in industrial energy consumption, responsible for approximately 90% of the total. Energy management in industrial sector has been an area of interest for many researchers in recent years [2–6] and the energy efficiency has become an important topic beyond traditional energy-intensive industries such as steel, cement, and chemical manufacturers [7]. Practices, such as energy waste reduction through energy-aware and optimized production, and improving engineering and business processes within production systems are now among the top business priorities for many companies [8–10].

Improving energy efficiency at machine tool and process levels have been addressed extensively in the literature [11–14]. A number of research works focus on production factory level and offer several techniques and tools for energy management, including machine level control and optimization [15–18]. May et al. present a methodology to develop key performance indicators for improving energy efficiency in an industrial environment and measure the energy efficiency performance of equipment, processes and factories [19]. Khayyam et al. address optimizing production processes to achieve desired quality levels with the lowest energy consumption. They present a stochastic optimization model to reduce energy consumption over a given range of quality properties [20].

* Corresponding author.
*E-mail addresses:* nsalahi@rutgers.edu (N. Salahi), jafari@rci.rutgers.edu (M.A. Jafari).

http://dx.doi.org/10.1016/j.apenergy.2016.04.085
0306-2619/Published by Elsevier Ltd.

In recent years, the economic potential of energy-aware production planning and scheduling in industrial processes has been recognized by a number of institutions and authors. For the operation of a single machine, Mouzon et al. [21] study the scheduling of a CNC machine in a machine shop in order to minimize total energy consumption. They reported that up to 80% of the total energy consumed during idling, start up, and shut down could be saved if the machine was turned off until needed. In a follow-up work, Mouzon et al. [22] proposed a meta-heuristic framework to compute schedules that minimize the total energy consumption and the total tardiness on a single machine. At a process level, a number of research works addressed the energy-aware scheduling using a flow shop approach, which takes into account several objectives, namely, energy consumption, productivity and make span. There are other works [23,24] that utilize metaheuristic techniques to solve energy-ware scheduling problems. The work by Chen et al. investigates energy reduction in serial production systems through efficient scheduling of machine startup and shutdowns and discusses the tradeoff between productivity and energy-efficiency in these systems [25].

We note that balancing energy efficiency and production targets could be quite challenging in real life systems. This article addresses the problem by introducing a two-dimensional measure, namely "Energy-Performance" profile, and integrating it into traditional production planning to achieve balanced energy efficiency in manufacturing processes. The resulting production plan simultaneously incorporates machine-level specifications and process-related measures. Given these profiles, production planner will be able to decide on a balanced target in an energy efficiency and performance space, depending on process control, tool degradation, elasticity of production schedules, and other important factors. This is a novel approach to integrating energy efficiency and production requirements, and the methodology to compute and incorporate these profiles to production planning is the main contribution of this article. More preliminary discussion on our approach follows.

At machine-level, the "Energy-Performance" measure is described by "Specific Energy" which is the energy used per single product or a certain number of pieces. In case of continuous or batch processes, energy per batch or per some certain volume is used instead. "Specific Energy" of single machines has been addressed extensively in academic and industry literature [26,27]. As proposed by Gutowski et al., a machine's total electricity consumption can be decomposed into a fixed part, corresponding to the total standby power, and a variable part, representing the value added process such as material removal [28]. The following formulation is commonly used:

$$E_{spec} = \frac{P_0}{\dot{\upsilon}} + k \quad (1)$$

where $P_0$ is the fixed part and $\dot{\upsilon}$ represents the actual processing rate. For a milling operation, this rate is Material Removal Rate (MRR) and is typically measured in $cm^3/s$ units. $k$ is a constant, with units of $kJ/cm^3$. Eq. (1) can also be used to represent "Energy-Performance" of other machining processes with discrete loading such as bending and press brake operations. Fig. 1 presents the "Energy-Performance" for a milling operation as a function of MRR [29]. Energy and MRR are defined in kJ and $mm^3/s$ units, respectively.

Furthermore, for a given machine, "Energy-Performance" varies depending on the type of materials processed or products produced. Machine's "Energy-Performance" is also correlated with degradation and tool wear, as depicted in Fig. 2 [30]. With longer cutting time, the tool-wear increases resulting in higher energy consumption rate during machining. The "Specific Energy" values can be more than double at higher tool wears.

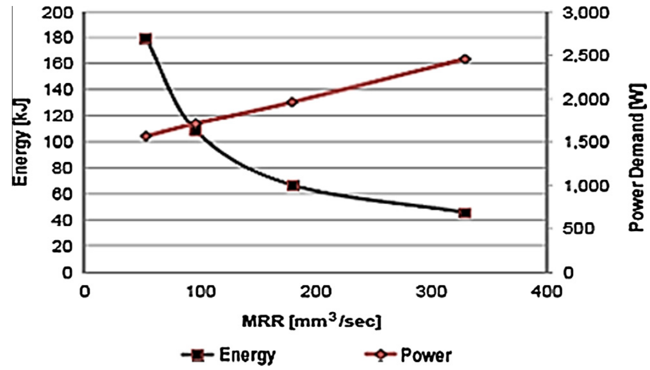


**Fig. 1.** Energy-Performance for a milling machine [29].

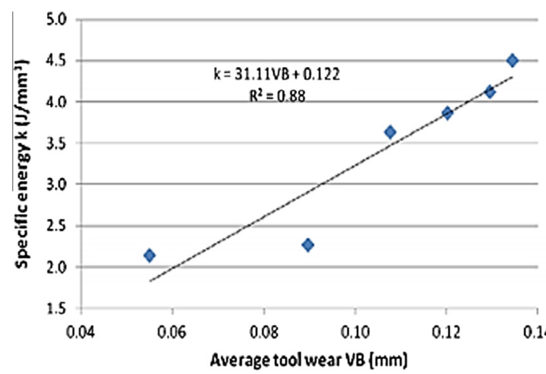


**Fig. 2.** Specific cutting energy induced at different tool wear [30].

Extending to process level (e.g. multiple machines working in series), the "Energy-Performance" depends not only on individual machines' specifications (e.g. Process rate or MRR), but also on the type of process control strategies at system level. A control strategy normally takes advantage of production process' elasticity, defined in terms of slack times, to optimize the process. Such slack times depend on a number of factors including machines' operational modes flexibility and demand frequency/volume. An ideal control strategy reduces the slack times to zero and potentially lead to optimal process with substantial energy savings. Such process would have a steady operation with no idle time in between. However, most control strategies are far from ideal; therefore various demand patterns (e.g. different demand frequencies and volumes) generate different slack times, which in turn generate random "Energy-Performance" profiles. This suggests a stochastic "Energy-Performance" profile for any given process control scheme which are determined as a function of products processed per unit time. Note that for the purpose of control strategy comparison, an average "Energy-Performance" can be used.

Given the average "Energy-Performance" profile and process throughput, the energy consumption patterns are determined for a production system. In order to construct the "Energy-Performance" curve and carry out energy calculation, metered or summary data on machine/process power rates, energy intake and performance features are required. Salahi et al. define several metering approaches, namely, physical, virtual and simulated metering. In physical metering approach, data are directly obtained from sensors or smart meters. Historical data along with inferential statistical techniques using facility utility bills, accounting databases, and equipment specification and performance data may be used to derive the virtual metered data. In the absence of meters and historical data, simulation may be utilized to obtain the necessary information [31].