Int. J. Production Economics 156 (2014) 246–259

Contents lists available at ScienceDirect

Int. J. Production Economics

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

Time-of-use based electricity cost of manufacturing systems: Modeling and monotonicity analysis

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ARTICLE INFO

Article history:
Received 14 January 2014
Accepted 14 June 2014
Available online 21 June 2014

Keywords:
Time-of-use
Electricity cost
Energy efficiency
Peak demand response
Manufacturing system

ABSTRACT

Traditionally, manufacturing enterprises pay flat rates for each kiloWatt-hour (kWh) of electricity consumed. Newly available electric tariffs that charge both energy consumption (in kWh) and peak demand (in kiloWatts, i.e., kW) with varying time-of-use (TOU) rates have started to gain popularity. In this paper, the per-product electricity cost as a function of manufacturing system parameters and the TOU rates is modeled. The contributions of both electricity energy consumption and peak demand are combined to formulate the electricity cost of manufacturing systems with multiple machines and buffers. New knowledge of the effects of various modeling parameters on the electricity cost is acquired through monotonicity analysis. The formulated model is utilized to answer the following two questions facing manufacturers: With the availability of TOU rates in mind, is switching from the flat rates to the TOU rates economically sound? What changes can be made on electric use routines to take advantage of the TOU rates? The findings based on case studies show that with appropriate adjustment of production routines, a significant saving of up to 24.8% of the per-product electricity cost can be achieved by adopting the TOU rates.

1. Introduction

The industrial sector is the largest energy consumer and greenhouse gas (GHG) emitter in the world. It accounts for 52% of the total energy consumed globally (U.S. Energy Information Administration, 2013). It is reported that 90% of industrial energy consumptions and 84% of energy-related industrial CO_2 emissions are ascribable to manufacturing activities (Schipper, 2006). For manufacturing enterprises, the share of energy costs has been on the rise among the overall production costs. This trend is expected to accelerate and be more pronounced in the future due to the expected more stringent carbon tax regulations as well as the increasing energy demands from developing countries (Fang et al., 2011; Rentizelas et al., 2012; U.S. Energy Information Administration, 2013).

Electricity supplies an increasing share of the world's total energy and it accounts for a major portion of energy consumption in manufacturing activities (U.S. Energy Information Administration, 2013). Traditionally, manufacturing enterprises pay flat rates for each kiloWatt-hour (kWh) of electricity they consumed. A representative example is given in Table 1 (Orange and Rockland Utilities, 2013a). However, the real cost of electricity generation varies greatly due to the daily demand cycle. The flat rates are not able to represent such real cost at the time of consumption.

With the help of recent research and technology developments, the electric power industry is undergoing a transition to a more modern and smarter grid (Gungor et al., 2013; Klemes et al., 2012; Lima and Navas, 2012). During this period of transition, utility companies around the world are implementing new tariff plans in order to increase the elasticity of electricity consumers and moderate the extreme demand variation. One such plan is the time-of-use (TOU) pricing (Australia Ausgrid, 2012; Ipsos MORI, 2012; King, 2010; Ontario Ministry of Energy, 2013; Torriti, 2012; Zeng et al., 2008). Similar to the one implemented by Orange and Rockland Utilities (2013b) in Table 2, the TOU pricing generally divides the day into on- and off-peak periods and assigns prices accordingly. Both electricity energy consumption (measured by an energy meter) and power demand (measured by a demand meter) are counted in industrial consumers' monthly bill. The difference between the energy meter and the demand meter is like the difference between the odometer and the speedometer (Orange and Rockland Utilities, 2013d): "*An odometer records the accumulated miles traveled, the same way the electric (energy) meter records your total energy consumption. The speedometer measures speed, the same way the demand meter registers your rate of consumption*".

As illustrated in Table 2, the on-peak rates of power demand (\$/kW) and energy consumption (\$/kWh) in a typical electric bill are

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http://dx.doi.org/10.1016/j.ijpe.2014.06.015
0925-5273/

much higher than the rates during off-peak periods. The TOU pricing encourages consumers to change their regular usage patterns in response to the variation in the price of electricity over time. Consumers have the opportunity to lower their electric bill by shifting the use from on-peak periods to off-peak periods. In doing so, the reliability of the electric power grid is enhanced and the peak generating capacity is reduced. In fact, a 5% reduction of peak power demand in the U.S. would lead to eliminating the need for installing about 625 peak power plants and associated power delivery infrastructure, which translates into an annual saving of $3 billion (Faruqui et al., 2007). Intensive CO_2 emissions due to low-efficient back-up generators will also be curtailed, and the consumers who choose to comply are rewarded with a lower electric bill.

TOU programs are widely available from utility companies. For example, there are more than 150 utility companies offering TOU rates in the U.S. alone (U.S. Federal Energy Regulatory Commission, 2012). However, customer participation in these programs is still low. Due to the differences in the modeling methods and pricing components considered (Huisman et al., 2009; Nikzad et al., 2012; Zeng et al., 2008), the designed TOU tariffs may vary greatly from company to company. There is no guarantee that the consumers will end up paying less on the TOU rates. With this in mind, consumers are facing the following two questions: Is switching from the flat rates to the TOU rates economically sound? What changes can be made on the electric use routines to take advantage of the TOU rates? To answer these questions, the knowledge about the electricity cost as a function of manufacturing system parameters and the TOU rates is needed.

Such knowledge is still missing in the manufacturing literature. Recent advancements in energy or electricity related research for manufacturing mainly focus on machine tool level energy consumption modeling and monitoring (Balogun and Mativenga, 2013; Behrendt et al., 2012; Duflou et al., 2012; Hu et al., 2012; Santos et al., 2011). Some system level research on energy efficiency improvement also exist (Li and Sun, 2013; Liu et al., 2013; Luo et al., 2013), but the demand charge, which can make up as high as 70% of the electric bill (National Grid USA, 2006), has not been well considered especially from the analytical point of view (Bego et al., 2014; Fernandez et al., 2013; Sun and Li, 2013).

In summary, motivated by the above-mentioned status quo, we propose in this paper to establish an analytical model to measure the electricity cost of manufacturing systems based on the TOU rates. It is our goal to generate new knowledge of the electricity cost as a function of manufacturing system parameters and the TOU rates. The research outcomes will enable manufacturers to make the best use of TOU incentives offered by utility companies and achieve significant savings in electricity cost without compromising productivity. The new knowledge generated can be implemented to discrete manufacturing in various industries such as automotive, electronics, appliances, aerospace, etc.

In a closely related paper (Wang and Li, 2013), we have proposed a systems approach for TOU based electricity demand response for sustainable manufacturing systems under the production target constraint. The approach is made possible by the utilization of buffers in the system that allow for temporary stoppage of work in one area without affecting the entire system throughput. A schedule has been created to control the status of each machine to minimize concurrent operations of all the machines during peak hours. While the work in Wang and Li (2013) is concerned with the ***control*** perspective, the present paper is more focused on the design and operational perspectives. From the ***design*** perspective, the modeling and monotonicity analysis can be used to provide guidance on how to select machine and buffer parameters so that per-product energy consumption e_{UNIT} and per-product electricity cost c_{UNIT} can be maintained at a low level. From the ***operational*** perspective, it can be used to justify whether it is economically sound to switch from the flat rates to TOU rates.

2. Production modeling

Production modeling forms the basis of the modeling and monotonicity analysis of per-product electricity cost in manufacturing. The diagram of a typical manufacturing system is shown in Fig. 1. The following assumptions and notation are adopted for the study in this paper:

(i) The system consists of N machines (denoted by squares) and $N-1$ buffers (denoted by circles) connected in series.
(ii) A finite planning horizon of H hours during a workday is evenly discretized into T slots, with $t=1$ being the first slot, and $t=T$ being the last. The slot duration is equal to the cycle time t_C of the machines, i.e., $t_C=H/T$. The cycle time represents the time needed by a machine to process a product. All the machines have the same cycle time.
(iii) Let the capacity of buffer b_i $(i=1,\dots,N-1)$ be C_i, which is the largest number of products the buffer can hold. Buffer states are defined by the number of products it contains at the end of a time slot. Let $h_i(t)$ be buffer b_i's state (occupancy) at the end of time slot t. Then $h_i(t)$ ranges from 0 (empty) to C_i (full) and it can change in each time slot at most by one product.
(iv) Due to random failure, machine m_i $(i=1,\dots,N)$ is up during time slot t with probability p_i and down with probability $1-p_i$. Each machine's uptime and downtime are determined independently from the other machines'. Machine states are defined by its working status during a time slot. The decomposition of machine states is shown in Fig. 2. It is assumed that the first machine is never starved and the last machine is never blocked.
(v) The blocked-before-service and time-dependent-failure conventions are adopted (Gershwin, 1994; Li and Meerkov, 2008). Blocked-before-service means that machine m_i cannot process any product during time slot t if the following three events are all true: machine m_i is up, buffer b_i is full as the end

Table 1
A representative pricing profile with flat rates (Orange and Rockland Utilities, 2013a, 2013c).

Season	Time of day	Energy rate ($/kWh)	Account and other fixed charges ($/month)
Summer (June–September)	All time	0.18015	33.15
Winter (October–May)	All time	0.16052	

Table 2
A representative pricing profile with TOU rates (Orange and Rockland Utilities, 2013b, 2013c).

Season	Time of day	Energy rate ($/kWh)	Demand rate ($/kW)	Account and other fixed charges ($/month)
Summer (June–September)	7 pm–1 pm (Off-peak)	0.10551	0	51.32
	1 pm–7 pm (On-peak)	0.18815	19.41	
Winter (October–May)	9 pm–10 am (Off-peak)	0.10551	0	
	10 am–9 pm (On-peak)	0.13065	8.38	