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Time-of-use based electricity demand response for sustainable manufacturing systems

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ABSTRACT

As required by the *Energy Policy Act of 2005*, utility companies across the U.S. are offering TOU (time-of-use) based electricity demand response programs. The TOU rate gives consumers opportunities to manage their electricity bill by shifting use from on-peak periods to mid-peak and off-peak periods. Reducing the amount of electricity needed during the peak load times makes it possible for the power grid to meet consumers' needs without building more costly backup infrastructures and help reduce GHG (greenhouse gas) emissions. Previous research on the applications of TOU and other electricity demand response programs has been mainly focused on residential and commercial buildings while largely neglected industrial manufacturing systems. This paper proposes a systems approach for TOU based electricity demand response for sustainable manufacturing systems under the production target constraint. Key features of this approach include: (i) the electricity related costs including both consumption and demand are integrated into production system modeling; (ii) energy-efficient and demand-responsive production scheduling problems are formulated and the solution technique is provided; and (iii) the effects of various factors on the near-optimal scheduling solutions are examined. The research outcome is expected to enhance the energy efficiency, electricity demand responsiveness, and cost effectiveness of modern manufacturing systems.

1. Introduction

The industrial sector is the largest energy consumer in the United States [1]. It consumes 31% of the total energy and is responsible for about one third of the total GHG (greenhouse gas) emissions in the country [2,3]. A major portion of the energy consumed by the industrial sector is in the form of electricity [1]. Electricity is a form of energy that cannot be effectively stored in bulk. It must be generated, distributed, and consumed immediately. Consumers' needs change vastly in different seasons and even at different time of a day [4]. In order to meet the needs during peak periods, a huge array of expensive equipment including generators, transformers, wires, and substations has to be kept on constant standby, otherwise the system will become unstable and blackouts may occur. This requires large extra investments for those backup infrastructures. By 2030, about $2 trillion investments for new generation capacities, transmission, and distribution will be required to satisfy the growing needs [5]. On average, 1 kW hour (kWh) of electricity generation causes 1.56 pounds (0.71 kg) of GHG emissions [6]. Backup generators are often dirtier and less efficient than base load generators, and therefore create more GHG emissions for each kWh of electricity generated.

GHG emissions have become a vital issue to the sustainable development of human society since they are recognized as the leading cause of global warming and climate change. Under the increasingly rising pressures of reducing GHG emissions from both domestic and international society, many regulations have been enacted to curb the emissions. The U.S. government has set up a target to reduce energy use to 17% below 2005 levels by 2020 [7]. Accordingly, technologies that may promisingly reduce GHG emissions and postponing or eliminating the huge extra investments have attracted great public interests. One such technology is demand response.

The U.S. *FERC (Federal Energy Regulatory Commission)* [8] defines demand response as *"changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."* Demand response targets at reducing peak demand to control the risk of potential disturbances, avoiding extra investments in additional infrastructures, avoiding use of more expensive and less efficient generators, and thus cutting GHG emissions. It is estimated that the implementation of

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Nomenclature

Bold face
- $\boldsymbol{S}$ position matrix of the binary PSO algorithm
- $\boldsymbol{S}_{\mathrm{PB}}$ personal best position matrix of the binary PSO algorithm
- $\boldsymbol{S}_{\mathrm{GB}}$ global best position matrix of the binary PSO algorithm
- $\boldsymbol{V}$ velocity matrix of the binary PSO algorithm
- $\boldsymbol{X}(t)$ a column vector containing the state probabilities of the system at the end of time slot t

Upper case
- $\mathrm{BL}_i(t)$ blockage probability of machine m_i during time slot t
- C_i capacity of buffer b_i (the largest number of parts the buffer can hold)
- CP average cumulative production of the system during the planning horizon
- *CPo* target cumulative production of the system during the planning horizon
- H number of hours in the finite planning horizon
- N number of machines in the manufacturing system
- N_{P} swarm size of the binary PSO algorithm
- N_{T} iteration number of the binary PSO algorithm
- $\mathrm{PR}_i(t)$ production rate of machine m_i ($i = 1$ or N) during time slot t
- $\mathrm{PR}_{\mathrm{SYS}}(t)$ production rate of the system during time slot t
- $Q_{i,(j_2|j_1)}(t)$ transition probability from state j_1 to j_2 during time slot t for buffer b_i
- $\mathrm{ST}_i(t)$ starvation probability of machine m_i during time slot t
- T number of total time slots during the planning horizon
- $\mathrm{WIP}_i(t)$ work-in-process inventory of buffer b_i at the end of time slot t
- $\mathrm{WIP}_{\mathrm{SYS}}(t)$ total work-in-process of the system at the end of time slot t

Lower case
- b_i index of the ith buffer in the manufacturing system, $i = 1, ..., N-1$
- $b(t)$ billable cost indicator
- c_{DT} cost of the billable power demand of the system during the planning horizon
- $c_{\mathrm{D}}(t)$ TOU demand rate ($/kW) during time slot t
- c_{ET} cost of the total electricity consumption of the system during the planning horizon
- $c_{\mathrm{E}}(t)$ TOU consumption rate ($/kWh) during time slot t
- c_{Fixed} fixed charge during the planning horizon
- c_{T} total electricity cost
- d_i electric power (in kW) drawn by machine m_i when it is up
- $d_{\mathrm{SYS}}(t)$ power demand of the system during time slot t
- d_{T} billable power demand of the system (the highest average kW measured in any on-peak 15-minute interval during the planning horizon)
- e_i electric energy (in kWh) consumed by machine m_i when it is up
- $e_{\mathrm{SYS}}(t)$ electricity consumption of the system during time slot t
- e_{T} total electricity consumption of the system during the planning horizon
- i, j, j_1, j_2, k, t general indexes
- t_{C} cycle time (the time needed by a machine to process a part)
- l ceiling integer number of the time slots in any 15-minute interval
- m_i index of the ith machine in the manufacturing system, $i = 1, ..., N$
- p'_i reliability of machine m_i
- $p_i(t)$ probability of machine m_i being up during time slot t (considering both machine reliability and control signal)
- $q_{i,j}(t)$ probability of buffer b_i in state j ($j = 0, \ldots, C_i$) at the end of time slot t
- $s_i(t)$ scheduled control signal (“on” or “off”) for machine m_i during time slot t

Greek
- $\theta_0, \theta_1, \theta_2$ parameters of the binary PSO algorithm

Functions
- $G(\cdot)$ state transition dynamics function
- $\mathrm{rand}(\cdot,\cdot)$ uniformly distributed random number generator

demand response programs together with energy efficiency improvement can reduce the needs for new generation capacities from 214 GW to 133 GW in 2030, by 38% [5]. Recent research results have also suggested that demand response can be used as a solution to meet supply-demand fluctuations in the grid with significant penetration of variable renewable energy sources of intermittent nature [9–12].

The term demand response encompasses a wide range of solutions and mechanisms. According to the *2012 Survey on Demand Response and Advanced Metering* by U.S. FERC [8], TOU (time-of-use) pricing is among the most popular demand response mechanisms. It utilizes time sensitive pricing structures to spread the costs of the needs for extra equipment. The mechanism encourages the electricity consumers to shift their power demand from peak periods (with high prices) to off-peak periods (with low prices). TOU pricing is widely available from utility companies across the U.S. thanks to the *Energy Policy Act of 2005* [13]. There are about 150 entities providing different sorts of TOU pricing programs. These entities represent all aspects of the electricity delivery industry: investor-owned utilities, municipal utilities, rural electric cooperatives, power marketers, state and federal agencies, and other demand response providers. A full list of the entities' names is available in the appendix of the survey report [8]. TOU pricing is also one of the easiest implementations of demand response due to less stringent technological requirements.

Most TOU pricing profiles, like the one provided in Table 1 [14], divide the day into two or three periods and assign prices for each period [15]. Electricity consumption and demand are tracked by smart meters [16–18] and both components count towards consumers' monthly bill. The consumption rate is formulated in

Table 1
A representative TOU pricing profile [14].

Season	Type	Time of day	Consumption rate ($/kWh)	Demand rate ($/kW)	Fixed charge ($)
Summer (Jun–Sep)	Off-peak	7pm–1pm	0.08274	0	51.42
	On-peak	1pm–7pm	0.16790	18.80	
Winter (Oct–May)	Off-peak	9pm–10am	0.08274	0	
	On-peak	10am–9pm	0.11224	8.12	