Energy Efficiency Management and Electricity Demand Response for Sustainable Manufacturing Systems

BY

ZEYI SUN
B.Eng., Tongji University, Shanghai, China, 2002
M.Eng., University of Michigan, Ann Arbor, MI, 2010

THESIS

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Defense Committee:

Lin Li, Chair and Advisor
David He
Houshang Darabi
Jeremiah Abiade
Ning Ai, Urban Planning and Policy

DEDICATION

To my family for the unwavering support and encouragement over the years.

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CONTRIBUTION OF AUTHORS

Chapter 1 is an introduction that includes the background information and literature review to highlight the significance and challenge of my research.

Chapter 2 represents a published paper ("Li, L., and Sun, Z., 2013, Dynamic energy control for energy efficiency improvement of sustainable manufacturing systems using markov decision process, IEEE Transactions on Systems, Man, and Cybernetics: Systems, 43(5): 1195-1205") for which I was the major driver of the research. My advisor, Dr. Lin Li contributed to research idea generation and paper revision.

Chapter 3 represents three published papers. For the paper ("Sun, Z., and Li, L. 2013, Potential capability estimation for real time electricity demand response of sustainable manufacturing systems using Markov Decision Process, Journal of Cleaner Production, 65: 184-193") used in Section 3.2, I was the primary author and the major driver of the research. My advisor, Dr. Lin Li, contributed to the idea discussion of the research and proofreading of the manuscript. For the paper ("Sun, Z., and Li, L., Fernandez, M., and Wang, J. 2014, Inventory control for peak electricity demand reduction of manufacturing systems considering the tradeoff between production loss and energy savings, Journal of Cleaner Production, 82: 84-93") used in Section 3.3, I was the primary author and the major driver of the research. Ms. Mayela Fernandez contributed to the calculation using software in case study. My advisor, Dr. Lin Li, contributed to the proofreading of the manuscript. Dr. Jianghui Wang contributed to revising the paper with insightful comments from practical point of view. For the other paper ("Fernandez, M., Li, L., and Sun, Z., 2013 "Just-for-Peak" buffer inventory for peak electricity demand reduction of manufacturing systems, International Journal of Production Economics, 146(1): 178-184") used in Section 3.3, I contributed to the paper writing and revision. Ms. Mayela

Fernandez contributed to research idea generation and problem formulation. My advisor, Dr. Lin Li, contributed to the proofreading of the manuscript.

Chapter 4 represents one of my unpublished (under review) research focusing on plant level energy management in manufacturing considering combined manufacturing and heating, ventilation, and air conditioning system. I anticipate that this work will be published soon.

Chapter 5 represents my conclusions of the research presented in this thesis. The intellectual contribution and broad impact are summarized. The future directions in this area are discussed.

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CNC	Computer Numerical Controlled
FERC	Federal Energy Regulatory Commission
GHG	greenhouse gas
HVAC	heating, ventilation, and air conditioning
kW	kilowatt(s)
kWh	kilowatt-hour(s)
MDP	Markov decision process
OBMC	Optional Binding Mandatory Curtailment
PG&E	Pacific Gas & Electric
PSO	particle swarm optimization
TOU	time-of-use

SUMMARY

This doctoral thesis proposes a framework of implementing customer-side electric energy management for manufacturers towards sustainability. The methods developed can facilitate the technological readiness of manufacturing enterprises for the transition towards sustainable manufacturing in a carbon-constrained world. Detailed research tasks of the framework include energy efficiency management, electricity demand response for manufacturing system, and electricity demand response for the entire plant considering combined manufacturing and heating, ventilation, and air conditioning system. Specifically, the method of real time energy efficiency management for typical manufacturing systems with multiple machines and buffers under the constraint of system throughput is developed. Markov decision process is used to formulate the decision-making process and approximate dynamic programming is used to solve the problem on a real time basis. The implementation of electricity demand response for typical manufacturing systems is also studied. Both event-driven and price-driven programs are considered. After that, plant-level modeling on electricity demand response considering the combined manufacturing system and heating, ventilation, and air conditioning system is developed. The findings based on case studies show that with appropriate adjustment of production routines through joint consideration of both production and energy consumption, significant improvement in energy efficiency and reduction of power demand can be accomplished. The research outcomes can be applied to realize an energy-efficient and cost-effective operation mode to achieve the goal of sustainable manufacturing for the U.S. The new methods developed can be implemented in discrete part manufacturing in various industries such as automotive, electronics, appliances, aerospace, etc.

CHAPTER 1 INTRODUCTION

1.1. Introduction

The total electricity demand in the U.S. is expected to grow from 3,841 billion kilowatt hours (kWh) in 2011 to 4,930 billion kWh in 2040 (U.S. Energy Information Administration, 2012). To satisfy this growing demand, approximately $697 billion investment for new electricity generation capacity is required by 2030 (Chupka et al., 2008). Considering other auxiliary infrastructure for electricity transmission and distribution, the total investment will be approximately two trillion dollars (Chupka et al., 2008). Furthermore, great amount of Greenhouse Gas (GHG) emission can be anticipated because power generation plant is thought to be an important source of GHG emissions.

The industrial sector is a main contributor to this increasing trend of electricity demand. Approximately, over one-quarter of electricity is consumed by the industrial sector in the U.S. (U.S. Energy Information Administration, 2011). Manufacturing activities dominate industrial energy consumption (Duflou et al., 2012). It is reported that "about 90% of industry energy consumption and 84% of energy-related industry carbon dioxide emissions are contributed by manufacturing sector" (Schipper, 2006). In a typical manufacturing plant, the top two energy consumers are manufacturing system and heating, ventilation, and air conditioning (HVAC) system (Brundage et al., 2013). The corresponding costs of these two systems dominate the whole energy related cost for manufacturers (Brundage et al., 2013).

Traditionally, manufacturers focus more on the productivity analysis (Gershwin, 1994; Alden et al., 2006; Li and Meerkov, 2009) to improve the profit of their operation while considering less on reducing energy consumption and energy cost. Recently, with the increasing awareness of environmental protection from the society, “many countries have enacted legislation to curb carbon dioxide emissions. Carbon taxes, carbon offsets, carbon trades, and carbon caps are among the instruments being considered and developed by the legislative bodies around the world” (Sun and Li, 2013). Similar legislation is also being considered in various states in the U.S. as well as by the U.S. congress. For example, the U.S. government has announced a GHG emission reduction plan, which aims to cut 17% emissions based on the level of 2005 by 2020 (U.S. Department of Energy, 2009). Due to the aforementioned legislative pressure as well as moral responsibility concern and cost reduction for competitiveness goal, more and more manufacturing companies are eager to shift their current operation strategy to a sustainable one that jointly considers economic, environmental, and social aspects (Shahbazpour and Seidel, 2006).

Customer-side energy management has been considered an effective tool by both academia and industry that can help manufacturers achieve this transition towards sustainability and help government accomplish the reduction target of GHG emissions. It emphasizes the endeavors from the customers of electricity. The potential benefit of customer-side electric energy management is estimated to be 157–218 GW reduction of non-coincident summer peak by 2030, or 14–20% below projected level as shown in Figure 1 (Electric Power Research Institute, 2009).

Two main methods of customer-side energy management are energy efficiency management and electricity demand response (Goldman et al., 2010). The objective of energy efficiency management is to achieve the same amount of output with less energy consumption in an economically efficient way. It is recommended as the ‘first fuel’ choice to energy users due to its cheaper, cleaner, faster, and easier realization than any other resources (Friedrich et al., 2009). The cost of the energy obtained from energy efficiency management is estimated to be 1–3 cents per kWh (Cengel, 2011). It is much lower than the average retail price of the energy generated in the U.S., which is about 9.56 cents per kWh (U.S. Environmental Information Agency, 2013).

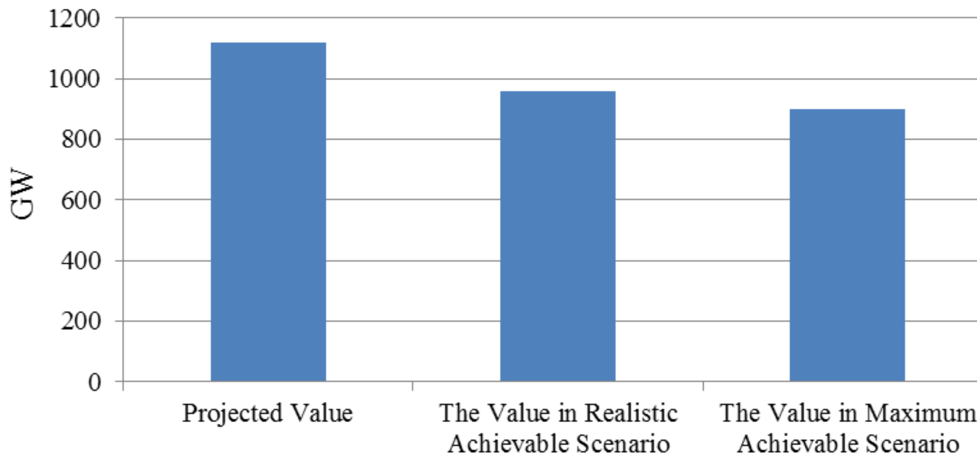

Figure 1. U.S. summer peak demand saving potentials by demand side management in 2030 under different scenarios

Electricity demand response encourages customers to change their regular usage patterns in response to the variation of electricity price over time to reduce the power demand during peak periods. It is defined as "changes in electric usage by demand side resources from their normal consumption patterns in response to the changes in the price of electricity over time, or to the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" (U.S. Federal Energy Regulatory Commission, 2012). It is reported that approximately 65 kWh energy saving can be achieved by reducing one kW power demand during peak periods (Electric Power Research Institute, 2008). In addition, it is also reported that a 5% reduction of peak power demand in the U.S. can eliminate the need for the operation of 625 peaking power plants and associated power delivery infrastructure, which translates into an annual saving of $3 billion (Faruqui et al., 2007). FERC has estimated that the existing demand response resources are about 41,000 MW, representing 5.8% of 2008 summer peak demand (U.S. Federal Energy Regulatory Commission, 2008). It is expected to increase to 138,000 MW, representing 14% of peak demand by 2019 (U.S. Federal Energy Regulatory Commission, 2009).

Existing literature for the energy efficiency management and electricity demand response mainly focuses on specific manufacturing processes or single machine manufacturing system (see details in Section 1.2.1 and 1.2.2). In practice, typical manufacturing system consists of multiple manufacturing machines and buffers that are deployed sequentially as shown in Figure 2 (Li and Meerkov, 2009) where the rectangles denote the machines (with index i, i=1, 2, …, I) and the circles denote the buffers (with index i, i=1, 2, …, I-1). Unlike the fact that rich knowledge has been acquired for single machine manufacturing systems or some specific manufacturing processes, the theory and method to address energy efficiency management and electricity demand response for the typical manufacturing systems with multiple machines and buffers are far less developed.

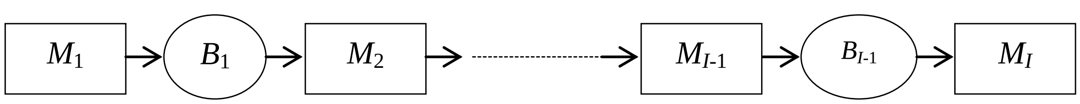

Figure 2. A typical manufacturing system with I machines and I-1 buffers

As for the HVAC system, the studies regarding the energy efficiency management and electricity demand response are usually conducted separately from manufacturing system (see details in Section 1.2.3). The interrelations between the heat generated due to manufacturing machine operation and the indoor temperature are less considered. The potential competition for the allocation of limited power consumption quotation between the two systems during peak periods is not well modeled.

1.2. Literature Review

Literature that focuses on energy efficiency management, electricity demand response, and HVAC system is reviewed in this section.

1.2.1. Energy Efficiency Management

The research on policy level regarding the strategies and barriers of the implementation of energy efficiency programs in different countries has been conducted (Bunse et al., 2011; Trianni et al., 2013; Walsh and Thornley, 2012). As for the technical point of view, the existing studies in manufacturing sector mainly focus on the single machine manufacturing system or specific manufacturing processes to improve energy efficiency. The energy efficiency for a certain manufacturing process was defined as the ratio of energy consumed by process itself to the total energy consumed by the manufacturing machine during the process (including the energy required by other auxiliary systems, e.g., coolant system and hydraulic system, etc.) (Dietmair and Verl, 2009a; Dietmair and Verl, 2009b). The general energy consumption model of individual manufacturing process has been developed by separating the total energy consumption into two parts, i.e., the fixed part that ensures the readiness of operation, and the variable part for the process (Dahmus and Gutowski, 2004; Gutowski et al., 2006; Li et al., 2011). The strategies of energy efficiency improvement considering the reduction opportunity from the energy consumption belongs to the fixed part were analyzed for different manufacturing processes (Abele et al., 2011).

In addition, many studies on energy efficiency improvement for different manufacturing processes from the perspective of process parameter optimization have been reported. For example, Li et al. (2014) proposed an empirical approach to characterize the energy efficiency on different injection molding machine tools. Winter et al. (2014a, 2014b) focused on the process parameters of grinding process to increase the process eco-efficiency and reduce the costs and environmental impacts under the consideration of technological requirements. Bhushan (2013) investigated the optimal machining parameters for the desired power consumption and tool life using the technique of design of experiments in computer numerical control (CNC) turning. Li et al. (2013) identified the energy consumption profiles to characterize the relationship between process parameters and energy consumption of milling process. Hu et al. (2012) developed an online model to monitor the power consumption of metal thread cutting process to improve energy efficiency. Li and Kara (2011) developed an empirical model for predicting energy consumption of turning process based on the power measurement under various cutting conditions with different process parameters. Anderberg et al (2010) conducted the experiments with different material removal rates to verify that the joint improvement of productivity, cost efficiency, and energy savings in a CNC machining environment can be achieved. Draganescu et al (2003) developed a statistic model of machine tool efficiency and specific consumed energy in machining using the experimental data through response surface method.

Besides the concern on process parameters, the methods from the perspective of scheduling have also been developed. For example, the production schedule for a single machine manufacturing system with multiple minimization objectives including both total energy consumption and tardiness was identified utilizing a greedy randomized adaptive search meta-heuristic (Mouzon and Yildirim, 2008). The “mathematical model to minimize energy consumption and reduce total completion time of a single machine" was proposed (Yildirim and Mouzon, 2012).

The state-of-the-art on single machine system or specific processes is the first important step for improving energy efficiency for manufacturers. However, these efforts alone may not be sufficient to achieve significant energy saving when each single machine belongs to part of the typical manufacturing system with multiple machines and buffers. Energy analysis of industrial facilities has indicated that process energy only accounts for a small percentage of total energy consumption. For example, in the metal working operation, the total energy requirement for physically performing an operation (e.g., deforming material and removing material) is quite small (10-20%) compared to the background functions needed for operating entire system (Dahmus and Gutowski, 2004; Gutowski et al., 2005).

However, on the system level, as indicated by a recent survey of the existing methodologies of energy efficiency improvement (Duflou et al., 2012), simulation is the main approach that is widely used (Thiede, 2012; Hermann and Thiede, 2009; Hermann et al., 2011; Thiede et al., 2011; Li et al., 2012). Nevertheless, simulation method cannot generate needed knowledge directly. It has several drawbacks such as lack of flexibility, time-consuming for model construction and execution, and intractable for real-time application, which greatly impede its wide application (Li et al., 2009). The research on the analytical method that can implement the energy efficiency management for the typical manufacturing systems with multiple machines and buffers is required; nonetheless, it has not attracted much attention in literature yet.

1.2.2. Electricity Demand Response

Extensive studies on electricity demand response have been conducted. The investigations on general policy of demand response programs were implemented (Greening, 2010; Vassileva et al., 2012). The topics regarding the management from electricity supply side when implementing demand response program, e.g., electricity price policy (Doostizadeh and Ghasemi, 2012; Faria et al., 2011), real time optimal pricing model (Yousefi et al., 2011; Yu et al., 2012), and the simulator that allows studying demand response actions and schemes in distribution networks (Faria and Vale, 2011) were investigated.

In addition, much work on the applications of the end-users in residential and commercial building sectors has been implemented. For example, the real time scheduling model in demand response for residential customers was studied (Chen et al., 2012; Yi et al., 2013). A hierarchical multi-agent control system with an intelligent optimizer to minimize the power consumption of the building without sacrificing the customer comfort was developed (Wang et al., 2012). An approach that can intelligently find the balance between user requirements and energy saving of the smart building was studied (Corno and Razzak, 2012). An optimal thermostat control policy that considers the tradeoff between the customer comfort and energy cost was proposed to implement demand response in residential buildings (Liang et al., 2012). The utilization of micro-Cogeneration Heat and Power (CHP) system in electricity demand response for residential buildings was investigated (Houwing et al., 2011). A set of general control strategies and techniques for demand response of commercial buildings was proposed (Motegi et al., 2007). The methods of thermal storage utilization (Henze et al., 2004) and cooling/heating requirement prediction (Braun and Chaturvedi, 2002) to reduce the electricity load of the buildings during peak periods were developed.

As for the end-users in industrial sector, the commonly used modeling method is to simplify the multi-machine manufacturing system into a single machine model and ignore the interconnection between the machines and buffers in the system. For example, Shrouf et al. (2013) proposed a "mathematical model to minimize electricity consumption costs for single machine production scheduling during production processes". Logenthiran et al. (2012) developed "a heuristic-based evolutionary algorithm to solve the mathematical formulation of the implementation of day-ahead load shift by minimizing the difference between the actual load curve and the desired load curve". Chao and Zhou (2005), Chao and Chen (2005), and Chao and Zipkin (2008) investigated "Optional Binding Mandatory Curtailment (OBMC) Plan" provided by Pacific Gas & Electric from the manufacturer's perspective to identify the optimal production strategies when that program is offered. In addition, some studies focusing on the peripheral or simple operations of specific industrial systems were also reported (Lewis, 2007; Lewis et al., 2009; McKane et al., 2008). In these peripheral or simple operation systems, the equipment is usually operated under a relatively isolated environment where the interrelationship among the equipment can be ignored.

Furthermore, some literature focusing on the electricity demand response for batch process industry was also reported. For example, Ashok and Baneerjee (2001) and Ashok (2006) developed the mathematical models to obtain optimal production schedule with minimum operation cost and energy cost for a flour plant and a steel plant, respectively. Luo et al. (1998) established "a mixed integer programming model to find an optimal load shed-restoration schedule for an underground coal-mining site". However, these methods have different limitations. The work of Ashok and Baneerjee (2001) and Luo et al (1998) did not consider the cost of the power demand in the objective function. The work of Ashok (2006) did not consider the random failures of the manufacturing equipment.

It can be seen that the state-of-the-art of electricity demand response for industrial manufacturing system is far less developed than the one in commercial and residential building sectors. The concerns about the impact on production, a key barrier towards industrial participation of electricity demand response (Ghatikar et al., 2012), cannot be effectively resolved and manufacturers are reluctant to venture their production throughput to participate in demand response programs. These facts emphasize the need for the methods that can be used for the electricity demand response for typical manufacturing systems with multiple machines and buffers. Unfortunately, such research has not attracted much attention in literature.

1.2.3. HVAC Systems

Most existing studies on customer-side energy management for manufacturing and HVAC systems are conducted separately. Sections 1.2.1 and 1.2.2 have provided a brief review on the state-of-the-art of energy efficiency management and electricity demand response for manufacturing system, respectively. In this section, a brief review on the HVAC system is given.

A great number of studies on HVAC system towards sustainability have been conducted to reduce the electricity consumption and power demand for buildings. For example, Nguyen and Aiello (2013) conducted a survey on intelligent energy control for building HVAC, lighting, and plug loads based on user activities. Erickson et al. (2013) developed "a complete closed-loop system for optimally controlling HVAC systems in buildings based on actual occupancy levels". Liao et al. (2012) proposed an offline learning method to implement electricity demand response for building HVAC system considering potential weather variations. Erickson and Cerpa (2010) developed an HVAC control strategy based on occupancy prediction and real time occupancy monitoring to reduce building energy consumption. Braun (1990) developed a thermal storage utilization method to reduce the power demand of buildings during peak periods.

As for the HVAC in manufacturing facility, many specific measures like turning off unnecessary lights, fans, and other equipment when production is off or during peak periods, periodical leakage checking for critical pipelines, and regular energy audit activities (Ghislain and Mckane, 2006; U.S. Environmental Protection Agency, 2009) have been widely implemented in HVAC system management in manufacturing plants. Recently, some initial investigations that jointly consider both manufacturing and HVAC systems have been launched. For example, Liu et al. (2012) developed a simulation-based method aiming at energy-efficient building design for a class of manufacturing plants considering HVAC configurations and production characteristics. Moynihan et al. (2012) implemented a case study by defining and simulating HVAC system in DesignBuilder and EnergyPlus for manufacturing plant facility design. Ball et al. (2011) proposed an overall framework for manufacturing plant design considering both production system and building. Niefer and Ashton (1997) conducted a review of building related energy use for manufacturing by investigating the characteristics of HVAC system and estimating energy intensity and energy saving potentials of HVAC system in manufacturing buildings.

However, the emerging work that jointly considers both systems usually focus on the design stage to identify the desired size, appropriate capability, and expected energy load of HVAC system, while neglecting the problem from operation point of view. It has been indicated that more than 90% of the environmental impact of some typical manufacturing activities is due to the energy consumption during the operation stage (Duflou et al., 2012). Thus, the study focusing on design stage alone is not sufficient to address the problem of the implementation of electric energy management for the combined manufacturing and HVAC system effectively.

In addition, the routine operation of HVAC system in manufacturing plant is usually independent from the operation of manufacturing system. The management of the two systems is usually conducted by two different teams. The enterprise control systems (e.g., Manufacturing Execution System (MES), Enterprise Resources Planning (ERP)) that are in charge of the management of manufacturing and HVAC systems are not connected. There is no communication between the two systems in daily operations (Brundage et al., 2013). The method on plant-level energy management considering combined manufacturing and HVAC system has not attracted wide attention yet.

1.3. Challenges and Objectives

It can be seen that the research in customer-side electric energy management for typical manufacturing systems is far less developed than the state-of-the-art of the research on single machine system or specific manufacturing processes. Moreover, the integration of manufacturing system and HVAC system on the plant level from operation point of view has not launched yet and the existing studies on customer-side electric energy management for two systems are usually conducted separately. The main **challenges** that lead to this situation can be summarized as follows.

1) *Complex interaction between the manufacturing system state evolution and energy control actions.* The energy control actions of energy efficiency management and electricity demand response are determined based on the operation and energy states of the machines in manufacturing system. Therefore, it is necessary to establish the model that can reflect

the relationship and interaction between system state evolution and energy control actions. Typical manufacturing system as shown in Figure 2 generally consists of multiple machines and buffers. Machines are not 100% reliable and random failures are expected to happen. The capacity of buffer is finite due to space limitation. Therefore, the state evolution of the machines and the buffers in manufacturing system cannot be deterministically identified. The integration of the energy control actions makes the problem even more complex. It is not easy to capture the states of manufacturing machines when energy management actions are conducted.

2) *Decision-making may need to be completed on a real-time basis.* "High dynamics of a manufacturing system leads to non-availability of a lookup table from which the predetermined decisions can be selected; but in practice, most decisions have to be made based on specific objectives and real time online data" (Li et al., 2012). In addition, the duration from the triggering of the decision-making algorithm to the implementation of the decisions made can be very short. It usually requires the decision-making be completed in a short period based on real time online data collected from the manufacturing system. Therefore, the computational complexity of the solution technique is "a key performance index for the developed method and thus needs to be carefully investigated" (Li et al., 2012).

3) *Production and energy consumption should be jointly considered when implementing energy management actions.* Production throughput has been traditionally considered first priority by manufacturers. Unlike the energy control for the single machine manufacturing system, the control actions can be implemented without considering the interdependency with other machines, since machine operation state is determined by itself and the potential

impact of energy control actions on throughput can be explicitly expressed as a simple linear relationship. For typical manufacturing system, the estimation of the throughput is very hard due to the characteristics of non-reliable machines and non-infinite buffers. The estimation of the potential impacts on the production throughput when the energy control actions are integrated becomes even more complex.

4) *The interrelationship between the manufacturing operation and HVAC control needs to be modeled*. The heat generated by manufacturing operation may influence the indoor temperature of the building of manufacturing plant. The HVAC control decisions depending on the indoor temperature will also be influenced. The optimal results for either manufacturing or HVAC systems obtained separately may not necessarily lead to an overall optimality for the combined system. In addition, there may be competition for the limited power consumption quotations between the manufacturing system and HVAC system during peak periods.

In summary, the aforementioned status quo motivates this doctoral research activity as shown in Figure 3. Energy efficiency management and electricity demand response for typical manufacturing systems is first studied as the first step to extend the existing methods from the single machine or process level to the manufacturing system level. After that, we further extend the methods to the plant level considering combined manufacturing and HVAC system in the second step. The **objectives** of this research are to develop the framework of customer-side electric energy management for manufacturers, advance the state-of-the-art of the existing methods from single machine or process level to the typical manufacturing system level and entire plant level, and provide a set of feasible methodologies that can be used to improve the energy efficiency and reduce the power demand for the manufacturers.

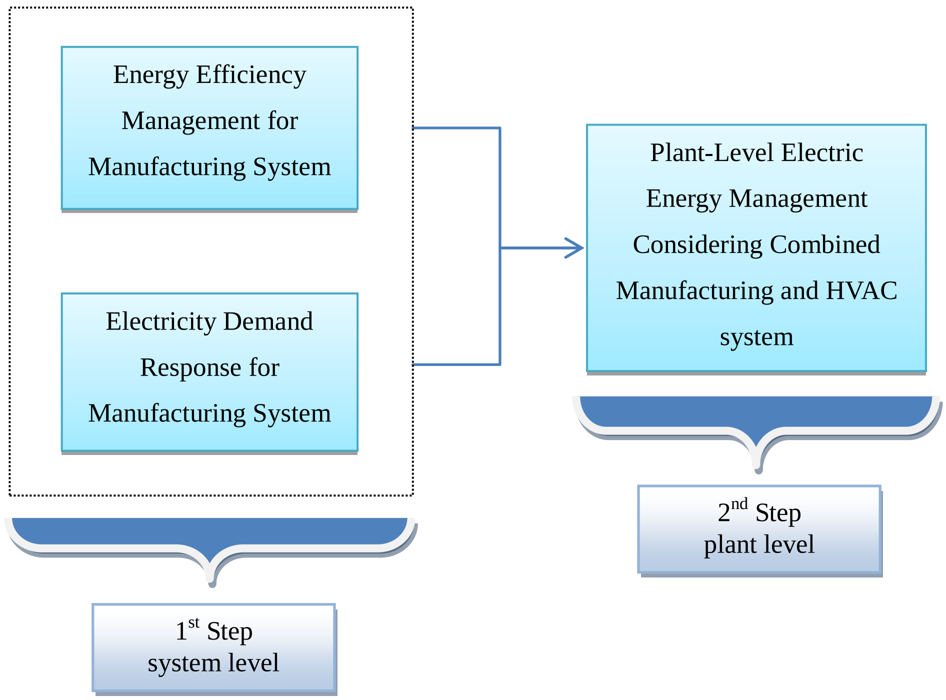

Figure 3. Research framework

In the first step, both energy efficiency management and electricity demand response are included. For the energy efficiency management, we develop a real time energy efficiency improvement method for the typical manufacturing systems with multiple machines and buffers. Our preliminary studies show that the energy waste due to the idle machines in the manufacturing system cannot be ignored (Sun et al., 2011; Li et al., 2012). Therefore, we implement energy control actions for the idle machines when the idle status is detected to improve the energy efficiency by reducing the energy waste of the entire manufacturing system. The proposed energy control decision-making is modeled by Markov decision process (MDP) to connect the operation/energy states of the manufacturing system, energy control actions, and system state evolution given certain states and actions. The algorithm is activated when the idle machine is detected. The objective is to identify the optimal power level for those idle machines under the constraint of system throughput. One-step ahead approximate dynamic programming is used to solve the objective function on a real time basis.

For the electricity demand response, both event-driven and price-driven programs (Goldman et al., 2010) are included. For the event-driven program, Markov decision process model that is established in the energy efficiency management model is partially utilized. The algorithm is triggered when the notification of demand reduction from the utility company is received. All the machines rather than only idle ones are considered as candidates that can receive energy control actions to respond to the utility request. Approximate dynamic programming is used to find the near optimal solution on a short-term basis. For the price-driven program, a novel "Just-for-peak" buffer inventory concept is proposed. The "Just-for-peak" buffer inventories are accumulated during off-peak periods and utilized during peak periods and thus some machines in the system can be turned off to reduce the electricity consumption and power demand during peak periods. The optimal demand response decisions and corresponding control policies for buffer inventory that can minimize the total cost including "Just-for-peak" buffer inventory holding cost, energy bill cost, and penalty cost due to potential throughput loss are obtained.

In the second step, we further extend our research from the system level to the plant level. The other major energy consumer in manufacturing plant, HVAC system is integrated. As the first exploration in this area, we focus on the electricity demand response for the plant-level energy management in this doctoral research. A mathematical model for the decision-making in electricity demand response for the combined manufacturing and HVAC system is developed considering power consumption competition between the two systems and the influence on the temperature due to the manufacturing operations. The production capability, electricity pricing, and ambient temperature are considered in the model to identify the optimal demand response strategy with respect to both production schedule and HVAC control.

The new knowledge generated by this framework can advance the state-of-the-art of energy management for industrial manufacturing sector from the level of single machine manufacturing systems or specific processes first to the level of typical manufacturing systems with multiple machines and buffers; and then to the level of the entire plant considering combined manufacturing and HVAC system. The outcomes of this research can be applied to discrete part manufacturing (Govil and Fu, 1999; Siemens, 2014) in various industries such as automotive, electronics, appliances, aerospace, etc. The technological readiness of the manufacturing enterprises to complete the transition towards sustainable manufacturing can be accelerated. Details of the proposed tasks regarding the framework are implemented in Chapters 2, 3, and 4.

1.4. Organization of Thesis

Chapter 1 provides a brief introduction of this doctoral thesis research. Background information, state-of-the-art, research motivation, and research objective are presented in this chapter. Chapter 2 presents an analytical method to improve energy efficiency for typical manufacturing systems with multiple machines and buffers on a real time basis. Chapter 3 models the electricity demand response for the manufacturing system. Both event-driven program and price-driven program are involved. Chapter 4 studies the energy management on the plant level considering combined manufacturing and HVAC system. Chapter 5 concludes the research and discusses future work.

CHAPTER 2 ENERGY EFFICIENCY MANAGEMENT FOR SUSTAINABLE MANUFACTURING SYSTEMS

This chapter was previously published as "Li, L., and Sun, Z. (2013) Dynamic energy control for energy efficiency improvement of sustainable manufacturing systems using markov decision process, IEEE Transactions on Systems, Man, and Cybernetics: Systems, 43(5): 1195-1205". © 2013 IEEE. Reprinted, with permission, from [Lin Li and Zeyi Sun, Dynamic energy control for energy efficiency improvement of sustainable manufacturing systems using markov decision process, IEEE Transactions on Systems, Man, and Cybernetics: Systems, May 2013]

2.1. Introduction

In this chapter, a real-time energy efficiency improvement method is developed to establish a systems (or holistic) view of energy efficiency management for the typical manufacturing systems with multiple machines and buffers. This research can greatly advance the existing methods on energy efficiency management from the level of single machine system or specific processes to the level of multi-machine system. The energy waste of the idle machines in the system is targeted. Markov decision process (MDP) is used to derive the proposed method to model the complicated interaction between the adopted energy control decisions and system state evolutions in decision-making. An approximate solution technique for the real time application is introduced to find a near-optimal solution. A numerical case study on a section of an auto assembly line is used to illustrate the effectiveness of the proposed approach.

The rest of this chapter is organized as follows. Section 2.2 presents the MDP modeling and solution technique. Section 2.3 introduces a numerical case study to illustrate the effectiveness of the proposed method. Finally, the conclusions of this chapter are drawn in Section 2.4.

The following notations are used in this chapter.

Boldface:

$\mathbf{A}^t$	action adopted for the system at decision epoch t
$\mathbf{A}^t_{BS}$	action adopted for all blockage/starvation machines at the decision epoch t

Upper Case:

A^t_i	action adopted for machine i at decision epoch t
A^t_u	action adopted for blockage/starvation machine u at decision epoch t
B_i	the set of states of buffer i
B^t_i	content of buffer i at decision epoch t, $i = 1, ..., I-1$
BL^{k-1}_i	observed blockage duration of the k-1th blockage of machine i
$\overline{BL}_i$	mean of the blockage duration of machine i
$\hat{B}L^k_i$	estimated blockage duration of the kth blockage of machine i

D_i	random variable to denote the repair time of machine *i*
$E_i^{rq} = P_i^{rq} \cdot T_i^{rq}$	transition energy for machine *i* from ready for operation state to H_{q_i} state, $q_i = 1,...h_i$
$E_i^{qr} = P_i^{qr} \cdot T_i^{qr}$	transition energy for machine *i* from H_{q_i} state to ready for operation state, $q_i = 1,...h_i$
H_{q_i}	a certain energy hibernation state of machine *i*
I_{H_t}	the set of machines that *H*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{BS\text{-}H}$	the set of blockage/starvation machines in hibernation energy state and *K*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{BS-R}$	the set of blockage/starvation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{OP-R}$	the set of operation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*
I_{W_t}	the set of machines that *W*-action is adopted at decision epoch *t*
N_i	capacity of buffer *i*, $i = 1, ..., I-1$
$p_u^{A_u^t r}$	the probability of blockage/starvation machine *u* belonging to category *r* (*r*=1,2,3) when the action A_u^t ($A_u^t = H, K$) is adopted

P_i^r power for machine i in ready for operation state

P_i^{rq} average transition power for machine i from ready for operation state to H_{q_i} state, $q_i = 1, ..., h_i$

P_i^q power for machine i in energy state H_{q_i}, $q_i = 1, ..., h_i$

P_i^{qr} average transition power for machine i from H_{q_i} state to ready for operation state, $q_i = 1, ..., h_i$

S_{Ei} set of energy states for machine i

S_{Oi} set of operation states for machine i

$S_{E_i}^t$ energy state of machine i at decision epoch t

$S_{O_i}^t$ operation state of machine i at decision epoch t

ST_i^{k-1} observed starvation duration of the k-1th starvation of machine i

$\overline{ST}_i$ mean of the starvation duration of machine i

$\hat{S}T_i^k$ estimated starvation duration of the kth starvation of machine i

T_i^q time for machine i to stay in the energy state H_{q_i}, $q_i = 1, ..., h_i$

T_i^{qr} transition time for machine i from H_{q_i} state to ready for operation

	state, $q_i = 1, ..., h_i$
T_i^{rq}	transition time for machine i from ready for operation state to H_{q_i} state, $q_i = 1, ..., h_i$
TC	cycle time of the system

Lower Case:

h_i	number of energy hibernation states of machine i
i	machine index, $i = 1, ..., I$
k	blockage/starvation occurrence index
q_i	energy hibernation state index of machine i, $q_i = 1, 2, ..., h_i$
u	the index of blockage/starvation machine

Greek:

β_i^{BL}	smoothing factor to predict blockage duration for machine i with exponential smoothing method
β_i^{ST}	smoothing factor to predict starvation duration for machine i with exponential smoothing method
δ_{BL}^i	coefficient to adjust the estimated blockage duration for machine i based on online buffer content
δ_{ST}^i	coefficient to adjust the estimated starvation duration for machine i based on online buffer content

2.2. Proposed Method

2.2.1. MDP Introduction and Model Assumptions

Markov decision process (MDP) is widely used in literature to model state-based decision-making problem. It "provides a mathematical framework for modeling decision-making in the situations where the outcomes are partly random and partly under the control of a decision maker" (Ye, 2011). Both stochastic and deterministic properties of the system can be captured by the model (Chatterjee and Doyen, 2011). More precisely, at each decision epoch *t* under the framework of MDP, the system is in a certain state s_t, and the decision agent can select the action a_t that can be adopted at state s_t. The system evolves at decision epoch *t*+1 by randomly moving into a new state s' and incurring a corresponding immediate cost $C(s_t, a_t)$. The probability that the system moves into the new state s' is influenced by both adopted action a_t and state s_t. Specifically, it is given by the state transition probability $P(s_{t+1} = s' | s_t, a_t)$. A value function is also formulated to integrate the incurred immediate cost between the current and the next decision epochs and the expectation of the subsequent cost between the next and the final decision epochs. Therefore, different actions can be evaluated and the objective function can be established accordingly (Givan and Parr, 2013).

In this section, we consider a typical manufacturing system with *I* machines and *I*-1 buffers as shown in Figure 2. The assumptions for the MDP model based on this system are shown as follows.

1) The cycle times of all the machines in the system are the same;
2) The machine failure is time-dependent;
3) The transitions of machine operation state and buffer state are assumed to occur at the beginning or ending of each cycle;

4) For machine energy state, besides the three conventional energy states, i.e., full operation, ready for operation, and turned-off (Li and Kara, 2011), we consider h_i different energy hibernation states with partial power consumption of ready for operation state;
5) No production activities can be implemented when machine is in hibernation energy mode;
6) No additional power control actions can be adopted when machine is in the power state transition process;
7) The first machine is never starved and the last machine is never blocked.

2.2.2. System state variables and state space

The system state space of the typical manufacturing system as shown in Figure 2 includes both machine state and buffer state. For the machine state, two kinds of information are recorded: operation state and energy state.

Machine operation state includes operation, blockage, starvation, and breakdown (Li and Meerkov, 2009). Blockage means that the machine itself is not failed while the completed part cannot be delivered to the downstream buffer due to the breakdown of specific downstream machines. Starvation means that the machine itself is not failed while there is no incoming part from the upstream buffer due to the breakdown of specific upstream machines. Let OP_i, BL_i, ST_i, and DN_i denote the above four operation states of machine *i*. Accordingly, the set of operation states of machine *i* can be described as $\mathrm{S}_{O_i} = \{OP_i, BL_i, ST_i, DN_i\}, i = 1, 2, ...I$.

For machine energy state, besides the three conventional energy states, i.e., full operation, ready for operation, and turned-off (Li and Kara, 2011), we consider h_i different energy hibernation states with partial power consumption of ready for operation state as shown in Figure

4. Let H_{q_i}, $q_i = 1,\ldots h_i$, denote these hibernation states. Thus, the set of energy states of machine *i* can be denoted as $\mathrm{S}_{Ei} = \{F_i, R_i, H_{q_i}, O_i\}$, $q_i = 1,\ldots h_i$ and $i = 1, 2, \ldots I$, where F_i, R_i, and O_i represent the state of full operation, ready for operation, and turned-off of machine *i*, respectively. In addition, we also assume that the energy state of machine *i* is R_i at the beginning of each cycle if the machine operation state is not breakdown and no energy control action is implemented. On the one hand, it can be automatically switched to F_i if the operation state of machine *i* is OP_i and switched back to R_i at the ending of the cycle when the processing is completed (note that the transition between R_i and F_i is assumed to be instantaneous). On the other hand, it will be kept in R_i if the operation state of machine *i* is BL_i / ST_i.

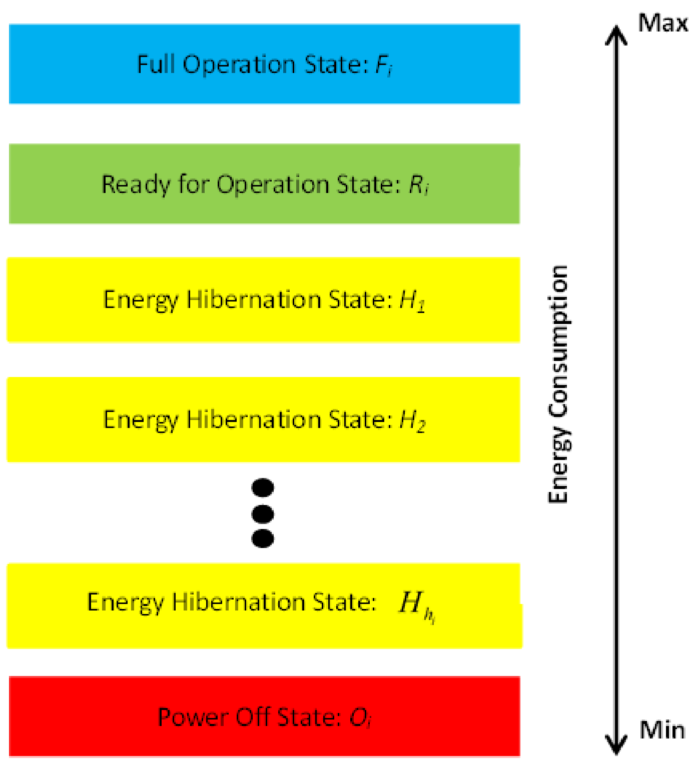

Figure 4. Machine energy states

For buffers, there is no energy consumption and the buffer state is defined as the number of the jobs waiting for being processed in the buffer location. Hence, the set of states for buffer i can be described as $B_i = \{0,1,2,...,N_i\}$, $i = 1,2,...,I-1$.

In summary, the set of system states can be denoted by $S=\{S_{O_i}, S_{E_i}, B_i\}$, where $i = 1,2,...,I$ for S_{O_i} and S_{E_i}; $i = 1,2,...,I-1$ for B_i.

2.2.3. Energy Control Action

Energy control actions for machine i can be divided into three categories. The first one is to keep the original energy state (K-action), which can be adopted under the following four situations: (1) the energy state of blockage/starvation machine cannot be adjusted due to some specific constraints; (2) the machine can be kept on a certain hibernation power level; (3) the operation state of machine i is OP_i; and (4) the operation state of machine i is DN_i.

The second one (H-action) can be used to adjust the energy state of blockage or starvation machine i from R_i to H_{q_i} or O_i if the no constraint is violated. It notifies the idle machine i to stay on a lower power level H_{q_i} or O_i.

The third one (W-action) is to adjust the energy state of machine i from H_{q_i} or O_i to R_i. It is used to waken the hibernation machines to resume operation. Table I summarizes the possible energy control actions applied for different operation-energy state pairs. It can be seen that this table actually sets up the rules for the energy control actions for different possible operation-energy state pairs except the blockage/starvation machines with energy state of ready for operation. We need to determine whether K-action or H-action should be adopted for those machines.

TABLE I. ENERGY CONTROL ACTIONS FOR DIFFERENT SCENARIOS IN ENERGY EFFICIENCY IMPROVEMENT

Operation State	Energy State	Power Control Action	Target Power Level
OP_i	R_i	K-action	R_i
OP_i	H_{q_i} or O_i	W-action	R_i
BL_i / ST_i	R_i	K-action	R_i
BL_i / ST_i	R_i	H-action	H_{q_i} or O_i
BL_i / ST_i	H_{q_i} or O_i	K-action	H_{q_i} or O_i
DN_i	O_i	K-action	O_i

Therefore the set of energy control actions for machine *i* can be denoted as $A_i = \{K_i, H_i, W_i\}$, $i = 1, 2, ..., I$ where K_i, H_i, and W_i denote *K*-action, *H*-action, and *W*-action for machine *i*, respectively. The actions for the system at decision epoch *t* can be described as $\mathbf{A}_t = (A_1^t, ..., A_i^t, ..., A_I^t)$, where A_i^t is the action adopted for machine *i* at decision epoch *t*.

2.2.4. System State Transition

The energy state of machine *i* at the next decision epoch *t*+1 is jointly determined by both its operation state at decision epoch *t*+1 and energy control action executed at the current epoch *t*. Since the outcome of energy state strictly follows energy control action, we focus on the calculation of the transition of buffer state and machine operation state considering machine reliability and energy control action as follows.

The buffer state at decision epoch t+1 can be obtained by (2.1) based on the states and the energy control actions adopted at decision epoch t by the adjacent upstream and downstream machines.

$$B_i^{t+1} = B_i^t + I(S_{O_i}^t, S_{E_i}^t, A_i^t) - I(S_{O_{i+1}}^t, S_{E_{i+1}}^t, A_{i+1}^t), \quad 0 \le B_i^t \le N_i \tag{2.1}$$

where

$$I(S_{O_i}^t, S_{E_i}^t, A_i^t) = \begin{cases} 1 & S_{O_i}^t = OP_i \text{ and } S_{E_i}^t = R_i \text{ and } A_i^t = K_i \\ 0 & S_{O_i}^t \ne OP_i \text{ or } S_{E_i}^t = H_{q_i} / O_i \text{ or } A_i^t = H_i \end{cases} \tag{2.2}$$

Refer to the literature focusing on the statistical methods for machine reliability (Meeker, and Escobar, 1998), we assume L_i, the random variable of lifetime of machine i, follows Weibull distribution with shape parameter and scale parameter considering the non-memoryless characteristic of machine lifetime. The probability that machine i goes into failure or not failure at the next decision epoch t+1, given it is not in failure at the current decision epoch t can be described by (2.3) and (2.4) respectively.

$$\Pr(S_{O_i}^{t+1} = DN \mid S_{O_i}^t \ne DN) = \Pr(L_i < t + TC) \tag{2.3}$$

$$\Pr(S_{O_i}^{t+1} \ne DN \mid S_{O_i}^t \ne DN) = \Pr(L_i \ge t + TC) \tag{2.4}$$

At the same time, we also assume D_i, the random variable of repair time of machine i, follows Exponential distribution (Dallery, 1994). The probability that machine i completes or does not complete the repair at the next decision epoch t+1, given it is in repair at the current decision epoch t can be described by (2.5) and (2.6) respectively.

$$\Pr(S_{O_i}^{t+1} \ne DN_i \mid S_{O_i}^t = DN_i) = \Pr(D_i < t + TC) \tag{2.5}$$

$$\Pr(S_{O_i}^{t+1} = DN_i \,\big|\, S_{O_i}^{t} = DN_i) = \Pr(D_i \geq t + TC) \tag{2.6}$$

The probability that machine i is in the starvation and blockage state can be described by (2.7) and (2.8) respectively.

$$\begin{aligned}\Pr(S_{O_i}^{t+1} = ST_i) = {} & \Pr(S_{O_i}^{t+1} \neq DN_i) \cdot \Pr(B_{i-1}^{t+1} = 0) \cdot \Pr(S_{O_{i-1}}^{t+1} = DN_{i-1}) \\ & + \Pr(S_{O_i}^{t+1} \neq DN_i) \cdot \Pr(B_{i-1}^{t+1} = 0) \cdot \Pr(S_{O_{i-1}}^{t+1} = ST_{i-1})\end{aligned} \tag{2.7}$$

$$\begin{aligned}\Pr(S_{O_i}^{t+1} = BL_i) = {} & \Pr(S_{O_i}^{t+1} \neq DN_i) \cdot \Pr(B_{i}^{t+1} = N_i) \cdot \Pr(S_{O_{i+1}}^{t+1} = DN_{i+1}) \\ & + \Pr(S_{O_i}^{t+1} \neq DN_i) \cdot \Pr(B_{i}^{t+1} = N_i) \cdot \Pr(S_{O_{i+1}}^{t+1} = BL_{i+1})\end{aligned} \tag{2.8}$$

The probability that machine i is in operation state can thus be described by (2.9).

$$\Pr(S_{O_i}^{t+1} = OP_i) = \Pr(S_{O_i}^{t+1} \neq DN_i) - \Pr(S_{O_i}^{t+1} = ST_i) - \Pr(S_{O_i}^{t+1} = BL_i) \tag{2.9}$$

Therefore, the transition probability of machine operation state between current decision epoch t and next decision epoch t+1 can be calculated using (2.3) to (2.9). The transition probability of machine energy state can thus be obtained considering both energy control action and transition probability of machine operation state. The transition probability of the entire system can also be obtained considering the transition probability of machine energy and operation states as well as the buffer state transition described in (2.1)-(2.2).

2.2.5 Optimization Formulation

The optimal energy control action needs to be determined when machine is detected to be blocked or starved, i.e., to turn it off, or to leave it alone, or to adjust its power level to a hibernation state (note that K-action is adopted for all non-blockage/starvation machine). The energy consumption incurred from decision epoch t to the final production horizon $V_t(\mathbf{S}_t)$ can be formulated by (2.10).

$$V_t(\mathbf{S}_t) = C(\mathbf{S}_t, \mathbf{A}_t) + \sum_{\mathbf{S}^{'} \in \mathbf{S}} \Pr(\mathbf{S}_{t+1} = \mathbf{S}^{'} \big| \mathbf{S}_t, \mathbf{A}_t)\, V_{t+1}(\mathbf{S}^{'}) \tag{2.10}$$

where $\Pr(\mathbf{S}_{t+1} = \mathbf{S}^{'} \big| \mathbf{S}_t, \mathbf{A}_t)$ is the probability of $\mathbf{S}_{t+1}$ given $\mathbf{S}_t$ and $\mathbf{A}_t$. $V_{t+1}(\mathbf{S}^{'})$ is the energy consumption from decision epoch *t*+1 to the end of the production horizon. $C(\mathbf{S}_t, \mathbf{A}_t)$ is the energy consumption in the duration from current decision epoch *t* to next decision epoch *t*+1. It can be formulated by (2.11).

$$\begin{aligned} C(\mathbf{S}_t, \mathbf{A}_t) = & \sum_{i \in \mathrm{I}_{H_t}} (\min(T_i^{rq}, TC) \cdot P_i^{rq} + \max(TC - T_i^{rq}, 0) \cdot P_i^{q}) \\ & + \sum_{i \in \mathrm{I}_{W_t}} (\min(T_i^{qr}, TC) \cdot P_i^{qr} + \max(TC - T_i^{qr}, 0) \cdot P_i^{r}) \\ & + \sum_{i \in \mathrm{I}_{K_t}^{OP-R}} P_i^{f} \cdot TC + \sum_{i \in \mathrm{I}_{K_t}^{BS-R}} P_i^{r} \cdot TC + \sum_{i \in \mathrm{I}_{K_t}^{BS-H}} P_i^{q} \cdot TC \end{aligned} \tag{2.11}$$

where $\mathrm{I}_{K_t}^{OP\text{-}R}$ is the set of operation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*. $\mathrm{I}_{K_t}^{BS\text{-}R}$ is the set of blockage/starvation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*. $\mathrm{I}_{K_t}^{BS\text{-}H}$ is the set of blockage/starvation machines in hibernation energy state and *K*-action is adopted at decision epoch *t*. I_{H_t} is the set of machines that *H*-action is adopted at decision epoch *t*. I_{W_t} is the set of machines that *W*-action is adopted at decision epoch *t*.

The objective function can be formulated by (2.12).

$$\min_{\mathbf{A}t \in \mathbf{A}} V_t(\mathbf{S}_t) = \min_{\mathbf{A}t \in \mathbf{A}} (C(\mathbf{S}_t, \mathbf{A}_t) + \sum_{\mathbf{S}^{'} \in \mathbf{S}} \Pr(\mathbf{S}_{t+1} = \mathbf{S}^{'} \big| \mathbf{S}_t, \mathbf{A}_t)\, V_{t+1}(\mathbf{S}^{'})) \tag{2.12}$$

Two constraints need to be considered. One is the system throughput invariant during energy control, which requires energy control action be performed during machine blockage and starvation. Equations (2.13) and (2.14) are used to describe the throughput constraints.

$$\hat{B}L_i^k > T_i^{rq} + T_i^{qr} \tag{2.13}$$

$$\hat{S}T_i^k > T_i^{rq} + T_i^{qr} \tag{2.14}$$

The other constraint is whether the energy consumption under the certain *H*-action is less than energy consumption with *K*-action. Energy consumed in transition also needs to be taken into account. Equations (2.15) and (2.16) are formulated to describe this energy saving constraint.

$$P_i^r \cdot \hat{B}L_i^k > P_i^q \cdot (\hat{B}L_i^k - T_i^{rq} - T_i^{qr}) + E_i^{rq} + E_i^{qr} \tag{2.15}$$

$$P_i^r \cdot \hat{S}T_i^k > P_i^q \cdot (\hat{S}T_i^k - T_i^{rq} - T_i^{qr}) + E_i^{rq} + E_i^{qr} \tag{2.16}$$

where $\hat{B}L_i^k$ and $\hat{S}T_i^k$ are obtained by

$$\hat{B}L_i^k = \delta_{BL}^i [(1-\beta_i^{BL})\hat{B}L_i^{k-1} + \beta_i^{BL} BL_i^{k-1}] \quad k = 2,3..... \tag{2.17}$$

$$\hat{B}L_i^k = \overline{BL}_i \ , \ k = 1 \tag{2.18}$$

$$\hat{S}T_i^k = \delta_{ST}^i [(1-\beta_i^{ST})\hat{S}T_i^{k-1} + \beta_i^{ST} ST_i^{k-1}] \quad k = 2,3..... \tag{2.19}$$

$$\hat{S}T_i^k = \overline{ST}_i \ , \ k = 1 \tag{2.20}$$

where k is the index of the occurrence of blockage and starvation. β_i^{BL} and β_i^{ST} are exponential smoothing factors which are generally between 0 and 1. Considering the fact that the higher (lower) the occupancy ratio of the downstream (upstream) buffer, the higher possibility the blockage (starvation) will occur. Let δ_{BL}^i and δ_{ST}^i be adjustment coefficients that are defined by (2.21) and (2.22).

$$\delta_{BL}^i = \begin{cases} 0.95 & \frac{1}{I-i}\sum_{j=i}^{I-1} B_i^t / N_i \le 0.5 \\ 1.05 & \frac{1}{I-i}\sum_{j=1}^{I-1} B_i^t / N_i > 0.5 \end{cases} \tag{2.21}$$

$$\delta_{ST}^{i} = \begin{cases} 0.95 & \frac{1}{i-1}\sum_{j=1}^{i-1} B_i^t / N_i > 0.5 \\ 1.05 & \frac{1}{i-1}\sum_{j=1}^{i-1} B_i^t / N_i \le 0.5 \end{cases} \tag{2.22}$$

Solving the optimization problem in (2.12) under the constraints (2.13)-(2.16) can give the optimal action at the current decision epoch.

2.2.6 Solutions Using Approximate Dynamic Programming

In previous sections, the MDP model of energy efficiency management for a typical manufacturing system with multiple machines and buffers has been established. The classical tool to solve MDP is dynamic programming that begins the algorithm at the final decision epoch and steps back by looping over all the possible states and available actions until the optimal action for current epoch is obtained (Bellman, 1957). Zero is set as an initial value for the value function for all the states at the final decision epoch.

The usefulness of backward method is limited due to the "curse of dimensionality" (Powell, 2011), which requires the algorithm to loop over all the states and actions, leading to computational intractability. In our problem, the solution needs to be identified immediately after the idle machine is detected. Therefore, we need to use an alternative forward method to obtain an approximate solution on a real time basis (Powell, 2011). The basic idea of typical forward method is to begin the algorithm at the current time, and initialize a set of estimated values for value functions of all states. A set of sample paths is randomly generated to simulate the evolution of system state. The algorithm runs from the current decision epoch to the final epoch along with each sample path iteratively. The value function for corresponding state-action pair is updated with each step and will be used for the next iteration.

The advantage of forward method over the backward one is that it avoids the problem of looping over all possible states (Powell, 2011). However, it still requires the calculation of the expectation of value function in the next decision epoch, which is often computationally intractable if the size of reachable states at the next decision epoch is too large (Powell, 2011). Furthermore, the estimation of the value function at decision epoch t is not easy and so zero is often used for initialization. Unlike the backward method, whose value function is estimated from the final decision epoch and thus zero is a reasonable initial value, huge error exists between initial estimation and actual value. Therefore, a great number of iterations running from the current epoch to the final epoch are required to smooth the error by updating the estimated value (Powell, 2011). It is very hard to obtain an approximate optimal solution in real time. Hence, in this section, we estimate the value function by state aggregation as described in the following paragraphs rather than by zero in order that the problem can be solved on a real time basis.

Considering the structure of the problem and energy control rules shown in Table I, we need to identify the energy control actions for the blockage/starvation machines. When energy control action (*H*-action) is adopted for blocked or starved machine, the value function of the system at decision epoch t+1 is influenced by the energy state adjustment and the system state evolution. Let C_b be a baseline estimation of energy consumption from decision epoch t+1 until the end of the production horizon when energy adjustment is not implemented. The mean value of historical data can be used to approximate this initial estimation. For the *H*-action, if the system evolution from t to t+1 is the same as the expectation when the decision is made at decision epoch t, then energy saving based on C_b can be approximately estimated as expected. If the system evolution from decision epoch t to t+1 is not as same as the expectation when the decision is made, then energy saving based on C_b needs to be re-estimated. Based on this, we can aggregate the system state at decision epoch *t*+1 into three different categories as follows in order that the calculation of the expectation of value function at the next decision epoch can be easily conducted.

Category 1

The machine whose power level is lowered at decision epoch *t* is still in blockage or starvation state at decision epoch *t*+1 as expected; the energy savings based on C_b due to the adjustment can be estimated.

Let C_s denote the approximation of expected energy savings. It can be formulated by (2.23) and (2.24).

$$C_s = P_i^r \cdot \hat{B}L_i^k - [P_i^q \cdot (\hat{B}L_i^k - T_i^{rq} - T_i^{qr}) + E_i^{rq} + E_i^{qr}] \tag{2.23}$$

$$C_s = P_i^r \cdot \hat{S}T_i^k - [P_i^q \cdot (\hat{S}T_i^k - T_i^{rq} - T_i^{qr}) + E_i^{rq} + E_i^{qr}] \tag{2.24}$$

Let ${V^{H_1}}_{t+1}$ be the value function at decision epoch *t*+1. It can be approximately estimated by (2.25).

$${V^{H_1}}_{t+1} = C_b - C_s \tag{2.25}$$

Category 2

The machine is not blocked or starved at decision epoch *t*+1 while its energy consumption state was adjusted into a particular hibernation mode at decision epoch *t*. In this situation, energy consumption may be higher than C_b due to the possibility of the high energy consumption in transition.

Let C_p be the energy waste of category 2. It can be formulated by (2.26).

$$C_p = E_i^{rq} + E_i^{qr} - P_i^r \cdot (T_i^{rq} + T_i^{qr}) \tag{2.26}$$

Let $V^{H_2}{}_{t+1}$ be the value function at decision epoch *t*+1. It can be approximately estimated by (2.27).

$$V^{H_2}{}_{t+1} = C_b + C_p \tag{2.27}$$

Category 3

The machine may fail at decision epoch *t*+1. Under this condition, the energy saving is only achieved during a very short period and we can assume it has no impact on C_b. Let C_f be the influence cost of this category. It can be formulated by (2.28).

$$C_f = 0 \tag{2.28}$$

Let $V^{H_3}{}_{t+1}$ be the value function at decision epoch *t*+1. It can be approximately estimated by (2.29).

$$V^{H_3}{}_{t+1} = C_b + C_f \tag{2.29}$$

As for the *K*-action adopted by the blockage/starvation machines, we can use C_b to approximate value function from decision epoch *t*+1 to the final for all three categories. The value function $V^{Kr}{}_{t+1}$ can be approximately estimated by (2.30).

$$V^{Kr}{}_{t+1} = C_b, \quad r = 1,2,3 \tag{2.30}$$

Table II summarizes the above discussion for estimation of value function at decision epoch *t*+1.

TABLE II. VALUE FUNCTION ESTIMATION FOR MACHINE

Decision Epoch t			Decision Epoch t+1		
State	Expected State at Decision Epoch t+1	Decision	Possible Operation State at Decision Epoch t+1	Possible Energy State	Estimated Value Function from t+1
			BL_i/ST_i	H_{q_i}/O_i	$V^{H_1}{}_{t+1} = C_b - C_s$
BL/ST	BL/ST	H-action	OP_i	H_{q_i}/O_i	$V^{H_2}{}_{t+1} = C_b + C_p$
			DN_i	H_{q_i}/O_i	$V^{H_3}{}_{t+1} = C_b + C_f$
BL/ST	whatever	K-action	whatever	whatever	$V^{Kr}{}_{t+1} = C_b,\ \ r = 1,2,3$

Let $\mathbf{A}^t_{BS}$ be the actions adopted for all blockage/starvation machines at the decision epoch t; u be the index of the blockage/starvation machines ($u = 1,2,...,bs$); and w be the index of the possible state of the blockage/starvation machines at decision epoch t+1 ($w = 1,2,...,W$). In addition, we define $p_u^{A_u^t r}$ as the probability of blockage/starvation machine u belonging to category r (r=1,2,3) when the action A_u^t ($A_u^t = H, K$) is adopted.

The objective function (2.12) can thus be solved by (2.31) for a near optimal energy state adjustment decision when blockage or starvation is detected at decision epoch t.

$$\begin{aligned}\mathbf{A}^t_{BS} &= (A_1^t,...,A_u^t,...,A_{bs}^t)\\ &= \arg\min_{A_u^t \in \mathrm{A}_u}[(C(\mathbf{S}_O^t, \ \mathbf{S}_E^t, \mathbf{A}^t_{BS}) + \sum_{w=1}^{W}(\Pr_w(\mathbf{S}_O^{t+1}, \ \mathbf{S}_E^{t+1} \big| \mathbf{S}_O^t, \ \mathbf{S}_E^t, \mathbf{A}^t_{BS}) \cdot V_w^{t+1})]\end{aligned} \tag{2.31}$$

where

$$\Pr_w(\mathbf{S}_O^{t+1}, \ \mathbf{S}_E^{t+1} \big| \mathbf{S}_O^t, \ \mathbf{S}_E^t, \mathbf{A}^t_{BS}) \cdot V_w^{t+1} = (\prod_{u=1}^{bs} p_u^{A_u^t r}) \cdot (\sum_{u=1}^{bs} V_{t+1}^{A_u^t r}), \quad r = 1,2,3, A_u^t = H, K \tag{2.32}$$

The total procedure of the decision-making can be described as follows:

Step 0: Initialization when blockage or starvation is detected

Step 0a: relevant online data sampling

Step 0b: make prediction of blockage or starvation duration

Step 1: Find all feasible actions based on prediction from Step 0

Step 1a: check throughput constraint for each action

Step 1b: check energy saving constraint for each action

Step 2: Find the optimal action among the feasible actions obtained from Step 1

Step 2a: estimate the value function at t+1

Step 2b: calculate the probability for each category at decision epoch t+1

Step 2c: Solve (2.31)

Step 3: updating smoothing constant β_i^{BL} and β_i^{ST} when blockage or starvation is over

2.3. Case Study

In this section, we use a five-machine and four-buffer manufacturing system from a section of an automotive assembly line as shown in Figure 5 as the numerical case to illustrate the effectiveness of the method proposed in Section 2.2. The basic settings for each machine, e.g., mean time between failures (MTBF), mean time to repair (MTTR), and cycle time, are listed in Table III. The information about each buffer, i.e., capacity and initial contents, is shown in Table IV. The different power modes are demonstrated in Table V. We use the power consumption of state R as our benchmark and assume the power consumption of state F is 5% higher than that of R.

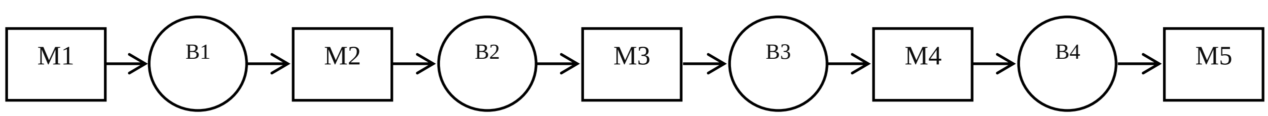

Figure 5. A five-machine and four-buffer serial line

TABLE III. BASIC SETTINGS OF EACH MACHINE

	MTBF (min)	Scale Parameter λ_i	Shape Parameter g_i	MTTR (min)	Exponential Parameter λ_i	Power Level of R (kW)	Cycle Time (min)	Warm-up Time (min)
M1	100	111.39	1.5766	4.95	0.2020	21	0.5	1.4
M2	45.6	51.1	1.6532	11.7	0.0855	14	0.5	0.9
M3	98.8	110.9	1.7174	15.97	0.0626	20	0.5	1.35
M4	217.5	239.1	1.421	27.28	0.0367	16	0.5	1.05
M5	109.4	122.1	1.591	18.37	0.0544	13	0.5	0.85

TABLE IV. BASIC SETTINGS OF EACH BUFFER

	Buffer1	Buffer2	Buffer3	Buffer4
Capacity	70	18	18	42
Initial Contents	32	8	8	8

TABLE V. DIFFERENT POWER STATES

Energy Consumption State	F	R	H_1	H_2	H_3	O
Power Level	105%	100%	50%	30%	10%	0%

To improve the accuracy of the prediction of blockage and starvation duration, historical data for this system are sampled for tuning the smoothing factor β_i^{BL} and β_i^{ST} (note that the starvation of machine 2 has rarely been detected and is thought to be negligible in this case). The results of the adopted values are underscored as shown in Table VI.

TABLE VI. β -VALUE TUNING BASED ON HISTORICAL DATA FOR EACH MACHINE

M1 Blockage	Sum of Square of error	M2 Blockage	Sum of Square of error	M3 Blockage	Sum of Square of error	M3 Starvation	Sum of Square of error
0.1	2931	0.1	1446	0.1	877	0.1	730
0.3	2702	0.3	1345	0.3	821	0.3	698
0.5	2532	0.5	1293	0.5	785	0.5	668
0.7	2412	0.7	1271	0.7	782	0.7	640
0.9	2383	0.9	1261	0.9	802	0.9	612

M4 Blockage	Sum of Square of error	M4 Starvation	Sum of Square of error	M5 Starvation	Sum of Square of error
0.1	326	0.1	1028	0.1	843
0.3	194	0.3	951	0.3	811
0.5	192	0.5	894	0.5	808
0.7	190	0.7	850	0.7	820
0.9	189	0.9	815	0.9	824

Based on 60 replications of simulation, the actual time length of different operation states for each machine is obtained as shown in Table VII. It can be observed that about 13% unscheduled downtime leads to serious blockage and starvation in the system, which accounts for about 26% of total operation time.

TABLE VII. TIME LENGTH OF EACH OPERATION STATE FOR EACH MACHINE

	Total Time (min)	Unscheduled Downtime (min)	Blockage (min)	Starvation (min)	Time Percentage of Energy Waste
M1	480	24	145	0	31%
M2	480	109	75	0.42	20%
M3	480	65	43	66	26%
M4	480	46	21	94	26%
M5	480	71	0	99	24%
Total	2400	315	280	259	Average: 26%

The result of the baseline model (without energy adjustment) is also examined; the energy consumption for each machine is demonstrated in Table VIII.

TABLE VIII. ENERGY CONSUMPTION FOR EACH MACHINE IN BASELINE MODEL (WITHOUT POWER ADJUSTMENT)

	Electricity Consumption (KWh)	BL/ST Time (min)	Waste (KWh)	Energy waste percentage
M1	166.56	145	47	28.5%
M2	93.80	75	18	18.9%
M3	142.74	109	36	24.7%
M4	121.19	115	31	25.6%
M5	93.23	99	21	22.6%
Total	617.55	539	153	Average: 24.7%

The comparison of energy consumption and throughput between baseline model and the proposed method is illustrated in Table IX. It can be observed that the energy consumption is significantly reduced and the throughput is statistically not affected in the proposed model compared with the baseline model.

TABLE IX. COMPARISON OF ENERGY CONSUMPTION & THROUGHPUT BETWEEN ENERGY STATE ADJUSTMENT MODEL AND BASELINE MODEL

		Energy Consumption with Power Adjustment	Energy Consumption without Power Adjustment	Difference
Electricity Consumed (kWh)	Mean	561.82	617.55	Energy Consumption Reduction
	95% Confidence Interval	(551.32, 572.32)	(609.39, 625.70)	9.02%
Throughput (Unit)	Mean	587.34	589.75	Mean Throughput Difference
	95% Confidence Interval	(561.38, 613.30)	(563.25,616.25)	0.4%
Energy Consumed per Product (kWh)		0.96	1.05	8.57%

2.4. Conclusions

In this chapter, an analytical model for energy efficiency management for typical manufacturing systems with multiple machines and buffers is established. Markov decision process (MDP) is used to model the complex interaction between energy control actions and system state evolutions in decision-making. An approximate solution technique is developed to find the near optimal solution on a real-time basis. A numerical case study based on a section of an automotive assembly line is used to verify the effectiveness of the proposed approach. Compared to the baseline model, the results illustrate that the energy consumption can be significantly reduced while the system throughput is well maintained.

CHAPTER 3 ELECTRICITY DEMAND RESPONSE FOR SUSTAINABLE MANUFACTURING SYSTEMS

The Section 3.2 of this chapter was previously published as "Sun, Z., and Li, L. (2013) Potential capability estimation for real time electricity demand response of sustainable manufacturing systems using Markov Decision Process, Journal of Cleaner Production, 65: 184-193". The Section 3.3 of this chapter was previously published as "Sun, Z., and Li, L., Fernandez, M., and Wang, J. (2014) Inventory control for peak electricity demand reduction of manufacturing systems considering the tradeoff between production loss and energy savings, Journal of Cleaner Production, 82: 84-93", and "Fernandez, M., Li, L., and Sun, Z., (2013) "Just-for-Peak" buffer inventory for peak electricity demand reduction of manufacturing systems, International Journal of Production Economics, 146(1): 178-184".

3.1. Introduction

Besides the energy efficiency management, electricity demand response is another important method for customer-side electric energy management. Generally, existing demand response programs can be categorized into two types as shown in Figure 6, event-driven program and price-driven program (Goldman et al., 2010). In event-driven program, the customers need to reduce their power consumption in response to the utility requests that are triggered by some specific events, e.g., extreme local weather, regional transmission congestion, and generation equipment failures. In price-driven program, for example, "Time of Use (TOU), Critical Peak Pricing (CPP), and Real Time Pricing (RTP)" (Goldman et al., 2010), the electricity rates vary over time to encourage customers to change their regular patterns of electricity consumption. (Goldman et al., 2010).

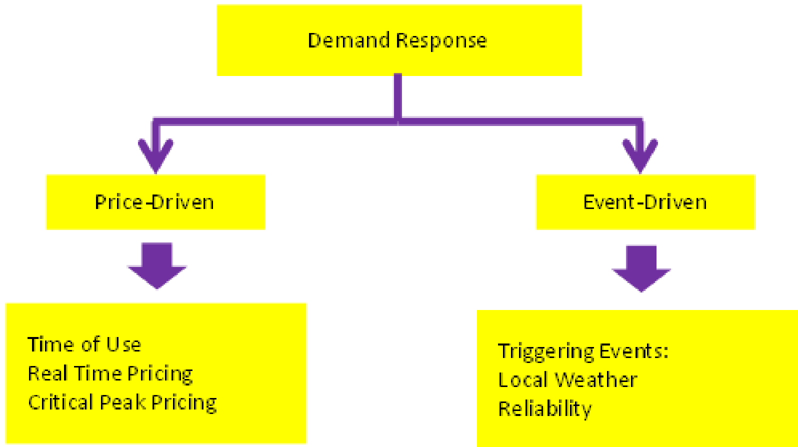

Figure 6. Two types of demand response programs

In this chapter, the implementation of electricity demand response for typical manufacturing systems with multiple machines and buffers is investigated. The methods for both event-driven program and price-driven program are introduced. For the event-driven program, we focus on the real time decision-making model using Markov decision process. Approximate dynamic programming is used to solve the problem on a short-term basis. For the price-driven program, we propose a novel “Just-for-peak” buffer inventory control method to reduce the energy consumption and power demand during peak periods. The optimal energy control actions and corresponding building policies for “Just-for-Peak” buffer inventory are obtained by minimizing the overall cost including the holding cost of the “Just-for-Peak” buffer inventory, the electricity bill cost, and the penalty cost due to potential production loss.

The rest of this chapter is organized as follows. Section 3.2 models the method for event-driven program. Section 3.3 introduces method for price-driven program. Finally, the conclusions of this chapter are drawn in Section 3.4.

The following notations are used in this chapter.

Boldface:

$\mathbf{A}_t$	demand response actions adopted for the whole system at decision epoch t
$\mathbf{S}_t$	system state at decision epoch t

Upper Case:

B_i	regular buffer location i in the manufacturing system, i=1,…, I-1
B_i^t	the content of buffer i at decision epoch t， $i = 1, ..., I - 1$
C_D	on-peak demand charge rate ($/kW)
C_P	on-peak energy consumption charge rate ($/kWh)
C_R	off-peak energy consumption charge rate ($/kWh)
E_i	the total energy cost per unit time of machine M_i during a production horizon
F_i	full operation energy state of machine i
H_{q_i}	a certain energy hibernation state of machine i
I_{H_t}	the set of machines that H-action is adopted at decision epoch t

$\mathrm{I}_{K_t}^{BS\text{-}H}$	the set of blockage/starvation machines in hibernation energy state and *K*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{BS-R}$	the set of blockage/starvation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{OP-H}$	the set of operation machines in hibernation energy state and *K*-action is adopted at decision epoch *t*
$\mathrm{I}_{K_t}^{OP-R}$	the set of operation machines in ready for operation energy state and *K*-action is adopted at decision epoch *t*
I_{W_t}	the set of machines that *W*-action is adopted at decision epoch *t*
J_i	"just-for-peak" buffer location *i* in the manufacturing system, $i = 1, ..., I-1$
$J_{i\max}$	the capacity of J_i
J_i^C	the maximum capable buffer inventory that can be accumulated in J_i during off-peak periods without influencing system throughput
J_i^R	the exact buffer level built in "Just-for-Peak" buffer location J_i for the purpose of operation resumption of downstream machine M_{i+1}

J_i^S	the accumulation level for "Just-for-Peak" buffer inventory built in J_i for each possible combination of the electricity demand response decision
J_i^T	the target unit of "Just-for-Peak" buffer inventory accumulated in J_i that can exactly ensure the production of the corresponding downstream machine M_{i+1} not to be influenced during the whole peak period when the upstream machine M_i is turned off
L_i^1	the average inventory level of the "just-for-peak" buffer contents accumulated in J_i with purpose in perspective 1) throughout the production horizon
L_i^2	the average inventory level of the "just-for-peak" buffer contents accumulated in J_i with purpose in perspective 2) throughout the production horizon
M_i	machine *i* in the manufacturing system, $i = 1, ..., I$
$MTBF_i$	the mean time between failures of machine M_i
$MTTR_i$	the mean time to repair of machine M_i
N_i	the capacity of buffer *i*

P_i^f	power of machine i in full operation state
P_i^q	power of machine i in a certain H_{q_i} state
P_i^{qr}	average transition power of machine i from H_{q_i} state to ready for operation state, $q_i = 1, \ldots, h_i$
P_i^r	power of machine i in ready for operation state
P_i^{rq}	average transition power of machine i from ready for operation state to H_{q_i} state, $q_i = 1, \ldots, h_i$
P_i^t	power level of machine i at decision epoch t
P_{saving}	the power reduction requirement during the peak periods
PEL_i	cost of production loss of machine M_i due to the adoption of "energy-oriented" policy
R_i	ready for operation energy state of machine i
T	the time duration of off peak periods
T_i^{qr}	transition time of machine i from H_{q_i} state to ready for operation state, $q_i = 1, \ldots, h_i$

T_i^{rq} transition time of machine i from ready for operation state to H_{q_i} state, $q_i = 1, ..., h_i$

T_{C_i} the duration when the accumulated "Just-for-Peak" buffer inventory in location J_i is consumed in peak periods

T_D the set of decision epochs between the time that demand response event begins and ends

T_E the last decision epoch in the event-driven demand response program

T_{H_i} the duration when the accumulated "Just-for-Peak" buffer inventory in location J_i is hold in peak periods

T_P the set of decision epochs between the time that the notification of demand response event arrives and demand response event begins

TC system cycle time

U_i the average holding cost per unit time for J_i considering the both perspectives altogether

U_i^1 the average holding cost per unit time for J_i during a production horizon considering the accumulation purpose from perspective 1)

U_i^2 the average holding cost per unit time for J_i during a production horizon considering the accumulation purpose from perspective 2)

Lower Case:

a_i the maximum capable accumulation rate (unites per hour) of the "Just-for-Peak" buffer inventory in location J_i without influencing system throughput during off-peak periods

a_i' the desired accumulation rate that can exactly build up the "Just-for-Peak" buffer inventory in location J_i to ensure the production of machine M_{i+1} during the period from the resumption of the operation to the end of the peak periods

c_i the consumption rate (unites per hour) of the buffer inventory accumulated in J_i during peak periods when electricity demand response is implemented

g_i the cost per unit production loss per unit time ($/production loss per unit time)

h_i the number of energy hibernation states of machine i

i index of the machines in the system, $i = 1, 2, \ldots, I$

k_i the binary variable to denote the initial electricity demand response decisions for machine M_i

q_i	energy hibernation state index of machine i, $q_i = 1, 2, ..., h_i$
r_i	the availability of machine M_i
t_p	the time duration of peak periods
t_{TP}	the last decision epoch in the set of T_P
t_{TD}	the first decision epoch in the set of T_D
u_i	the holding cost per unit held per unit time for the "Just-for-Peak" buffer inventory stored in J_i
ut_i	utilization ratio of buffer i

Functions:

$TC(k_i, V(k_i))$	the total cost per unit time throughout the production horizon
$V(k_i)$	the description of two follow-up policies
$W(i)$	the description of the relationship between J_i^C and J_i^T

3.2. Method for Event-driven Demand Response Program

3.2.1. Introduction and Assumptions

In this section, we focus on the research on the event-driven demand response program for typical manufacturing systems with multiple machines and buffers. An analytical model is established to identify the optimal energy control actions and estimate the potential capacity of power demand reduction of typical manufacturing system during the period of demand response event without compromising production throughput of the manufacturing system. Before we delve into the detail model derivation, we illustrate the assumptions that will be used in this section as follows.

1) The duration of the demand response event in this model is relatively short, e.g., 10-20 min. (the typical length of ancillary service (Goldman et al., 2010)), and thus the power demand during the demand response event is calculated by dividing the total electricity usage by the time length of the demand response event;
2) The cycle times of all the machines in the manufacturing system are the same;
3) The machine failure is time-dependent;
4) The time length of the period from the arrival of the notification of the demand response event to the ending of the demand response event equals to the product of a positive integer and system cycle time;
5) The time horizon is slotted with the durations equal to the system cycle time;
6) The decision epoch is at the beginning or ending of each cycle;
7) The transitions of machine operation state and buffer state are assumed to occur at the beginning or ending of each cycle;
8) For machine energy state, besides the three conventional energy states, i.e., full operation, ready for operation, and turned-off (Li and Kara, 2011), we consider h_i different energy hibernation states with partial power consumption of “ready for operation” state;
9) No production activities can be implemented when machine is in hibernation energy mode;

10) No additional power control actions can be adopted when machine is in the power state transition process;
11) The first machine is never starved and the last machine is never blocked.

3.2.2. Proposed Method

Markov decision process (MDP) is used to establish the model of the implementation of event-driven demand response program for typical manufacturing system. The definitions of system state, control action, state transition, and objective function are similar to the ones we define in the model of energy efficiency management in Chapter 2. It considers the opportunities for all the machines in the system rather than (idle) state-based opportunity in energy efficiency model. Therefore, the energy control actions for this model as shown in Table X are different from the contents in Table I. It can be seen that except the breakdown machine where the energy control action is determined (see the last row of Table X), all other operation-energy state pairs may have different action options from which the optimal action need be identified.

TABLE X. ENERGY CONTROL ACTIONS FOR DIFFERENT SCENARIOS IN ELECTRICITY DEMAND RESPONSE

Operation State	Energy State	Power Control Action	Target Power Level
OP_i	R_i	K-action	R_i
OP_i	R_i	H-action	H_{q_i} or O_i
OP_i	H_{q_i} or O_i	K-action	H_{q_i} or O_i
OP_i	H_{q_i} or O_i	W-action	R_i
BL_i / ST_i	R_i	K-action	R_i
BL_i / ST_i	R_i	H-action	H_{q_i} or O_i
BL_i / ST_i	H_{q_i} or O_i	K-action	H_{q_i} or O_i
BL_i / ST_i	H_{q_i} or O_i	W-action	R_i
DN_i	O_i	K-action	O_i

The notice of reduction is issued a short period (e.g., 15-30 minutes) before the occurrence of the demand response event. The customers need to make response about the reduction capability of power demand on a real-time basis. The energy control actions can be considered for all the machines in the system and the decisions will be a set of actions throughout the whole demand response duration. The objective function can be formulated as a minimization problem about the incurred electricity consumption from decision epoch t to the ending of the demand response event as shown in (3.1).

$$\min_{\mathbf{A}_t}(C(\mathbf{S}_t,\mathbf{A}_t)+\sum_{\mathbf{S}'\in\mathbf{S}}\Pr(\mathbf{S}_{t+1}=\mathbf{S}'\,|\,\mathbf{S}_t,\mathbf{A}_t)\,V_{t+1}(\mathbf{S}')) \tag{3.1}$$

where

$$\begin{aligned}C(\mathbf{S}_t,\mathbf{A}_t)=&\sum_{i\in\mathrm{I}_{H_t}}(\min(T_i^{rq},TC)\cdot P_i^{rq}+\max(TC-T_i^{rq},0)\cdot P_i^{q})\\&+\sum_{i\in\mathrm{I}_{W_t}}(\min(T_i^{qr},TC)\cdot P_i^{qr}+\max(TC-T_i^{qr},0)\cdot P_i^{r})\\&+\sum_{i\in\mathrm{I}_{K_t}^{OP-R}}P_i^f\cdot TC+\sum_{i\in\mathrm{I}_{K_t}^{OP-H}}P_i^q\cdot TC+\sum_{i\in\mathrm{I}_{K_t}^{BS-R}}P_i^r\cdot TC+\sum_{i\in\mathrm{I}_{K_t}^{BS-H}}P_i^q\cdot TC\end{aligned} \tag{3.2}$$

where $\mathrm{I}_{K_t}^{OP\text{-}R}$ is the set of operation machines in ready for operation energy state and K-action is adopted at decision epoch t. $\mathrm{I}_{K_t}^{OP\text{-}H}$ is the set of operation machines in hibernation energy state and K-action is adopted at decision epoch t. $\mathrm{I}_{K_t}^{BS\text{-}R}$ is the set of blockage/starvation machines in ready for operation energy state and K-action is adopted at decision epoch t. $\mathrm{I}_{K_t}^{BS\text{-}H}$ is the set of blockage/starvation machines in hibernation energy state and K-action is adopted at decision epoch t. I_{H_t} is the set of machines that H-action is adopted at decision epoch t. I_{W_t} is the set of machines that W-action is adopted at decision epoch t.

To ensure that the production is not influenced due to the demand response actions, the system throughput constraint need be considered. When the production of a certain machine is strategically stopped for the purpose of demand reduction, the downstream buffer contents will decrease. One previous study (Chang et al., 2007) showed that full utilization of buffer contents for maintenance purposes significantly influences the system throughput. To overcome this challenge, we refer to the results of (Sun and Li, 2013) and consider a partial buffer utilization policy as shown in (3.3) and (3.4) to ensure the throughput invariant.

$$A_i^t \neq H_i \text{ if } B_i^{t+1} < (1\text{-}ut_i) \cdot N_i, \text{ when } S_{E_i}^t = R_i \text{ and } S_{O_i}^t = OP_i \tag{3.3}$$

$$A_i^t = W_i \text{ if } B_i^{t+1} < (1\text{-}ut_i) \cdot N_i, \text{ when } S_{E_i}^t = H_{q_i} / O_i \text{ and } S_{O_i}^t = OP_i \tag{3.4}$$

where ut_i is the utilization ratio of buffer i. Formula (3.3) implies that the H-action that makes the downstream buffer level be lower than the predetermined value cannot be adopted when the operation state of machine i is OP_i and energy state is R_i. Formula (3.4) shows that a W-action has to be adopted when the downstream buffer level is expected to be lower than the predetermined value when the hibernation machine is in operation state.

In addition, the throughput bottleneck machine is not considered for implementing demand response since it may potentially influence the production throughput of the entire system with a strongest manner. It is described by (3.5).

$$A_{bn}^t = K_{bn} \tag{3.5}$$

where the subscript bn denotes the bottleneck machine of the system.

Finally, the last machine of the system cannot be stopped for demand response purpose if its upstream buffer is not empty; otherwise, the system throughput is influenced during the demand response event. It is formulated as shown in (3.6).

$$A_I^t = K_I, \, if \;\; B_{I-1}^t > 0 \tag{3.6}$$

To solve the aforementioned MDP problem to identify the optimal energy control actions for the entire manufacturing system during the demand response event, an approximate dynamic programming is proposed. Similar to the situation as we discuss in Chapter 2, the typical dynamic programming that begins at the final decision epoch and steps backward by looping over all the possible states and available actions until the optimal action for current epoch is obtained (Bellman, 1957) cannot solve the problem in a short period. In addition, we also consider the difference regarding the allowed computational time between this model and the model in Chapter 2. For the model in Chapter 2, the optimization results need be obtained instantaneously, while for the model in this chapter, we have a few minutes (between the notification from utility and the beginning of the demand response event) to implement the calculation. Therefore, we can employ the typical forward method that proceeds by estimating the approximation of value functions iteratively to obtain an approximate solution (Powell, 2011). A set of sample paths is randomly generated to simulate the evolution of system state. The algorithm runs from first decision epoch to the final one along with each sample path iteratively. The value function is updated accordingly with each step and used for the next iteration.

The benefit of the aforementioned forward algorithm is that it can get around the difficulty of looping over all states and the challenge of expectation calculation. The detail procedure of the solution technique referring to literature of Powell (2011) for decision-making is listed as follows.

1. Initialization
   a) Index decision epochs t from 0 to T_E
   b) Randomly generate G different sample paths ω^n ($n = 1, ..., G$) to describe G different possible paths of up/down state evolution for all the machines in the system from the

given state when notification arrives to the last decision epoch. Let Ω be the set of all sample paths, $\widehat{\Omega}_t$ $(t=1,2,...,T_E)$ be the subset of Ω that includes G evolution realizations between the decision epoch t-1 and t, $\widehat{\Omega}_{t,z}$ be the non-empty subset of $\widehat{\Omega}_t$ that includes z elements ($z \le G$), and ω_t^n $(t=1,2,...,T_E)$ be the specific evolution realization of sample path n between the decision epoch t-1 and t.

c) Set n=1

d) Initialize value function $\bar{V}_t^0(\mathbf{S}_t)$ for all $\mathbf{S}_t$ with zero, $t \in T_D$

2. Choose the sample path ω^n

3. For $t=0$ to t_{TP}, or $t \in T_P$, follow the sample path chosen in step 2 to obtain the system state $\mathbf{S}_t^n$ ($t=t_{TD}$). (In other word, we keep taking K-actions for all the t's belonging to T_P.)

4. For $t=t_{TD}$ to T_E, or $t \in T_D$

a) Choose a random sample of outcomes $\widehat{\Omega}_{t+1,z} \subset \Omega$ representing possible realizations of the machine up/down state evolution between t and t+1

b) Solve the equation (3.7)

$$\mathbf{A}_t^n = \arg\min_{\mathbf{A}_t \in \mathbf{A}_t^n}[C_t(\mathbf{S}_t^n, \mathbf{A}_t) + \sum_{\omega_{t+1} \in \widehat{\Omega}_{t+1,z}} p_{t+1}(\omega_{t+1}) \bar{V}_{t+1}^{n-1}(\mathbf{S}_{t+1})] \quad (3.7)$$

where $p_{t+1}(\omega_{t+1})$ is the probability that the evolution realization between decision epoch t and t+1 is ω_{t+1}, which is approximately obtained as $1/z$, and $\mathbf{S}_{t+1} = S^T(\mathbf{S}_t^n, \mathbf{A}_t, \omega_{t+1})$, where $S^T(\cdot)$ denote the system state transition function

c) Update value function $\bar{V}_t^{n\text{-}1}(\mathbf{S}_t)$ for next sample path by (3.8)

$$\bar{V}_t^n(\mathbf{S}_t) = \begin{cases} \hat{v}_t^n & \mathbf{S}_t = \mathbf{S}_t^n \\ \bar{V}_t^{n-1}(\mathbf{S}_t) & \text{otherwise} \end{cases} \tag{3.8}$$

where

$$\hat{v}_t^n = \min_{\mathbf{A}_t \in \mathbf{A}_t^n} [C_t(\mathbf{S}_t^n, \mathbf{A}_t) + \sum_{\omega_{t+1} \in \hat{\Omega}_{t+1,z}} p_{t+1}(\omega_{t+1}) \bar{V}_{t+1}^{n-1}(\mathbf{S}_{t+1})] \tag{3.9}$$

d) Compute

$$\mathbf{S}_{t+1}^n = S^T(\mathbf{S}_t^n, \mathbf{A}_t^n, \omega_{t+1}^n) \tag{3.10}$$

5. n=n+1. If $n \le G$, go to step 2, otherwise calculate the reduction potential by (3.11)

$$RED_P = P_{REG} - \frac{\hat{v}_t^{n-1}}{T_{DR}} \tag{3.11}$$

where RED_P is the power reduction potential, P_{REG} is the regular power consumption level during the period of demand response event, and T_{DR} is the duration of demand response event.

3.2.3 Case Study

In this section, we use a five-machine and four-buffer manufacturing system as shown in Figure 7 as the numerical case to illustrate the effectiveness of the proposed method. The parameters of the machines in the system are listed in Table XI. The parameters of each buffer including buffer capacity and initial contents are listed in Table XII. Machine 2 is identified as the throughput bottleneck machine of the system using the technique proposed by (Li et al., 2009). The assumed different power modes are demonstrated in Table XIII.

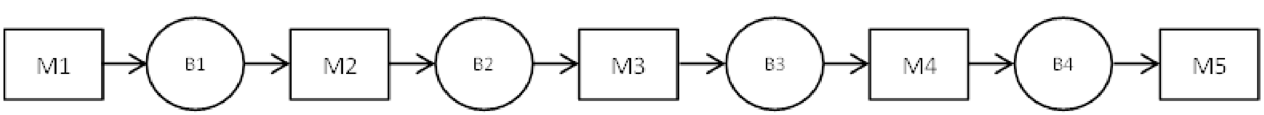

Figure 7. A five-machine and four-buffer serial line

TABLE XI. BASIC SETTINGS OF EACH MACHINE

	MTBF (min)	Scale Parameter g_i	Shape Parameter k_i	MTTR (min)	Exponential Parameter λ_i	Power of Ready for Operation State (kW)	Warm-up Time (min)	Cycle Time (min)
M1	100	111.39	1.5766	4.95	0.2020	21	1.4	0.5
M2	45.6	51.1	1.6532	11.7	0.0855	14	0.9	0.5
M3	98.8	110.9	1.7174	15.97	0.0626	20	1.35	0.5
M4	217.5	239.1	1.421	27.28	0.0367	16	1.05	0.5
M5	109.4	122.1	1.591	18.37	0.0544	13	0.85	0.5

TABLE XII. BASIC SETTINGS OF EACH BUFFER

	Buffer1	Buffer2	Buffer3	Buffer4
Capacity	70	40	30	42
Initial Contents (number of parts)	50	8	22	28

TABLE XIII. DIFFERENT POWER STATES

Energy Consumption State	Operation	Ready for Operation	Shallow Sleep	Median Sleep	Deep Sleep	Turned-off
Power Level	105%	100%	50%	30%	10%	0%

Assume a demand response event that is notified at the 45th minute of an 8-h shift, 15 min in advance of its beginning. The duration of the event is 15 min. The reduction capability of system power demand needs to be identified and replied to the utility.

In the case study, the simulation model is established by ProModel® to simulate the manufacturing system as described by Figure 7 with parameter settings shown from Table XI to Table XIII. ProModel® is a simulation software package for discrete systems by ProModel, Inc

(ProModel, 2014). It can be applied for “evaluating, planning or designing manufacturing, warehousing, logistics and other operational and strategic situations” (ProModel, 2014). The algorithm proposed in Section 3.2.2 is called when the demand response event occurs. The number of random sample paths *G* is set to be 30 and *z* is set to be 10. The algorithm is executed by a desktop with Intel(R) Core TM(2) Quad 2.83GHZ processor, and 4GB memory. The computation time is about 600 seconds. The optimal demand control actions during the periods of demand response event can thus be identified and used as the feedback to the simulation model.

After running 30 replications of an 8-h shift for both baseline model (demand response is not executed) and demand response model with buffer utilization ratio of 0.5, the system throughput and power consumption during the demand response event are shown in Table XIV.

TABLE XIV. COMPARISON OF POWER CONSUMPTION & THROUGHPUT BETWEEN BASELINE MODEL AND DEMAND RESPONSE MODEL

		Baseline Model	Demand Response Model	Difference
Power Demand (kW)	Mean	80.21	63.11	Power Consumption Reduction(kW)/ Reduction Percentage
	95% Confidence Interval	(77.43, 82.99)	(57.65, 68.57)	17.1/21.32%
Throughput (Unit)	Mean	623.13	620.23	Mean Throughput Difference
	95% Confidence Interval	(590.13, 656.13)	(590.87,649.59)	0.47%

It can be observed that the power demand during the period of the demand response event can be cut by about 21% and system throughput of the whole shift is statistically unchanged.

Concern about the buffer consumption by implementing demand response, we also compare the buffer level at the end of the 8-h shift between the baseline model and the demand response model as shown in Table XV. The buffer at the end of the shift when demand response is executed is very close to the scenario where no demand response is implemented; therefore, it can be inferred that the impact on the system throughput of the next shift can be ignored.

TABLE XV. COMPARISON OF BUFFER CONTENTS (NUMBER OF PARTS) AT THE END OF THE 8-HOUR SHIFT

		Buffer 1	Buffer 2	Buffer 3	Buffer 4
Baseline Model	Mean	67.3	9.4	5.5	14.7
	95% Confidence Interval	(62.9, 71.6)	(6.3, 12.5)	(2.7, 8.3)	(8.3, 21.2)
Demand Response Model	Mean	66.5	10.2	5.3	13.9
	95% Confidence Interval	(63.8, 69.2)	(7.1, 13.3)	(3.2, 7.4)	(6.5, 21.3)

3.2.4 Conclusion

In this section, we further developed the MDP model established in previous chapter for the application of event-driven demand response program. The optimal energy control actions and the potential capacity of power demand reduction based on online information of the manufacturing system during the period of demand response event without compromising system production are obtained. The energy reduction opportunity for all the machines in the system is considered. An approximate dynamic programming method utilizing randomly generated sample paths is used to find the near-optimal solution for the problem.

3.3. Method for Price-driven Demand Response Program

3.3.1 Introduction

Besides the event-driven demand response program, we also study the method to implement price-driven program for manufacturers. In price-driven program, the electricity price is generally different for different periods. The charges of both electricity consumption ($/kWh) and power demand ($/kWh) are included. The charge rate during peak periods is much higher than the one during off-peak periods. Thus, an effective way to handle this kind of program is to reduce the electricity consumption and power demand during peak periods and so the electricity bill cost can be reduced. Following this idea, we propose a buffer inventory control method to help manufacturers reduce the electricity consumption during peak periods in price-driven demand response program. The manufacturing system we consider in this section is shown in Figure 8 where additional *I*-1 "Just-for-Peak" buffer locations J_i paired with regular buffer B_i from typical *I*-machine-*I*-1-buffer manufacturing system are included.

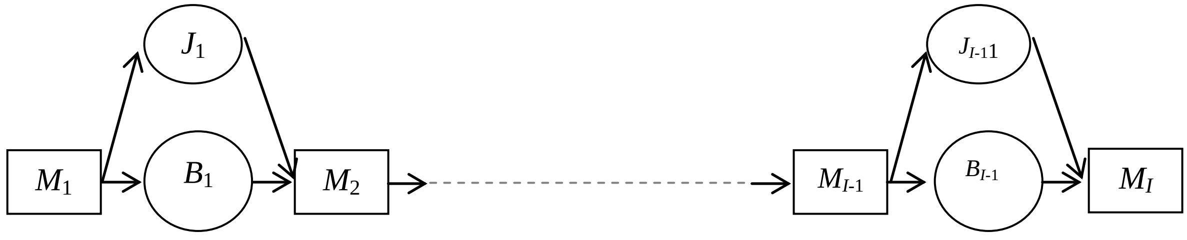

Figure 8. A manufacturing system with *I*-1 additional "Just-for-Peak" buffer locations

The "Just-for-Peak" buffer inventory is built up during off-peak periods in J_i and thus the corresponding upstream machines can be turned off during peak periods by utilizing the accumulated "Just-for-Peak" buffer inventory to maintain the production of the corresponding downstream machines. The optimal energy control actions and corresponding building policies for "Just-for-Peak" buffer inventory are obtained by minimizing the overall cost including the holding cost of the "Just-for-Peak" buffer inventory, the electricity bill cost, and the penalty cost due to potential production loss.

3.3.2 Proposed Method

We assume that the cycle times t_c of all the machines in the manufacturing system as shown in Figure 8 are the same. The production horizon includes a scheduled off-peak period and a follow-up scheduled peak period with both known durations of T and t_p, respectively. During the off-peak periods, the parts completed by machine M_i can be spared and stored in corresponding J_i to accumulate "Just-for-Peak" buffer inventory as a source for the implementation of demand response during peak periods. Hence, the corresponding upstream machines M_i's can be turned off during the peak periods by utilizing the "Just-for-Peak" buffer inventory to maintain the production of the downstream machine M_{i+1}.

Let a_i be the maximum capable accumulation rate (units per hour) of the "Just-for-Peak" buffer location J_i during off-peak periods, which represents the maximum allowed number of the completed parts by machine M_i that can be stored in J_i per unit time during off-peak periods without influencing the production throughput of the system. It is assumed to be an average value and is obtained by off-line simulation based on the system parameters including historical reliability data, machine cycle time, and buffer capacity. “Trial-and-error” method is used to test different values of a_i until the one without influencing the production is identified. Let J_i^C be the maximum capable buffer inventory that can be accumulated in J_i during off-peak periods. It can be formulated by (3.12).

$$J_i^C = a_i \cdot T \tag{3.12}$$

Let c_i be the consumption rate (units per hour) of the buffer inventory accumulated in J_i during peak periods when demand response is implemented. It can be determined by the system cycle time. We do not consider the random failures during peak periods in this model, and thus c_i is actually a conservative estimation (the cycle time will be longer when random failures are considered). Let J_i^T be the target unit of “Just-for-Peak” buffer inventory accumulated in J_i that can exactly ensure the production of the corresponding downstream machine M_{i+1} not to be influenced during the whole peak period when the upstream machine M_i is turned off. It can be obtained by (3.13).

$$J_i^T = c_i \cdot t_p \tag{3.13}$$

When J_i^C, the maximum capable buffer inventory that can be accumulated in J_i, is less than the target number J_i^T that can ensure the production of the downstream machine if it is determined to be kept on during the whole peak periods, a follow-up decision is needed when the built-up “Just-for-Peak” buffer inventory runs out before the end of peak periods. We may either resume the operation of the shutdown machine to maintain the production or keep the shutdown machine being off. The potential production loss will be considered and integrated into the objective function of this model along with the holding cost of the built-up “Just-for-Peak” buffer inventory and electricity bill cost for decision-making. In other words, the machines that are determined to be kept on at the beginning of peak periods will keep the states throughout the whole peak periods and no more decisions will be received. In contrast, for the machines that are determined to be turned off at the beginning of peak periods, a second decision regarding either resuming operation or keeping inactive may be received depending on the accumulated level of the "Just-for-Peak" buffer inventory and other factors.

Define function $W(i)$ by (3.14) to describe the relationship between J_i^C and J_i^T.

$$W(i) = \begin{cases} 1, & \text{if } J_i^C < J_i^T \\ 0, & \text{if } J_i^C \geq J_i^T \end{cases} \tag{3.14}$$

Figure 9 illustrates the cycle of the change of the "Just-for-Peak" buffer inventory in one production horizon when $W(i) = 1$.

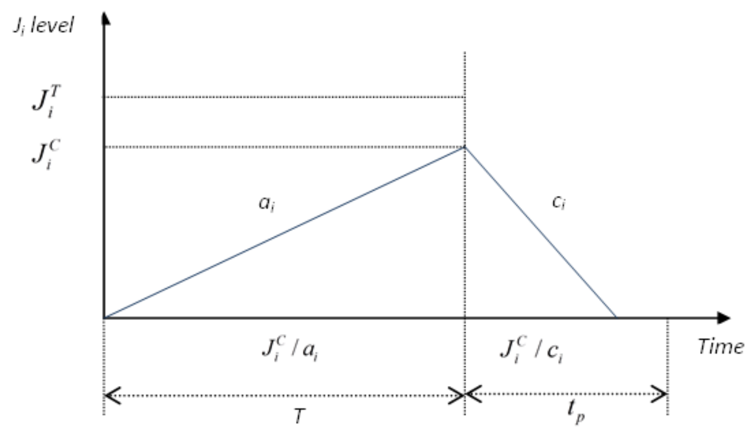

Figure 9. "Just-for-Peak" buffer inventory behaviors during a production horizon when $W(i) = 1$

From Figure 9, it can be seen that the "Just-for-Peak" buffer inventory is accumulated in J_i during off-peak periods and thus the upstream machine M_i can be turned off at the beginning of peak periods. The accumulated "Just-for-Peak" buffer inventory in J_i can maintain the production of the downstream machine M_{i+1} for partial duration of the peak periods and will run out before the end of the peak periods. As is mentioned, we may either resume the operation of the shutdown upstream machine M_i to maintain the production or keep the machine M_i being off. The first option can be thought as a "throughput-oriented" policy since the throughput maintaining is thought to be prior to energy saving. The second option can be thought as an "energy-oriented" policy since it prefers energy saving instead of throughput maintaining.

Unlike the method in Fernandez et al. (2013) where only the actions "shutdown for entire peak period" are considered under the constraint of system throughput (i.e., J_i^C has to be no less than J_i^T), the proposed method relaxes the throughput constraint and allows some machines to be turned off for partial duration of the peak periods. The follow-up decisions either "throughput-oriented" or "energy-oriented" are needed to be further identified. Therefore, we can see that more energy management actions will be available compared with the model introduced by Fernandez et al. (2013). At the same time, the problem also becomes more complex. Both initial decisions made at the beginning of the peak periods and the follow-up decisions with respect to two different policies need to be determined. The tradeoff between the potential production loss, the energy cost, and the additional holding cost of the buffer to ensure the production resumption, need to be considered carefully.

Let function $V(k_i)$ describe these two follow-up policies as shown in (3.15).

$$V(k_i) = \begin{cases} 1, \text{ if } k_i = 0, k_{i+1} = 1, W(i) = 1, \text{machine } M_i \text{ resumes operation when } J_i \text{ runs out} \\ 0, \text{ if } k_i = 0, k_{i+1} = 1, W(i) = 1, \text{machine } M_i \text{ does not resume operation when } J_i \text{ runs out} \end{cases} \tag{3.15}$$

where k_i is a set of binary variables to denote the initial energy management actions for machine M_i at the beginning of peak period, which can be defined by (3.16).

$$k_i = \begin{cases} 0, & \text{turn off machine } M_i \text{ at the beginning of peak period} \\ 1, & \text{keep machine } M_i \text{ on at the beginning of peak period} \end{cases} \tag{3.16}$$

For the "throughput-oriented" policy that will resume the operation of machine M_i, we assume that it can be implemented under the condition that either additional "Just-for-Peak" buffer inventory is built in J_{i-1} or machine M_{i-1} is determined to keep production during the whole peak periods and so the resumption of the operation of machine M_i can be ensured. Therefore, the general purpose of "Just-for-Peak" buffer inventory that provides parts to maintain the production of downstream machine when the upstream machine is turned off can be specifically described from two perspectives: 1) turning off the upstream machine M_i and maintaining the production of downstream machine M_{i+1} at the beginning of peak periods; or 2) resuming the operation of the downstream machine M_{i+1} when the downstream "Just-for-Peak" buffer inventory J_{i+1} runs out and the upstream machine M_i is determined to be turned off for the whole peak periods (see Figure 10).

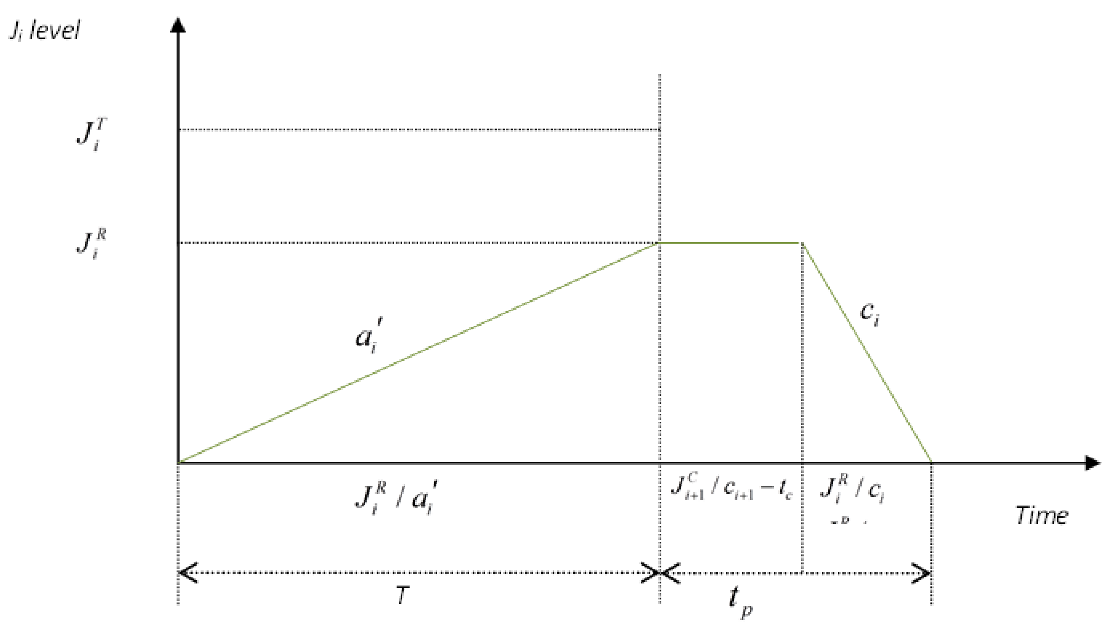

Figure 10. “Just-for-Peak” buffer inventory behaviors during a production horizon for resuming the operation of downstream machine

In Figure 10, we define J_i^R be the exact buffer level built in “Just-for-Peak” buffer location J_i for the purpose of operation resumption of downstream machine M_{i+1}. It can be formulated by (3.17).

$$J_i^R = a_i' \cdot T \tag{3.17}$$

where a_i' is the desired accumulation rate that can exactly build up the “Just-for-Peak” buffer inventory in location J_i to ensure the production of machine M_{i+1} during the period between the resumption of the operation and the end of the peak periods. It can be formulated by (3.18).

$$a'_i = \frac{c_i[t_p - \frac{J_{i+1}^C}{c_{i+1}}] + 1}{T}, \quad (J_{i+1}^C < J_{i+1}^T) \tag{3.18}$$

Equation (3.18) implies that the operation resumption of machine M_{i+1} needs to be scheduled one cycle earlier than the time when the “Just-for-Peak” buffer contents in J_{i+1} run out to ensure the production of M_{i+2} can be maintained seamlessly. In other words, one more part is needed to be prepared in the J_i .

Note that for simplicity, we assume the building of the “Just-for-Peak” buffer inventory in J_i for the purpose of operation resumption of downstream machine M_{i+1} can only be implemented when $J_i^R \le J_i^C$ is satisfied.

Next, we discuss the holding cost of the “Just-for-Peak” buffer inventory in terms of the two perspectives aforementioned. On the one hand, for the “Just-for-Peak” buffer inventory that is accumulated for turning off the upstream machine M_i and maintaining the production of downstream machine M_{i+1} at the beginning of the peak periods as described from perspective 1), the average inventory level for J_i can be obtained by (3.19).

$$L_i^1 = \frac{\frac{\min(J_i^C, J_i^T)\cdot T}{2} + \frac{\min(J_i^C, J_i^T)\cdot T_{C_i}}{2}}{T+t_p} = \frac{\frac{(\min(J_i^C, J_i^T))^2}{2\cdot a_i} + \frac{(\min(J_i^C, J_i^T))^2}{2\cdot c_i}}{T+t_p} \tag{3.19}$$

where T_{C_i} is corresponding consumption time of the "Just-for-Peak" buffer inventory accumulated in location J_i, which may be less than t_p. Let U_i^1 be the corresponding average holding cost per unit time for J_i during a production horizon considering the accumulation purpose from perspective 1). It can be obtained by (3.20).

$$U_i^1 = u_i\left[\frac{\frac{(\min(J_i^C, J_i^T))^2}{2\cdot a_i} + \frac{(\min(J_i^C, J_i^T))^2}{2\cdot c_i}}{T+t_p}\right] \tag{3.20}$$

where u_i is the holding cost per unit held per unit time for the "Just-for-Peak" buffer inventory stored in J_i.

On the other hand, for the "Just-for-Peak" buffer inventory that is accumulated in J_i to ensure the resumption of the operation of machine M_{i+1} as described from perspective 2), the average inventory level associated with the "Just-for-Peak" buffer inventory J_i can be obtained by (3.21):

$$\begin{aligned} L_i^2 &= \frac{\frac{J_i^R}{2}\cdot T + J_i^R\cdot T_{H_i} + \frac{J_i^R}{2}\cdot T_{C_i}}{T+t_p} = \frac{\frac{J_i^R}{2}\cdot\frac{J_i^R}{a_i'} + J_i^R\cdot(\frac{J_{i+1}^C}{c_{i+1}} - t_c) + \frac{J_i^R}{2}\cdot(\frac{J_i^R}{c_i})}{T+t_p} \\ &= \frac{\frac{(J_i^R)^2}{2a_i'} + J_i^R\cdot(\frac{J_{i+1}^C}{c_{i+1}} - t_c) + \frac{(J_i^R)^2}{2c_i}}{T+t_p}, \qquad (J_{i+1}^C < J_{i+1}^T) \end{aligned} \tag{3.21}$$

where T_{H_i} is the duration when the accumulated “Just-for-Peak” buffer inventory J_i^R is hold. Let U_i^2 be the corresponding average holding cost per unit time during a production horizon considering the accumulation purpose from perspective 2). It can be obtained by (3.22).

$$U_i^2 = u_i\left[\frac{\dfrac{(J_i^R)^2}{2a_i'} + J_i^R \cdot \left(\dfrac{J_{i+1}^C}{c_{i+1}} - t_c\right) + \dfrac{(J_i^R)^2}{2c_i}}{T + t_p}\right] \tag{3.22}$$

Considering the both perspectives altogether, the holding cost per unit time during a production horizon for J_i can be formulated by (3.23):

$$U_i = (1-k_i)\cdot k_{i+1}\cdot U_i^1 + (1-k_i)\cdot(1-k_{i+1})\cdot V(k_{i+1})\cdot U_i^2 \tag{3.23}$$

The energy cost per unit time throughout the whole production horizon for machine M_i can be formulated as the function of k_i, $W(i)$ and $V(k_i)$. It includes the charge of electricity bill during off-peak periods, and both consumption charge and demand charge during peak periods as well. It can be formulated by (3.24).

$$E_i = \frac{\left(P_i^f(T)(r_i)C_R + P_i^f(t_p)C_Pk_i + P_i^f k_i C_D + (1-k_i)k_{i+1}W(i)V(k_i)\left[P_i^f\left(t_p - \dfrac{J_i^C}{c_i} + t_c\right)C_P + [P_i^f\left(t_p - \dfrac{J_i^C}{c_i} + t_c\right)/t_p]C_D\right]\right)}{T + t_p} \tag{3.24}$$

where E_i is the total energy cost per unit time of machine M_i during a production horizon; P_i^f is the rated power of machine M_i; C_P is on-peak energy consumption charge rate (\$/kWh); C_R is off-peak energy consumption charge rate (\$/kWh); C_D is on-peak demand charge rate (\$/kW); and r_i is the availability of machine M_i which is obtained by (3.25).

$$r_i = \frac{MTBF_i}{MTBF_i + MTTR_i} \tag{3.25}$$

where $MTBF_i$ is mean time between failures of machine M_i; and $MTTR_i$ is mean time to repair of machine M_i. Please note that the transition energy between OFF state and ON state of machine and the energy consumption for the accumulation/utilization of the "Just-for-Peak" buffer inventory are assumed to be negligible and thus are not considered. It can be seen that the energy cost incurred by the machines that will resume operations during peak periods is included in the fourth item of the numerator of (3.24).

Finally, we formulate an additional cost term to describe the possible production loss of machine M_i due to the "energy-oriented" policy, i.e., when the "Just-for-Peak" buffer inventory accumulated in J_{i-1} is less than J_{i-1}^T and machine M_{i-1} is not scheduled to resume operation when the "Just-for-Peak" buffer inventory accumulated in J_{i-1} runs out. It can be formulated by (3.26).

$$PEL_i = k_i(1-k_{i-1})W(i\text{-}1)[1\text{-}V(k_{i-1})]\cdot(g_i)\cdot[\frac{c_{i-1}(t_p - \frac{J_{i-1}^C}{c_{i-1}})}{(T+t_p)}] \tag{3.26}$$

where g_i is the cost per unit production loss per unit time ($/production loss per unit time).

By now, we have different combinations of k_i, k_{i+1}, and $V(k_i)$. The different combinations of these variables may define the different demand response decisions and corresponding building policies for "Just-for-Peak" buffer inventory, as we discussed as follows.

1) $k_i = 1$ and $k_{i+1} = 1$

The "Just-for-Peak" buffer inventory does not need to be built in J_i during off-peak period since both adjacent upstream machine M_i and downstream machine M_{i+1} will be kept on during peak period. (The value of $V(k_i)$ and $V(k_{i+1})$ does not need to be discussed since both k_i and k_{i+1} are set to be one.)

2) $k_i = 1$ and $k_{i+1} = 0$

2a) $V(k_i) = 1$: It is not feasible since it contradicts the definition in (3.15) (since $k_i = 1$).

2b) $V(k_i) = 0$: It is not feasible since it contradicts the definition in (3.15) (since $k_i = 1$).

2c) $V(k_{i+1}) = 1$: The "Just-for-Peak" buffer inventory does not need to be built during off-peak period in J_i since the resumption of the operation of machine M_{i+1} can be supported by the operation of machine M_i.

2d) $V(k_{i+1}) = 0$: The "Just-for-Peak" buffer inventory does not need to be built during off-peak period in J_i since the adjacent upstream machine M_i will be kept on and the adjacent downstream machine M_{i+1} will be turned off during peak period.

3) $k_i = 0$ and $k_{i+1} = 0$

3a) $V(k_i) = 1$: It is not feasible since it contradicts the definition in (3.15) ($V(k_i)$ is defined when $k_i = 0$ and $k_{i+1} = 1$).

3b) $V(k_i) = 0$: It is not feasible since it contradicts the definition in (3.15) ($V(k_i)$ is defined when $k_i = 0$ and $k_{i+1} = 1$).

3c) $V(k_{i+1}) = 1$: The "Just-for-Peak" buffer inventory needs to be built during off-peak period in J_i to support the resumption of the operation of machine M_{i+1} since the upstream machine M_i will be turned off during the peak period.

3d) $V(k_{i+1})=0$: The "Just-for-Peak" buffer inventory does not need to be built during off-peak period in J_i since both adjacent upstream machine M_i and downstream machine M_{i+1} will be turned off during peak period.

4) $k_i=0$ and $k_{i+1}=1$

4a) $W(i)=0$, and $V(k_i)=0$: The "Just-for-Peak" buffer inventory needs to be built in J_i during off-peak period since the adjacent upstream machine M_i will be turned off for the whole peak period and the adjacent downstream machine M_{i+1} has to utilize the "Just-for-Peak" buffer inventory to maintain production during peak period. The buffer built during off-peak period will be enough to maintain the production of the downstream machine M_{i+1} during the peak period without influencing the throughput.

4b) $W(i)=1$, and $V(k_i)=0$: the "Just-for-Peak" buffer inventory needs to be built during off-peak period in J_i since the adjacent upstream machine M_i will be turned off for the whole peak period and the adjacent downstream machine M_{i+1} has to utilize the "Just-for-Peak" buffer inventory. The buffer built during off-peak period will not be enough to maintain the production of the downstream machine M_{i+1} during the whole peak period. The corresponding upstream machine M_i will not resume operation when the "Just-for-Peak" buffer inventory runs out. Consequently, the throughput will be affected.

4c) $W(i)=1$, and $V(k_i)=1$: the "Just-for-Peak" buffer inventory needs to be built in J_i during off-peak period since the adjacent upstream machine M_i will be turned off at the beginning of the peak period and the adjacent downstream machine M_{i+1} has to utilize the "Just-for-Peak" buffer inventory. The buffer built during off-peak period will not be enough to maintain the production of the downstream machine M_{i+1} during the whole peak period. The upstream machine M_i will resume operation and thus the throughput can be maintained.

4d) $W(i)=0$, and $V(k_i)=1$: It is not feasible since it contradicts the definition in (3.15) ($W(i)=1$ is the necessary condition for $V(k_i)=1$).

4e) $V(k_{i+1})=1$ or $V(k_{i+1})=0$: It is not feasible since it contradicts the definition in (3.15) (since $k_{i+1}=1$).

Hence, the objective function can be formulated by (3.27).

$$\min TC\ (k_i, V(k_i)) = \min(\sum_{i=1}^{I-1} U_i + \sum_{i=1}^{I} E_i + \sum_{i=1}^{I} PEL_i) \tag{3.27}$$

where $TC(k_i, V(k_i))$ is the total cost per unit time throughout the production horizon.

Let J_i^S be the corresponding accumulation level for "Just-for-Peak" buffer inventory built in J_i for each possible combination of the demand response decision. It can be obtained by (3.28).

$$J_i^S = \begin{cases} \min(J_i^C, J_i^T), \text{if } k_i = 0, k_{i+1} = 1 \\ J_i^R, \text{if } k_i = 0, k_{i+1} = 0, V(k_{i+1}) = 1, J_i^R \le J_i^C \\ 0, \text{otherwise} \end{cases} \tag{3.28}$$

The upper row of the right hand side of (3.28) indicates that the "Just-for-Peak" buffer inventory is built for turning off the upstream machine and keeping production of the downstream machine at the beginning of the peak period (i.e., see the combination 4a), 4b), and 4c)). The mid row of the right hand side of (3.28) indicates that the "Just-for-Peak" buffer inventory is built for resuming the operation of the downstream machine (i.e., see the combination 3c)). The lower row of the right hand side of (3.28) indicates that "Just-for-Peak" buffer inventory does not need to be built.

Several constraints need to be considered as follows.

1) The last machine of the system cannot be turned off; otherwise, the production will be influenced during the peak periods,

$$k_I = 1 \tag{3.29}$$

2) The corresponding accumulation level J_i^S built in "Just-for-Peak" buffer location J_i has to be no more than the capacity of J_i ,

$$J_i^S \leq J_{i\max} \tag{3.30}$$

where the $J_{i\max}$ is capacity of J_i .

3) The power reduction during the peak period has to be greater than or equal to the demand reduction requirement. It can be described by (3.31).

$$\sum_{i=1}^{I-1}\{W(i)\{[P_i^f(1-k_i)\cdot\frac{J_i^S}{c_i}+P_i^f(1-V(k_i))(1-k_i)(t_p-\frac{J_i^S}{c_i})]\}+[1-W(i)][P_i^f(1-k_i)\cdot t_p]\}\geq P_{saving}\cdot t_p \tag{3.31}$$

where P_{saving} is the power reduction requirement during the peak periods.

4) The machine M_{i+1} can resume operation if either the upstream machine M_i keeps in operation during the whole peak periods (i.e., $k_i = 1$) or J_i^C , the maximum capable accumulated "Just-for-Peak" buffer inventory in location J_i , is no less than J_i^R .

$$V(k_{i+1})(J_i^C - J_i^R)(1-k_i) \geq 0 \tag{3.32}$$

By now, a Nonlinear Integer Programming (NIP) problem with nonlinearities in the objective function and corresponding constraints is formulated. By solving the objective function

(3.27), we can identify the optimal demand response actions during peak periods and corresponding building policies of “Just-for-Peak” buffer inventory during off-peak periods. The optimal decision variables of k_i and $V(k_i)$ that can minimize the summation of the holding cost of the “Just-for-Peak” inventory, the electricity bill cost, and the potential production loss cost during a production horizon can be obtained. Corresponding J_i^S can also be identified.

Commercial software packages are mature and convenient for this type of formulations (Bussieck and Pruessner, 2003). In this section, we will use GAMS (General Algebraic Modeling System) (GAMS, 2013) platform with the solver Simple Branch & Bound (SBB) to solve the NIP problem.

3.3.3 Case Study

To illustrate the effectiveness of the method proposed in Section 3.3.2, a section of an automotive assembly line with seven machines and six buffers (see Figure 11) is studied. Six addition “Just-for-peak” buffer locations are also deployed paired with six regular buffers. Table XVI shows the basic settings of the machines such as cycle time, mean time between failures (MTBF), mean time to repair (MTTR), and rated power. Table XVII shows the parameters of the regular buffer locations. It includes both initial contents and buffer capacity.

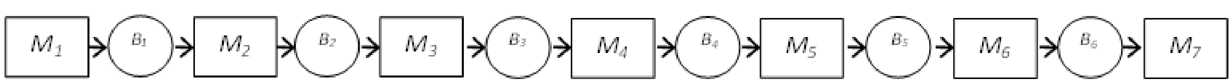

Figure 11. A seven-machine and six-buffer serial production system

TABLE XVI. BASIC SETTING OF THE MACHINE

Machine	Cycle Time (min)	MTBF (min)	MTTR (min)	Power, P_i^f (kW)
1	0.455	100.0	4.95	14
2	0.492	45.6	11.7	24
3	0.473	98.8	16.0	14
4	0.489	217.5	27.3	15
5	0.483	109.4	18.4	25
6	0.469	107.7	15.6	25
7	0.482	127.5	19.98	13

TABLE XVII. PARAMETERS OF THE REGULAR BUFFERS

Buffer B_i	Capacity of B_i (unit)	Initial contents of B_i (unit)
1	70	32
2	80	30
3	50	40
4	42	30
5	45	42
6	90	30

The parameters of the "Just-for-Peak" buffer locations are shown in Table XVIII and Table XIX. The accumulation rate (a_i), consumption rate (c_i), the capacity of "Just-for-Peak" buffer location J_i ($J_{i\max}$), holding cost per unit held per unit time for the "Just-for-Peak" buffer inventory stored in J_i (u_i), accumulation rate to ensure the operation resumption (a_i'), target of "Just-for-Peak" buffer inventory that can satisfy the production of the downstream machine for the whole peak periods (J_i^T), maximum capable accumulated "Just-for-Peak" buffer inventory (J_i^C), "Just-for-Peak" buffer inventory for the operation resumption for the downstream machine (J_i^R), and corresponding $W(i)$ are included.

TABLE XVIII. PARAMETERS OF THE "JUST-FOR-PEAK" BUFFER LOCATIONS

"Just-for-Peak" buffer location J_i	Capacity of J_i, $J_{i\,max}$ (unit)	Accumulation rate, a_i (unit/hour)	Accumulation rate for resumption, a_i' (unit/hour)	Consumption rate, c_i (unit/hour)	Holding cost, u_i ($/unit /hour)
1	70	34.3	-	122	0.05
2	80	12.1	2.5	127	0.05
3	50	5.9	8.2	123	0.05
4	42	0.2	8.5	125	0.05
5	45	0.1	8.7	128	0.05
6	90	0.1	-	125	0.05

TABLE XIX. PARAMETERS OF THE "JUST-FOR-PEAK" BUFFER LOCATIONS (CONT.)

"Just-for-Peak" buffer location J_i	Target of "Just-for-Peak" buffer inventory (J_i^T) (unit)	Maximum Capable "Just-for-Peak" buffer inventory (J_i^C) (unit)	"Just-for-Peak" inventory for operation resumption (J_i^R) (unit)	$W(i)$
1	61	257	-	0
2	64	90	19	0
3	62	44	61	1
4	63	1	63	1
5	64	0	65	1
6	63	0	-	1

The assumed beginning time, duration, and the requirement of demand reduction of the peak periods and the electricity rates from the actual bill of our industrial partner are shown in Table XX and Table XXI respectively.

TABLE XX. PRODUCTION HORIZON AND REDUCTION REQUIREMENT

Duration of off-peak period T (hour)	Duration of peak period t_p (hour)	Demand reduction requirement P_{saving} (kW)
7.5	0.5	16

TABLE XXI. ELECTRICITY RATE

On peak demand charge rate C_D ($/kW)	On peak electricity consumption charge rate C_P ($/kWh)	Off-peak electricity consumption charge rate C_R ($/kWh)
9.58	0.029	0.016

Finally, the cost of production loss per unit time of each machine is assumed as shown in Table XXII.

TABLE XXII. COST OF PRODUCTION LOSS PER UNIT TIME FOR EACH MACHINE

Machine	Cost of production loss per unit time (g_i) ($/production loss per unit time)
1	10
2	20
3	80
4	20
5	20
6	20
7	50

GAMS with solver SBB is used to solve the objective function (3.27) with corresponding constraints to finally obtain the total cost per unit time, the binary variables k_i, $V(k_i)$, and corresponding accumulated "Just-for-Peak" buffer inventories as shown in Table XXIII. The major difference between the results in Table XXIII and the ones obtained by the method proposed by Fernandez et al. (2013) is the value of k_3. In this section, machine M_3 can be turned off at the beginning of the peak periods and then resumed, while in Fernandez et al. (2013) k_3 is one. Therefore, a lower total cost per unit time ($101.85/hour) can be obtained compared to the result in Fernandez et al. (2013) ($113.62/hour).

TABLE XXIII. OPTIMIZATION RESULTS OF THE PROPOSED METHOD

Machine	k_i	$V(k_i)$	"Just-for-Peak" buffer inventory built in J_i, J_i^S (unit)	Total cost per unit time ($/hour)
1	0	Not Applicable	0	101.85
2	0	Not Applicable	19	
3	0	1	44	
4	1	Not Applicable	0	
5	1	Not Applicable	0	
6	1	Not Applicable	0	
7	1	Not Applicable	-	

The comparison of the electricity bill cost among the baseline model (no "Just-for-Peak" buffer inventories are accumulated during off-peak periods and no demand response actions are implemented during peak periods, the production is kept throughout the whole shift), the method proposed by Fernandez et al. (2013), and the proposed method in this section is illustrated in Table XXIV. The comparison of the overall cost among three models is shown in Table XXV. The comparison of the power demand during peak periods among three models is shown in Table XXVI. In addition, the simulation model in ProModel® is used to implement the demand response actions obtained by GAMS to compare the throughput among three models as shown in Table XXVII. The comparison of the cost per product among three models is also shown in Table XXVIII.

TABLE XXIV. COMPARISON OF THE ELECTRICITY BILL AMONG THREE MODELS

Model	Energy consumption charge ($)	Demand charge ($)	Total electricity charge($)	Charge reduction ($)	Reduction percentage (%)
Baseline Model	15.10	1075.75	1090.85		
Method by Fernandez et al. (2013)	14.81	881.36	896.17	194.68	17.8
Proposed Method	14.67	787.52	802.19	288.66	26.5

TABLE XXV. COMPARISON OF THE TOTAL COST AMONG THREE MODELS

Model	Electricity charge($)	Holding charge ($)	Production shortage charge ($)	Total charge ($)	Reduction (%)
Baseline Model	1090.85	0	0	1090.85	
Method by Fernandez et al. (2013)	896.17	12.80	0	908.97	16.7
Proposed Method	802.19	12.61	0	814.80	25.3

TABLE XXVI. COMPARISON OF THE POWER DEMAND DURING PEAK PERIODS AMONG THREE MODELS

	Baseline Model	Method by Fernandez et al. (2013)	Proposed Method
Power demand during peak periods (kW)	112.3	92.0	82.2
Reduction percentage (%)		18.1%	26.8%

TABLE XXVII. COMPARISON OF THE THROUGHPUT AMONG THREE MODELS

	Baseline Model	Method by Fernandez et al. (2013)	Proposed Method
Production throughput	699.96 (673.96, 726.02)	698.77 (666.99, 730.53)	689.90 (662.57, 716.69)

TABLE XXVIII. COMPARISON OF THE COST PER PRODUCT AMONG THREE MODELS

	Baseline Model	Method by Fernandez et al. (2013)	Proposed Method
Cost per product ($/unit product)	1.56	1.30	1.18
Reduction percentage (%)		16.7	24.4

Compared with the baseline model, it can be observed that 1) 26.5% saving of electricity bill charge can be achieved; 2) 25.3% reduction of the overall cost can be accomplished; 3) 26.8% power demand can be reduced during peak periods; and 4) 24.4% reduction of unit cost per product can be achieved with the method developed in section.

3.3.4 Conclusions

In this section, we propose an advanced buffer inventory management method to reduce the electricity consumption during peak periods for typical manufacturing system with multiple machines and buffers utilizing “Just-for-Peak” buffer inventory that is built up during off-peak periods. The optimal demand response decisions and corresponding building policies of “Just-for-Peak” buffer inventory are identified by minimizing the sum of the holding cost of “Just-for-Peak” buffer inventory, the electricity bill cost, and the cost due to the potential production loss throughout the production horizon. Nonlinear Integer Programming framework is used to establish the mathematical model. The results of the case study illustrate that significant reduction of energy consumption and cost can be achieved.

3.4. Conclusions

This chapter proposes the methods for both event-driven and price-driven demand response programs. For the event-driven program, we use Markov decision process to establish the energy control model for decision-making. An approximate dynamic programming is used to identify the near optimal demand response decisions on a short-term basis. For the price-driven program, we propose a novel “Just-for-Peak” buffer inventory management method to reduce the electricity consumption during peak periods. The optimal demand response decisions and corresponding building policies of “Just-for-Peak” buffer inventory are identified by minimizing the sum of the holding cost of “Just-for-Peak” buffer inventory, the electricity bill cost, and the cost due to the potential production loss throughout the production horizon.

CHAPTER 4 PLANT-LEVEL ELECTRIC ENERGY MANAGEMENT FOR COMBINED MANUFACTURING AND HVAC SYSTEM

4.1. Introduction

The research outcomes in Chapter 2 and Chapter 3 provide the manufacturers with the methods of customer-side electric energy management on the manufacturing system level towards sustainability. In manufacturing plants, besides the manufacturing system, the other top contributor of electricity consumption is facility HVAC system (Brundage et al., 2013). The corresponding costs of manufacturing system and HVAC system dominate the whole energy related cost for manufacturers (Brundage et al., 2013). The joint consideration for these two systems can help to establish the plant-level energy management model towards sustainability. However, the studies regarding these two systems are traditionally conducted separately, while neglecting the potential interaction in-between. The heat generated due to the manufacturing operation influences the indoor temperature that is used as an important parameter to determine the HVAC operation. There may be a potential competition relationship between the manufacturing system and HVAC system for the limited power consumption quotation during the duration of demand response event. Therefore, in this chapter, we focus on the energy management for the combined manufacturing and HVAC system to further extend the previous research outcomes to the entire plant level. An integrated model regarding electricity demand response for combined manufacturing and HVAC system is proposed in this chapter. The production capability, electricity pricing, power demand limitation during the demand response event, and ambient temperature are considered in the model to identify an optimal demand response strategy regarding both production schedule and HVAC control. A numerical case study under the temperature profile of a summer day in mid-west is used to illustrate the effectiveness of the proposed integrated model.

The rest of this chapter is organized as follows. Section 4.2 introduces the proposed method. Section 4.3 introduces a numerical case study. Finally, conclusions of this chapter are drawn in Section 4.4.

The following notations are used in this chapter.

Boldface:

DR	the set of intervals that belong to demand response event
OP	the set of intervals that belong to peak periods

Upper Case:

BU_{it}	buffer level of buffer i at the beginning of interval t
C_i	capacity of buffer i
C_{CON}	the electricity consumption cost
C_{DEM}	the electricity demand cost
C_{ELE}	electricity cost during the planning horizon
D_P	power demand of the combined system

E_{HVAC_t}	electricity consumption of the HVAC system during interval t
EFF_i	efficiency of machine i
H	duration of each interval
P_i	rated power of machine i
PR_i	production rate of machine i
R_P	committed limitation of power demand during the duration of demand response event
T_L	lower bound of allowed indoor temperature
T_{sur}	the outdoor temperature
T_U	upper bound of allowed indoor temperature
TA	production target
TEI_t	indoor temperature at the beginning of interval t
TEO_t	outdoor temperature at the beginning of interval t
TP	production throughput

Lower Case:

d_p electricity demand charge rate ($/kW)

i machine index, $i = 1, 2, ..., N$

k positive constant of the Newton's law of cooling

k_1 heat capacity (kWh/^{o}F) of plant building

q rate of the thermal energy generated by the manufacturing operation

r_t electricity consumption charge rate ($/kWh) for interval t

t index of all the discretized intervals

x_{it} decision variable for machine i at interval t

y_t decision variable denoting the target temperature set by the HVAC at the beginning of interval t

4.2. Proposed Method

We consider a typical demand response program as follows. When enrolling into the program, the manufacturer has to make a commitment of the limitation of power demand when requested during the duration of demand response event. Rewards will be paid if the committed power demand limitation is not violated, as otherwise penalty will be assessed. The notification of the demand response event is issued one day in advance. The start time and the duration of the event are included in the notification. The manufacturer needs to identify an optimal schedule of their manufacturing system and optimal control of their HVAC system to minimize the electricity billing cost while maintaining the production target, indoor temperature, and the commitment of the limitation of power demand.

The manufacturing system modeled here is shown in Figure 12, a typical serial *N*-machine-*N*-1-buffer line. The machines are represented by the rectangles and the buffers are represented by the circles. Let i be the index of the machines (i=1, …, N) and the buffers (i=1, …, N-1) in the system.

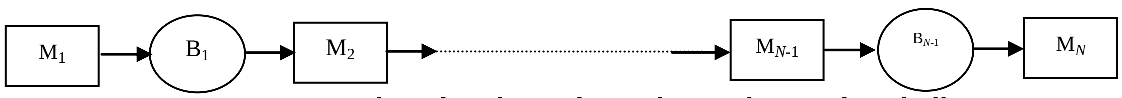

Figure 12. A typical serial production line with *N* machines and *N*-1 buffers

The production horizon is slotted into a set of intervals with the same duration H. Let t, t=1, …, t_e, be the index of these discretized intervals. These intervals can belong to either peak or off-peak periods. We assume that the demand response event occurs in the peak periods. Let x_{it} be the binary decision variable to represent the production schedule. It equals to one if machine i is determined to keep producing in interval t, and zero otherwise; y_t be the decision variable denoting the target temperature set by the HVAC at the beginning of interval t; and C_{ELE} be the electricity billing cost throughout the planning horizon. The problem can be formulated by the objective function (4.1) and the constraints (4.2)-(4.6) as follows:

$$\min_{x_{it},y_t} C_{ELE} \tag{4.1}$$

$$s.t.\quad D_P \le R_P \tag{4.2}$$

$$TP \ge TA \tag{4.3}$$

$$0 \le BU_{it} \le C_i \quad i = 1, ..., N\text{-}1;\, t = 1, ..., t_e \tag{4.4}$$

$$T_L \le TEI_t \le T_U \qquad t = 2, ..., t_e \tag{4.5}$$

$$T_L \le y_t \le T_U \quad t = 1, ..., t_e \tag{4.6}$$

where D_P is the power demand of the plant including both manufacturing and HVAC systems during demand response event; R_P is the committed limitation of power demand during the duration of demand response event; TP is the production throughput of the manufacturing system throughout the planning horizon; TA is the production target of the planning horizon; BU_{it} is the buffer contents in buffer i at the beginning of interval t; C_i is the capacity of buffer i; TEI_t is the indoor temperature of the plant building at the beginning of interval t; and T_U and T_L are the upper bound and lower bound of acceptable indoor temperature, respectively.

C_{ELE} in (1) can be formulated by (4.7).

$$C_{ELE} = C_{CON} + C_{DEM} \tag{4.7}$$

where C_{CON} is the electricity consumption cost and C_{DEM} is the power demand cost. They can be formulated by (4.8) and (4.9), respectively.

$$C_{CON} = \sum_t r_t (\sum_i x_{it} P_i H + E_{HVAC_t}) \tag{4.8}$$

$$C_{DEM} = d_p \max_{t \in \mathbf{OP}} (\sum_i x_{it} P_i + \frac{E_{HVAC_t}}{H}) \tag{4.9}$$

where r_t is the charge rate of electricity consumption (\$/kWh) for interval t; d_p is the charge rate of power demand (\$/kW) during peak periods; **OP** is the set of intervals that belong to peak periods; P_i is the rated power of machine i; and E_{HVAC_t} is the electricity consumption of the HVAC system during interval t, which can be formulated by (4.10).

$$E_{HVACt} = k_1 \cdot |TEI_t - y_t| \tag{4.10}$$

where k_1 is the heat capacity (kWh/$^{\circ}$F) of plant building. The whole plant building is treated as one object and thus the single parameter k_1 is assumed to take into account all the possible factors that may have influence on the thermal capability of plant (Liang et al., 2012). In addition, the

HVAC system efficiency is assumed to be one. To obtain the TEI_t at each time point for decision-making, Newton's law of cooling considering an internal heat source due to manufacturing operation is derived as follows.

The rate of the change of the temperature in plant building due to the temperature difference between the inside building and outdoor areas can be formulated by (4.11).

$$\left.\frac{dT}{dt}\right|_{\Delta T(out-in)} = -k(T_t - T_{sur}) \tag{4.11}$$

where T_t is the indoor temperature of the plant building at time t; T_{sur} is the outdoor temperature; and k is a positive constant of the Newton's law of cooling.

The rate of the change of the temperature in plant building due to the manufacturing operation can be formulated by (4.12).

$$\left.\frac{dT}{dt}\right|_{\substack{Manufacturing \\ operation}} = q / k_1 \tag{4.12}$$

where q is the rate of the thermal energy generated by the manufacturing operation (kW).

Considering both effects described by (4.11) and (4.12), the net rate of the change of the temperature of the plant building can be formulated by (4.13).

$$\frac{dT}{dt} = q / k_1 - k(T_t - T_{sur}) \tag{4.13}$$

Reorganizing the right hand side of (4.13), we can obtain (4.14).

$$\frac{dT}{dt} = -k[T_t - (T_{sur} + \frac{q}{kk_1})] \tag{4.14}$$

It can be seen that (4.14) is a separable differential equation. After separating the variables, we can obtain (4.15) as follows.

$$\frac{dT}{[T_t - (T_{sur} + \frac{q}{kk_1})]} = -kdt \tag{4.15}$$

Taking integration on both sides, we can obtain (4.16).

$$\ln[T_t - (T_{sur} + \frac{q}{kk_1})] = -kt + C \tag{4.16}$$

where C is a constant. Considering the initial condition T_0 (initial temperature), we can solve C by (4.17).

$$C = \ln[T_0 - (T_{sur} + \frac{q}{kk_1})] \tag{4.17}$$

Substituting (4.17) into (4.16), we can obtain (4.18).

$$\ln[T_t - (T_{sur} + \frac{q}{kk_1})] - \ln[T_0 - (T_{sur} + \frac{q}{kk_1})] = -kt \tag{4.18}$$

Using the Logarithmic quotient property, we obtain (4.19).

$$\ln \frac{[T_t - (T_{sur} + \frac{q}{kk_1})]}{[T_0 - (T_{sur} + \frac{q}{kk_1})]} = -kt \tag{4.19}$$

Reorganizing (4.19), we can find the solution of plant building temperature at time t with the desired format as shown in (4.20).

$$T_t = (T_{sur} + \frac{q}{kk_1}) + [T_0 - (T_{sur} + \frac{q}{kk_1})] \cdot e^{-kt} \tag{4.20}$$

Applying the formulation in (4.20) for each interval, the indoor temperature of the plant building at the beginning of next interval t+1 can be formulated by (4.21).

$$TEI_{t+1} = (TEO_t + \frac{q(t)}{kk_1}) + [y_t - (TEO_t + \frac{q(t)}{kk_1})] \cdot e^{-kH} \tag{4.21}$$

where TEO_t is the outdoor temperature at the beginning of interval t. $q(t)$ is the rate of the thermal energy generated due to the manufacturing operation during interval t. It can be calculated by the production of fraction radiant and the rated power of each machine. Here the assumption that the temperature change by HVAC is instantaneous (Liang et al., 2012) is followed, and thus y_t can be used in (4.21) to represent T_0 in (4.20). In addition, we also assume that the outdoor temperature keeps constant in each individual interval t and the time constant k stays constant throughout the entire planning horizon.

The constraint (4.2) describes that the power demand D_P during the duration of the demand response event cannot exceed the committed value R_P. D_P can be formulated by (4.22).

$$D_P = \max_{t \in \mathbf{DR}} \left(\sum_i x_{it} P_i + \frac{E_{HVAC_t}}{H} \right) \tag{4.22}$$

where **DR** is the set of intervals that belong to demand response event.

The constraint (4.3) describes that the production target TA needs to be satisfied. The production throughput of the serial manufacturing system TP is same as the production count of the last machine of the system, which can be calculated by (4.23).

$$TP = \sum_t (x_{Nt} \cdot PR_N \cdot EFF_N \cdot H) \tag{4.23}$$

where PR_i is the production rate of machine i (unit per interval); and EFF_i is the efficiency of machine i.

The constraint (4.4) describes the balance of the material flow in the manufacturing system. BU_{it} can be calculated by (4.24).

$$\begin{gathered} BU_{it} = BU_{i(t-1)} + x_{i(t-1)} \cdot PR_i \cdot EFF_i \cdot H - x_{(i+1)(t-1)} \cdot PR_{i+1} \cdot EFF_{i+1} \cdot H \\ i = 1, \ldots, N-1; t = 1, \ldots, t_e \end{gathered} \tag{4.24}$$

The constraints (4.5) and (4.6) describe both the indoor temperature and target temperature set by the HVAC need to be maintained in the acceptable range.

Particle swarm optimization (PSO) is used to solve the problem formulated in (4.1)-(4.6) to obtain the near optimal production schedule and HVAC control strategy. PSO is suitable for solving non-linear and non-differentiable problems in high dimension space (Kennedy et al., 2001). In PSO, each possible solution is considered a particle in the swarm. In the encoding scheme of this study, each particle has an $(N+1)\times t_e$ dimension among which the $N\times t_e$ sub matrix indicates the production scheduling of an N-machine-N-1-buffer manufacturing system throughout the planning horizon with t_e intervals (denoted by planning sub matrix); and the $1\times t_e$ sub matrix indicates the target temperature set by the HVAC for all t_e intervals (denoted by temperature sub matrix). The particles fly in the search space based on the updated velocity towards its best location over time. After each flight (or iteration), the velocity and location of each particle are updated according to (4.25).

$$\begin{aligned} &V(s+1)=\alpha V(s)+c_1w_1(L_{PB}-L(s))+c_2w_2(L_{GB}-L(s)) \\ &L(s+1)=L(s)+V(s+1) \end{aligned} \tag{4.25}$$

where $V(s)$ and $L(s)$ are the matrices of the velocity and location of individual particle at iteration s and s+1, respectively. Also, c_1 and c_2 are the learning factors and w_1 and w_2 are random real numbers between zero and one. α is the inertia weight. L_{PB} is the particle's best solution that has been identified up to the sth iteration. L_{GB} is the global best solution of the entire swarm.

The swarm is initiated by a given number of matrix L (i.e., particles). In each matrix, the temperature sub matrix is initialized by randomly selecting the value in the acceptable range. Note that we aggregate the temperature values into several discretized values to make the problem more easily handled in PSO. The available target temperature y_t can be drawn from the discrete set $\{T_L, T_L + \Delta T, T_L + 2 \cdot \Delta T, ..., T_U - \Delta T, T_U\}$, where ΔT can be obtained by solving (4.26).

$$T_U = T_L + \Delta T \cdot z \tag{4.26}$$

where z is a positive integer.

The elements of the initial velocity V for temperature sub matrix of each particle is randomly generated from the set $\{-\Delta T,\ 0,\ \Delta T\}$. Further steps as shown in (4.27) and (4.28) are needed to make the velocity and location for the temperature sub matrix be in the desired range, respectively.

$$V_{y_t}(s+1) = \begin{cases} -\Delta T, & \text{if } V_{y_t}(s+1) \le -\Delta T \\ 0, & \text{if } -\Delta T < V_{y_t}(s+1) < \Delta T \\ \Delta T, & \text{if } V_{y_t}(s+1) \ge \Delta T \end{cases} \tag{4.27}$$

$$L_{y_t}(s+1) = \begin{cases} L_{y_t}(s) + V_{y_t}(s+1), \text{ if } T_L \le L_{y_t}(s) + V_{y_t}(s+1) \le T_U \\ T_L, \text{ if } L_{y_t}(s) + V_{y_t}(s+1) < T_L \\ T_U, \text{ if } L_{y_t}(s) + V_{y_t}(s+1) > T_U \end{cases} \tag{4.28}$$

where the notations with subscript y_t are used to denote the individual elements of the temperature sub matrix**.**

The initialized planning sub-matrix with dimensions $N \times t_e$ consists of all the elements valued by one (note that randomly drawing number from the set {0, 1} to initiate planning sub matrix may greatly decrease the number of feasible solutions due to the constraint (4.4)). The elements of the initial velocity V for planning sub matrix of each particle is randomly generated from the set {-1, 0, 1}. Since both V and L are updated using real numbers for planning sub matrix, further steps as shown in (4.29) and (4.30) are needed to make V and L be in the set {-1, 0, 1} and the set {0, 1}, respectively (Wang and Li, 2013).

$$V_{x_{it}}(s+1)=\begin{cases}-1, & \text{if } V_{x_{it}}(s+1)<-0.5\\ 0, & \text{if } -0.5\le V_{x_{it}}(s+1)\le 0.5\\ 1, & \text{if } V_{x_{it}}(s+1)>0.5\end{cases} \tag{4.29}$$

$$L_{x_{it}}(s+1)=\begin{cases}L_{x_{it}}(s)+V_{x_{it}}(s+1), \text{ if } 0\le L_{x_{it}}(s)+V_{x_{it}}(s+1)\le 1\\ 0, \text{ if } L_{x_{it}}(s)+V_{x_{it}}(s+1)<0\\ 1, \text{ if } L_{x_{it}}(s)+V_{x_{it}}(s+1)>1\end{cases} \tag{4.30}$$

where the notations with subscript x_{it} are used to denote individual elements of the planning sub matrix.

The fitness function of individual particle can be formulated by in (4.31) where the constraints (4.2)-(4.6) are integrated as penalty terms.

$$\begin{aligned} &C_{ELE}+A_1\cdot[\min(TP-TA,0)]^2+A_2\cdot[\min(R_P-D_P,0)]^2\\ &+A_3\cdot\sum_{t=2}^{t_e}[\min(TEI_t-T_L,0)]^2+A_4\cdot\sum_{t=2}^{t_e}[\min(T_U-TEI_t,0)]^2\\ &+A_5\cdot\sum_{t}\sum_{i=1}^{N-1}[\min(C_i-BU_{it},0)]^2+A_6\cdot\sum_{t}\sum_{i}[\min(BU_{it},0)]^2\end{aligned} \tag{4.31}$$

where A_1, A_2, A_3, A_4, A_5,and A_6 are six large real numbers.

When implementing the PSO, we will first generate a swarm of particles and initialize the velocity. The fitness of each particle will be evaluated using (4.31). The locations with the best fitness of each particle so far will be identified as L_{PB} and stored. The global best of the entire swarm L_{GB} will be updated if necessary. The velocity and location of each particle then will be updated using (4.25)-(4.30). We will repeat the above steps until the maximum iteration number is reached.

It is known that in PSO, generally there is a tradeoff between the computational cost and the quality of the solution. More iterations of the algorithm may lead to a higher possibility for an improved solution, but it will inevitably increase the computational cost (Wang et al., 2012).

Different combinations for the parameters for the swarm size and iteration number will be tried to balance the computational cost and solution quality in this study.

4.3. Case Study

In this section, we implement a numerical case study of a five-machine-four-buffer serial manufacturing system as shown in Figure 13 under the temperature profile of a summer day in Chicago to illustrate the effectiveness of the proposed integrated model on the electricity demand response for the combined manufacturing and HVAC system. The parameters of each machine and each buffer are given in Table XXIX. The profile of the outdoor temperature of the planning horizon is shown in Table XXX.

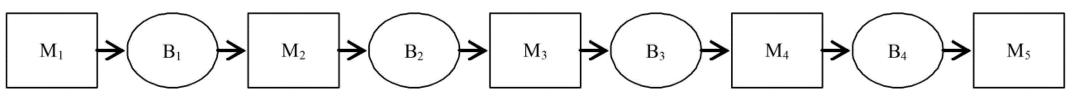

Figure 13. A five-machine-four-buffer serial manufacturing system

TABLE XXIX. PARAMETERS OF THE MACHINES AND THE BUFFERS IN THE SYSTEM

	Machine 1	Machine 2	Machine 3	Machine 4	Machine 5
Production Rate (units/hour)	40	40	40	40	40
Efficiency	0.9	0.9	0.9	0.9	0.9
	Buffer 1	Buffer 2	Buffer 3	Buffer 4	
Initial Contents (units)	90	80	75	80	
Capacity (units)	180	160	150	180	

TABLE XXX. OUTDOOR TEMPERATURE FOR EACH INTERVAL (^{o}F)

Interval 1	Interval 2	Interval 3	Interval 4	Interval 5	Interval 6	Interval 7	Interval 8
65	66	67	69	70	71	72	73
Interval 9	Interval 10	Interval 11	Interval 12	Interval 13	Interval 14	Interval 15	Interval 16
74	75	76	77	77.5	78	78.5	79
Interval 17	Interval 18	Interval 19	Interval 20	Interval 21	Interval 22	Interval 23	Interval 24
79.5	80	80.5	81	81.5	82	82.5	83
Interval 25	Interval 26	Interval 27	Interval 28	Interval 29	Interval 30	Interval 31	Interval 32
82.5	82	81.5	81	80.5	80	80	80

Source:

http://www.wunderground.com/history/airport/KMDW/2013/7/12/DailyHistory.html?req_city=NA&req_state=NA&req_statename=NA

Suppose the planning horizon is an eight-hour shift (from 7:00 AM to 3:00 PM). The production target *TA* is assumed to be 280. The duration *H* of each interval in the planning horizon is 15 minutes and thus the entire planning horizon is divided into 32 intervals. The value of fraction radiant of all the machines is assumed to be 0.08. The charge rates of the electricity consumption and the power demand for different intervals are provided in Table XXXI. The demand response event occurs between 12:00PM to 1:00PM during which the limitation of the power demand is 90kW. The initial indoor temperature is assumed to be 68^{o}F. The range of the acceptable indoor temperature is set to be between 70^{o}F and 76^{o}F. The parameters k_1 and k are assumed to be 1.5 and 1.2, respectively. ΔT is assumed to be 0.5^{o}F, and thus the available target temperature y_t can be drawn from the discrete set {70^{o}F, 70.5^{o}F, 71^{o}F, 71.5^{o}F, 72^{o}F, 72.5^{o}F, 73^{o}F, 73.5^{o}F, 74^{o}F, 74.5^{o}F, 75^{o}F, 75.5^{o}F, 76^{o}F }.

TABLE XXXI. ELECTRICITY CONSUMPTION RATE AND POWER DEMAND RATE

Type	Time of Day	Consumption Rate ($/kWh)	Demand Rate ($/kW)
On-peak	12 pm-7 pm	0.17	18.8
Non-peak	7 pm-12 pm	0.08	0

Source: https://www.oru.com/documents/tariffsandregulatorydocuments/ny/electrictariff/electricsc20.pdf

Different PSO parameter combinations are tuned. We find that 3000 and 1000 is a reasonable parameter combination regarding swarm size and iteration number of PSO for balancing the solution quality and computational cost. After implementing the PSO algorithm, the obtained system throughput is 288. The optimal target temperature set by HVAC system y_t and corresponding indoor temperature evolution are shown in Figure 14. The power consumption of the combined system of each interval throughout the planning horizon are shown in Figure 15. The power demand during peak periods, off-peak periods, and the demand response event is 91kW, 97kW, and 88kW, respectively. It can be seen that the power demand during peak periods (91kW) is lower than the one during off-peak periods (97kW) and the power demand during the demand response event (88kW) can be effectively controlled below the committed limitation (90kW).

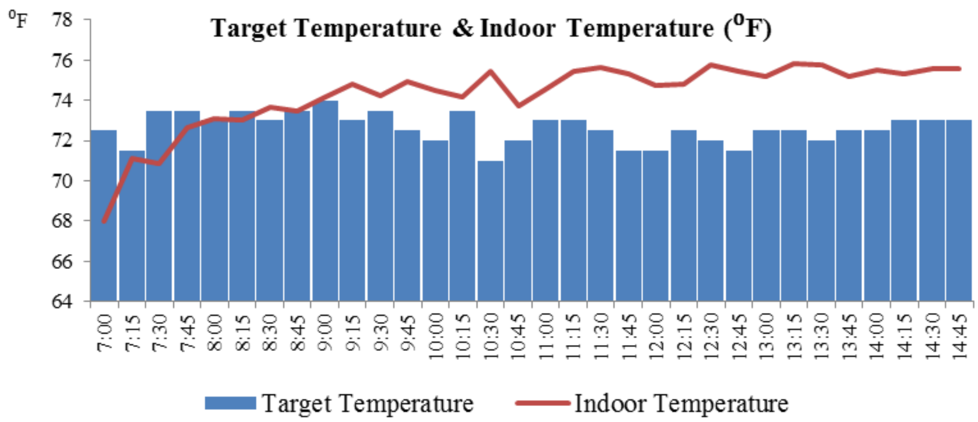

Figure 14. Target temperature by HVAC & indoor temperature evolution

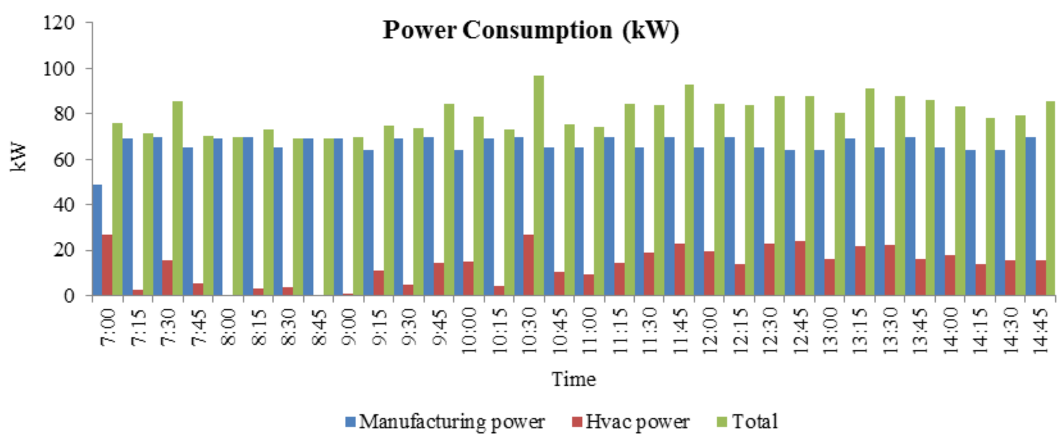

Figure 15. Power consumption of each interval

4.4. Conclusions

This chapter presents an electricity demand response method for combined manufacturing and HVAC system. The production capability, electricity pricing, limitation of power demand, and ambient temperature are considered in the model and thus the optimal electricity demand response strategy with respect to both production schedule and HVAC control is identified. The results of the numerical case study illustrate the effectiveness of the proposed integrated modeling methodology.

As for the future work, the decision-making for the combined system in electricity demand response on a real-time basis, which can be used for emergency demand response programs, will be investigated.

CHAPTER 5 CONCLUSIONS

5.1. Introduction

The main objective of this doctoral thesis research is to develop a framework for customer-side electric energy management for manufacturers. To achieve this objective, we conducted the research by two steps: 1) manufacturing system-level energy management including both energy efficiency management and electricity demand response; 2) plant-level energy management considering combined manufacturing and HVAC system.

5.2. Intellectual Contributions and Broader Impacts

We propose a research framework of customer-side electric energy management towards sustainability for manufacturers. The contribution of this research is two-folded. First, it advances the previous energy management methods in manufacturing mainly focusing on single machine level or specific manufacturing process level to the multi-machine system level. Secondly, unlike most existing literature where the energy management studies for HVAC and manufacturing systems are conducted separately, we propose a plant-level energy management model focusing on electricity demand response considering both manufacturing and HVAC systems. The intellectual merit of this research includes the formulation and optimization of the analytical models to implement customer-side electric energy management for both typical manufacturing system and the entire plant considering combined manufacturing and HVAC system. The research outcomes can provide insights on optimal customer-side electric energy management for manufacturers. Both manufacturing and HVAC systems are involved. It can bring economic, societal, and ecological benefits to the U.S. by cutting power demand, energy consumption, energy cost, and GHG emissions.

In terms of broader impacts, the proposed research will help manufacturing sector better implement customer-side electric energy management and offer a competitive edge to the U.S. manufacturers in a carbon-constrained world. The urgency to reduce GHG emissions and energy consumption in manufacturing sector has been recognized by our society. The outcomes of this thesis can provide quantitative tools that manufacturers can adopt to implement optimal customer-side electric energy management and will lead to both economic and environmental benefits.

5.3. Future Work

The future work that can further extend this thesis research is discussed as follows.

The other types of demand response programs and energy efficiency management can be considered for the combined manufacturing and HVAC system. Real time decision-making problem need be considered.

A longer duration of demand response event or peak period needs to be considered. The problem formulation of the power demand during the event duration or peak period is more complex rather than just take the average through dividing the total electricity consumption by the total duration.

In addition, renewable energy options can be further integrated into our plant-level model. For example, the utilization of the wind turbine for the electric energy management for the entire plant can be considered. The potential benefits and cost viability need to be examined.

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VITA

NAME:	Zeyi Sun
EDUCATION:	B.Eng., Material Science and Engineering, Tongji University, Shanghai, China, 2002 M.Eng., Manufacturing, University of Michigan, Ann Arbor, MI, 2010
EXPERIENCE:	*Research Assistant*, Sustainable Manufacturing Systems Research Laboratory, Department of Mechanical & Industrial Engineering, University of Illinois at Chicago, January 2011 – May 2015 *Teaching Assistant*, Department of Mechanical & Industrial Engineering, University of Illinois at Chicago, January 2011 – May 2015 *Production Runtime Intern*, Corporate Technology, Siemens Corporation, Princeton, NJ, May 2014 – August 2014 *Production Planner*, GKN Torque Technology (Shanghai) Co., Ltd, Shanghai, China, January 2008 – July 2009 Production Planner, Shanghai Asahi Electronic Glass Co., Ltd, Shanghai, China, April 2005 – May 2007 *Raw Material Engineer*, Shanghai Asahi Electronic Glass Co., Ltd, Shanghai, China, July 2002 – April 2005
PUBLICATIONS:	*Archival Journal*
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