NETWORK MODELING APPROACH TO ENERGY-PERFORMANCE OPTIMIZATION IN INDUSTRIAL SYSTEMS

by

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A dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

In partial fulfillment of the requirements

For the degree of

Doctor of Philosophy

Graduate Program in Industrial and Systems Engineering

Written under the direction of

Professor Mohsen A. Jafari

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New Brunswick, New Jersey

JANUARY, 2016

ABSTRACT OF THE DISSERTATION

Network Modeling Approach to Energy-Performance Optimization in Industrial Systems

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With approximately 95 quadrillion Btu, the United States accounts for nearly 18% of the world's total energy demand, and industrial sector within U.S. consumes as much as 34% of this energy intake. Growing energy demands, continuous worldwide depletion of natural resources and environmental regulations, have become a strong factor in the industrial sector for reducing energy consumption in the recent years. However, manufacturing facilities are often complex systems consisting of different components that have strict requirements in terms of productivity and throughput, making it particularly challenging to achieve ambitious energy reduction targets. Moreover, owners of such manufacturing enterprises are reluctant to make changes in their processes to avoid jeopardizing performance optimality; prompted by the aforementioned, the following questions arise:

(1) How to simultaneously account for energy reduction goals and performance requirements in an industrial facility?

(2) How to incorporate the existing infrastructure and practices in an industrial facility to reduce the energy consumption and expenditure without sacrificing the productivity?

(3) How to incorporate the dynamic interdependencies inherent in the components of a manufacturing environment to achieve optimal energy efficiency?

This work aims at providing the owner of a manufacturing enterprise with a modeling framework to achieve cost effective energy reduction while maintaining productivity and profitability. We provide a stochastic energy-aware production planning optimization based on a two-dimensional measure, “Energy-Performance”, and propose a scenario generation approach to solve the planning problem. At the building level, we propose a “business value-driven” energy asset management to achieve energy reduction at the building level while assuring business objective and occupant productivity requirements are maintained. Using a network modeling approach, we provide a framework to calculate the dynamic interdependencies between the components of an industrial facility and define the optimal share of energy reduction for each such component, given a set of alternative solutions. Finally, since most of the underlying Energy-Performance analysis and optimization models are highly data-intensive, we provide a data and metering infrastructure to support the proposed modeling approaches.

Acknowledgements

I would like to express my sincerest gratitude and appreciation to my advisor, Professor Mohsen Jafari for his continuous support of my PhD study, for his patience, motivation, and immense knowledge. He has not only been an outstanding advisor, but also a tremendous mentor in life and I would like to thank him for believing in me even when I did not so myself. His advice on both research as well as on my career has been priceless. I could not have imagined having a better advisor and will continue to strive to make him proud. I am extremely grateful to have him as a dear friend and a supportive guide as I move toward to next steps of my life and career.

Besides my advisor, I would like to thank the rest of my thesis committee: Professor Myong K. Jeong, Professor Kang Li, and Professor Kevin Lyons, for taking the time to review my dissertation and for providing insightful comments, constructive suggestions and encouragement.

I also want to thank the Departments of Industrial & Systems Engineering and CAIT for their continuous support during my PhD years.

Finally, no words can express my gratitude and love to my dearest parents, for their unconditional love and support. They have always been the greatest source of inspiration to me and my sister. I also cannot put into words the love I have for the best sister in the world, Sara, who has been and always will be my role model. It is the most wonderful feeling to know that she is there for me helping me find my way to excellence. I consider myself the luckiest for having the most caring, wonderful and loving family. Thank you for having faith in me and help me become the person I am now. I love you! Last but not least, I would like to thank my best friend and loving husband, Onur, for being with me every step of the way in this journey. He has stood by me through the good times and bad with his patience, understanding, support and selfless love. I am so blessed to have you!

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Chapter 1

1. Introduction

1.1. Motivation

According to International Energy Outlook 2013, world energy consumption is expected to rise up to 56% by 2020 [1]. Growing energy demands, continuous worldwide depletion of natural resources and environmental regulations have become a strong factor in the industrial sector for reducing energy consumption in recent years. With approximately 95 quadrillion Btu, the United States takes in nearly 18% of world total energy consumption in 2012. Energy demand has been doubled since 1990 and it is projected to grow by 81% from 2011 to 2035. Furthermore the industrial sector in the U.S. accounts for up to 24.5 quadrillion Btu in 2013, representing approximately 34% of total energy consumption [2]; therefore, there is a mounting interest in manufacturing companies across the United States to adopt energy efficiency practices. This has motivated many researchers and practitioners to devote attention to the area of industrial energy efficiency. However, it is particularly challenging to achieve ambitious energy reduction targets across industrial enterprises without sacrificing service and productivity requirements; thus appropriate aggregated measures shall be employed to assure stable manufacturing operations, while achieving simultaneous energy conservation goals. This calls for a more holistic and integrated view/perspective of industrial environments. Although prior research work and industrial practices have been significantly contributing to improving industrial energy consumption, they still lack such holistic perspective and/or applicable modeling approaches and tools to practically address the integrated view. In the recent years, the new type of industrialization, "*Industry 4.0*", has initiated the move towards an infrastructure that supports such interconnected view in a manufacturing environment through "Cyber-Physical Systems" (CPS). The CPS comprise of smart machines and production facilities capable of exchanging information, triggering actions and controlling each other independently. Evidently there is a rising potential to expand the notion of such CPS in the area of industrial energy efficiency.

Prompted by such potential and the discrepancy between existing energy efficiency solutions and implementation, in this thesis, we aim at developing models that can support owners of manufacturing companies to achieve cost and energy savings when planning and managing their production facilities. The factors differentiating the work presented in this thesis from the existing research are: (1) The "Network Modeling" approach, in which an integrated and holistic perspective of energy efficiency in an industrial facility is adopted. That is, besides the energy-consuming manufacturing processes and machinery, the industrial facility's building and technical services are also accounted for in energy efficiency optimization models discussed here. (2) We target "Energy" and "Performance" objectives simultaneously and introduce a novel measure, "Energy-Performance", through which we ensure that energy reduction is achieved without jeopardizing performance requirements within an industrial system. (3) We provide a metering infrastructure that supports the data and information requirements for our energy modeling and optimization.

1.2. Objective

With the foregoing discussion in mind, this thesis is organized as follows: In chapters 2, we focus on the manufacturing process and provide models to achieve cost/energy savings through energy-aware production planning. We concentrate on the building facility in chapter 3 and present a Business Value-driven asset management as a viable energy saving solution at the building level. Chapter 4 provides models to measure the dynamic inherent interdependencies between components of an industrial environment and present optimal ways to achieve energy saving while maintaining performance requirements. In chapter 5 we introduce appropriate metering and modeling infrastructures to support the work presented throughout the thesis. We intend to address and tackle the following research challenges:

1. Provide an energy-aware production planning to achieve savings on energy expenses while maintaining service level requirements. The following, highlights the main achievements:
    - A two-dimensional measure, namely “Energy-Performance” is introduced and integrated into the production planning model to account for simultaneous energy saving goals and performance requirements.
    - An optimization model with risk-averse constraints is presented for determining the optimal production plan that ensures maximum expected profit as well as service level requirements.
    - Energy price volatility is accounted for in the optimal production planning using time-sensitive electricity prices.

2. Provide a novel energy efficiency optimization at the building level. The highlights are as follows:
   - Asset management and reliability theory are integrated with building energy simulation technology to develop optimal maintenance strategies to reduce the building's energy consumption.
   - An Asset Business Value Model ("BVM") is developed to map the business value of the building, to the constituent assets whose operations are critical for the accomplishment of those business objectives. These business values then provide inputs to asset management processes for the allocation of investment in labor and materials and for the organization of maintenance workflow.
   - Integrate the business value model into the building energy optimization to ensure that building performance and business objectives are met.
3. Provide a network energy optimization model to determine the optimal energy saving in an industrial environment using the modeling approaches listed below:
   - The manufacturing facility is considered as a network of interdependent nodes and general models are provided for "Energy" calculation in such a network.
   - A framework is provided to define the dynamic interdependencies between nodes of the network. These dependencies are computed in terms of nodes' "Energy Consumption" and "Performance" demonstrated by appropriate node-specific "Key Performance Indicators" (KPI).

- An optimization model is presented to define the nodes' optimal share of energy reduction given a set of energy saving solutions for each node.

4. Define a framework to define the energy and information flow of a consumer product at micro level. This framework defines an information infrastructure to support the modeling approaches introduced throughout this dissertation.
    - A "Top-down" hierarchal mapping of energy flow across the two dimensions of the product's "Life Cycle" and "Supply Chain" is proposed to define a consumption-production network as well as ownership allocation within such a network.
    - An energy calculation engine is proposed to quantify energy consumption in the aforementioned network. This engine characterizes energy consuming elements in each step of the network and provides guidelines for energy quantification.
    - Data sourcing and metering infrastructure, consisting of three classes of metering structure: Physical Metering, Virtual Metering, and Simulated Metering, is proposed. This data infrastructure supports the energy calculations throughout the chapters.

1.3. Technical Approach and Synopsis of Contributions

The contributions of this dissertation can be summarized as follows:

1.3.1. Energy-Performance as the Driver for Optimal Production Planning:

In Chapter 2, we focus on the production process within a manufacturing company and present an energy-aware production planning for a manufacturer, based on a two dimensional "Energy-Performance" measure. This measure takes into account the type of machinery used, products being produced and the process control strategies practiced. Using the "Energy-Performance", we define the energy consumption as a function of production output, namely the quantity produced per unit time, and incorporate it in the energy-aware production planning process. In the succeeding chapter 5, we provide a framework to generate the "Energy-Performance" profile at machine and process levels. Furthermore, the proposed production plan incorporates volatile electricity pricing schemes and helps the decision-maker optimize the production schedules with respect to these price fluctuations to achieve operating cost reduction. The problem is formulated as a stochastic optimization subject to (stochastic) production requirement and service level constraints. Moreover, the manufacturers' risk-averseness is also accounted for in the production planning optimization using Conditional Value at Risk (CVaR) of the manufacturer's loss function.

The primary contribution of this chapter is incorporating the "Energy-Performance" measure in the production planning optimization, which leads into the explicit inclusion of physics-based specifications, process control schemes, demand patterns and a host of other variables. We propose Scenario Generation approach to solve the optimization problem and provide experiments in which the formulation is applied to a day ahead production planning for two distinct "Energy-Performance" profiles. Furthermore, the impact of various electricity pricing schemes is tested for performance of the model using two electricity pricing schemes, namely Real Time Pricing (RTP), or spot pricing, and Time of Use (TOU) pricing schemes.

1.3.1. Business Value-Driven Asset Management for Building Energy Efficiency Optimization:

In Chapter 3, we address the energy efficiency optimization at the building level and argue that there is a significant potential for energy savings through effective asset management practices (i.e. Optimal Maintenance planning). Thereby, we provide a model to optimally plan maintenance strategies for the purpose of reducing energy consumption while ensuring that building performance requirements are met. We present the maintenance planning as a cost minimization problem, with three main cost elements, namely maintenance cost, "Business Value" cost (i.e. Penalty cost), and asset energy cost. We use building energy simulation approach to determine the assets' energy cost element and use U.S. Department of Energy's EnergyPlus simulation package for this purpose. Moreover, to ensure that building performance requirements are accounted for, we introduce a new term, asset "Business Value", into the maintenance planning, which is defined as the economic consequence of asset failure or performance degradation. A novel model is provided to measure the "Business Value" of energy consuming assets, using a modification of the classical Analytic Hierarchy Process (AHP) method and occupant thermal comfort analysis. This model provides methods to determine easy to measure outcomes of asset degradation, such as replacement/repair costs, as well as outcomes that are not easily quantifiable, such as building zones' function loss, occupant dissatisfaction, and productivity loss. The maintenance planning is formulated as a multi-objective stochastic optimization problem (MOSOP) with binary decision variables defining the optimal maintenance option applied to building energy assets. Sources of stochasticity in this optimization problem are weather profile, asset failures and a number of other asset specifications such as load profile. The contributions of this chapter are twofold: (1) Integrating the theory of reliability and asset management with building energy simulation. (2) Incorporating the energy consuming assets' business value, into the energy and performance optimization model.

1.3.2. Network Energy Efficiency Optimization in Industrial Systems:

In Chapter 4, an integrated view for a manufacturing facility is adopted and energy efficiency optimization is formulated as a network optimization problem. Given a set of feasible energy saving solutions for nodes of such a network, the objective is to define the share of energy saving for each node, according to appropriate economic, energy and performance requirements. We argue that dynamic interdependencies, in terms of "Energy Consumption" and "Performance", exist between production systems, equipment and facility's technical services; thus, we present an innovative framework to model and effectively capture such interdependencies between components of a manufacturing environment. "Performance" requirements at node level are measured in terms of appropriate Key Performance Indicators (KPI). By integrating these KPIs into the optimization process, we ensure feasible energy reduction according to industry specifications. The conceptual framework and optimization model are generic, but calculation details are application dependent. Therefore, we will use a case study that includes a manufacturing facility with a production line and building services including Heating, Ventilation and Cooling (HVAC) system, to demonstrate the modeling approaches. Furthermore, borrowing from the concept of "Specific Energy Consumption" in the machining operations, in this chapter, we present models to define the "Energy-Performance" profile, for the case of a single and multiple machine(s) manufacturing processes. In order to capture the optimizations parameters and energy consumption at node levels, simulation approach is used.

Primary contributions of this chapter are: (1) providing a framework for modeling dynamic energy and performance interdependencies between components of an industrial environment. (2) Incorporating such interdependencies into the energy efficiency optimization model. The modelling approach introduced is novel and unique in that it integrates the different aspects of an industrial system into a single model and explicitly includes the building energy dynamics, labor productivity and thermal comfort.

1.3.3. Data and Metering Infrastructure for Energy Efficient Industrial Systems:

In chapter 5, we introduce appropriate metering and modeling infrastructure to support the work in the previous chapters. The objective is to define a framework to construct a distributed information and computation engine to calculate the energy, material and information flow of a consumer product over the two dimensions of "Lifecycle" and "Supply Chain". These two dimensions construct a network in which energy content calculation is performed using hierarchical "Top-down" mapping of energy flow. At the network atomic level (representing industrial or business processes), energy consuming activities as well as data requirements at process or activity level are defined. The question of data metering infrastructure as a critical and key component of such energy content calculation is also addressed. Overall, the approach is to relate system information and metrics on multiple scales and levels of complexity and to integrate this input within a dynamic information processing and knowledge generating framework. Data sourcing and metering infrastructure proposed here consists of three classes of metering structure: Physical Metering, Virtual Metering, and Simulated Metering.

Chapter 2

2. Energy-Performance as the Driver for Optimal Production Planning

2.1. Introduction

The industrial sector in the U.S. currently accounts for 24.5 quadrillion Btu in 2013, representing approximately 34% of total energy consumption and the consumption of energy by the sector has almost doubled over the last 60 years. Furthermore, industrial energy consumption is expected to increase at an annual rate of 1.3% from 2013 to 2025 [3]. Given mounting concerns related to climate change as well as increasing cost of energy, resulting from likely taxes and regulations related to carbon emissions and increasing energy demands of developing countries, manufacturing enterprises is facing growing pressure to reduce their energy consumption. Production processes and manufacturing activities play a major role in industrial energy consumption, responsible for approximately 90% of energy consumption. For manufacturing enterprises, the share of energy costs has been on the rise among the overall production costs. This trend is expected to accelerate and be even more pronounced in the future due to the increasing energy demands [4]. However, balancing energy efficiency and production targets are challenging mainly due to rigorous demand requirements the manufacturers encounter. In order to ensure such balance, in this chapter, we integrate a two-dimensional measure, namely “Energy-Performance”, into traditional production planning to achieve energy efficiency in manufacturing processes. The resulting production plan simultaneously incorporates machine-level specifications as well as process-related measures.

At manufacturing machine-level, the "Energy-Performance" is described according to the definition of "Specific Energy" which is the energy used per single product or a certain number of pieces. In case of continuous or batch processes, energy per batch or per some certain volume can be used. "Specific Energy" of single machines has been addressed extensively in academic and industry literature [5-10]. As proposed by Gutowski et al. (2006), a machine's total electricity consumption can be decomposed into a fixed part, corresponding to the total standby power, and a variable part, representing the value added process such as material removal [11]. The following formulation is commonly used:

$$E_{spec} = \frac{P_0}{\dot{v}} + k \tag{2.1}$$

Where P_0 is the fixed part and $\dot{v}$ represents the actual processing rate. For a machining operation in a milling machine, this rate is denoted as Material Removal Rate (MRR) and is typically measured in ${cm^3}/{s}$ units. Equation (2.1) can also be used to represent "Energy-Performance" of other machining processes with discrete loading such as bending and press brake operations. Figure 2.1 presents for a milling operation the "Energy-Performance" as a function of MRR.

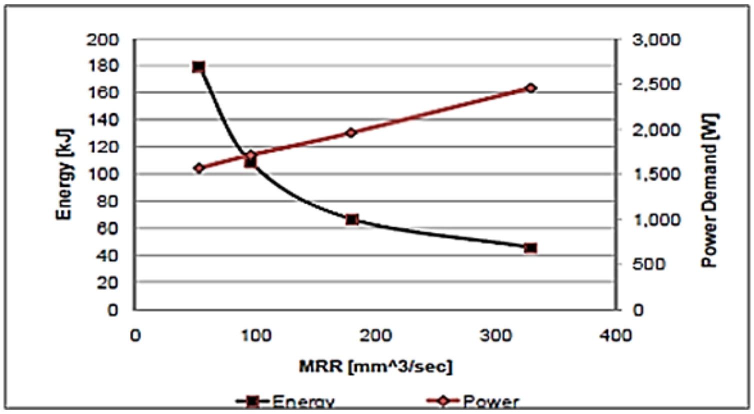


Figure 2.1: Energy-Performance for a Milling Machine

Furthermore, for a given machine, "Energy-Performance" varies depending on the type of materials processed or products produced. Machine's "Energy-Performance" is also correlated with degradation and tool wear, as depicted in Figure 2.2 [12]. With longer cutting time, the tool-wear increases resulting in higher energy consumption rate during machining. The "Specific Energy" values can be more than double at higher tool wears.

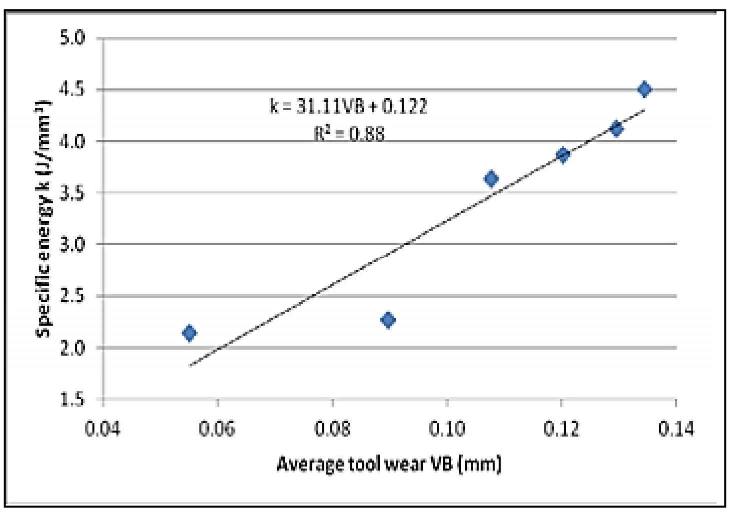


Figure 2.2: Specific cutting energy induced at different tool wear [12]

Extending to process level (e.g. Multiple machines working in series), the "Energy-Performance" depends not only on the individual machines' specifications (e.g. Process rate or MRR), but also on the type of process control strategies practiced. A control strategy normally takes advantage of production process' elasticity, defined in terms of slack times, to optimize the process. Such slack times depend on a number of factors, including machines' operational modes flexibility and demand frequency/volume. An ideal control strategy reduces the slack times to zero and potentially lead to optimal process with substantial energy savings. Such process would have a steady operation with no idle time in between. However, most control strategies are far from ideal; therefore various demand patterns (e.g. Different demand frequencies and volumes) generate different slack times, which in turn generate random "Energy-Performance" profiles. This suggests a stochastic "Energy-Performance" profile for any given process control scheme. In the succeeding chapters, we provide details on "Energy-Performance" calculation of industrial production processes and provide an illustrative case of a process consisting of three consecutive machine tools. The corresponding "Energy-Performance" profiles, determined as a function of the products processed per unit time, are reported for two distinct control schemes. Note that for the purpose of control strategy comparison, an average "Energy-Performance" can be used [13].

Given the average "Energy-Performance" profile and process throughput, the energy consumption patterns are determined for any production system. In order to construct the "Energy-Performance" curve and carry out the energy calculation, metered or summary data on machine/process power rates, energy intake and performance features are required. Salahi et al. (2013) define several metering approaches, namely, physical, virtual and simulated metering. In physical metering approach, data are directly obtained from sensors or smart meters. Historical data along with inferential statistical techniques using facility utility bills, accounting databases, and equipment specification and performance data may be used to derive the virtual metered data. In the absence of meters and historical data, simulation may be utilized to obtain the necessary information [14].

With the foregoing discussion in mind, the primary contribution of this work is incorporating the “Energy-Performance” measure in the optimal production planning, which leads into the explicit inclusion of physics-based specifications, process control schemes, demand patterns and a host of other stochastic variables. Furthermore the presented production plan takes into account volatile electricity pricing strategies. It is argued that adjusting the production with the knowledge of the cost of energy can lead to a significant cost savings in the electricity bills. In the absence of risk-aversion measures, an optimal production plan policy may incur significant economic losses with a positive probability. For that matter, in order to alleviate such risks we incorporate some risk measures, namely Conditional Value at Risk (CVaR), in the planning constraints.

2.2. Literature Review

In recent years the economic potential of energy-aware production planning in industrial processes has been recognized by a number of institutions and authors which has largely centered on scheduling with energy considerations. For the operation of a single machine, Mouzon et al. (2007) [15] study the scheduling of a CNC machine in a machine shop in order to minimize total energy consumption. They reported that up to 80% of the total energy consumed during idling, start up, and shut down could be saved if the machine was turned off until needed, instead of being left on all the time. In a follow-up work, Mouzon et al. (2009) [16] proposed a metaheuristic framework to compute schedules that minimize the total energy consumption and the total tardiness on a single machine. At the process level, a number of research works addressed the energy-aware scheduling using a flow shop problem that considers several objective optimizations including energy consumption, productivity and make span. For example, an optimal scheduling procedure for vehicle sequencing has been proposed by Wang et al. (2009) [17] to reduce energy consumption in an automotive paint shop. Along with energy consumption reduction, it was found that the paint quality can be improved and repaints can be reduced if appropriate batch and sequence rules are used. Other research utilized methods such as metaheuristic randomized neighborhood search algorithm and branch and bound methods and genetic algorithm solve such the scheduling problems [18-21]. The work by Chen et al. (2013) investigates energy reduction in serial production systems through efficient scheduling of machine startup and shutdowns and discussed the tradeoff between productivity and energy-efficiency in such systems [22].

Traditionally, manufacturing enterprises pay flat rates for each kilo Watt-hour (kWh) of electricity they consumed. However, in recent years, many markets have been created in order to deal with trade and supply of the electricity and to express the real price of energy. This changed the business model of manufacturers and their energy purchasing policies. Different types of piecing schemes, namely “time of use” contract

(TOU, on and off peak) and day-ahead market, which provides hourly varying price, have started to gain popularity. Integration of such energy management contracts with scheduling in the steel making industry is discussed in the research by Labrik (2014) [23]. Wang et al. (2013) proposed a schedule to control the status of the machines in a manufacturing system according to a TOU-based electricity price model under the production target constraint [24]. As opposed to this control perspective, in another related paper, the authors address the electricity cost as a function of manufacturing system parameters and the TOU to be used in profitability investigation energy pricing scheme [25]. Most of the researches in the energy-aware production planning focus on modeling of operational transitions that result from switching the operating modes when adjusting production planning according to time-dependent electricity pricing schemes [26]. In this chapter, we rather utilize the "Energy-Performance" measure in the conventional production planning. Borrowed from machine-level, this measure takes into account type of machinery used, products being produced and the process control strategies practiced. This chapter aims to provide an energy-aware production planning model that helps decision-makers optimize their production schedules with respect to fluctuations in electricity prices in order to reduce operating costs. The model is subject to (stochastic) production requirement as well as service level and risk constraints.

Risk management is not a new topic in production planning specifically in the area of the production plan and inventory modelling. A number of authors have incorporated financial risk measures, namely Value at Risk (VaR) and CVaR (Conditional Value at Risk) into classical inventory models. For instance, Tapiero et al. (2005) considers a classic inventory model which minimizes VaR [27]. Jammernegg et al. (2007) consider CVaR in a newsvendor problem [28]. Ahmed et al. (2009) investigate a coherent risk measure for both a single period newsvendor problem and a multi-period inventory control problem [29]. Zhang et al. (2009) expanded these models by addressing both expected values (losses, costs) and risk-aversion [30]. In this chapter we have incorporated Zhang et al.'s CVAR calculations as a risk measure in our production planning optimization model.

The remainder of this chapter is outlined as follows: The production planning problem is formulated next, followed by solution approach in section 2.4. In order to illustrate the applicability of the production planning, optimization model, a set of experiments is carried out in section 2.6 in which the optimization formulation is applied to a day ahead production planning for two distinct "Energy-Performance" profiles. The impact of various electricity pricing schemes is tested for performance evaluation of the model using two electricity pricing schemes, namely Real Time Pricing (RTP) or spot pricing and Time of Use (TOU) pricing schemes. The chapter concludes with model limitations, concluding remarks and an outlook on the future work.

2.3. Problem Statement

We start with nomenclature:

q_t = Production quantity for period t, decision variable

T = The length of the planning horizon, positive integer

I_j= inventory level at the end of period $t, t = 1,2, \dots, N$

ζ_t = Demand in period t, a continuous stochastic variable

P_t= Unit selling price in period t

b_t= Unit shortage (backorder) cost for unsatisfied demand in period t

h_j = Unit inventory holding cost in period t

E_t= Specific energy consumption in period t (kWh/item)

e_t= Unit energy price in period t ($/kWh)

$\pi_t(q_t, \zeta_t)$ = Profit realized during period t

$\Pi(\boldsymbol{q}, \boldsymbol{\zeta})$= total profit realized over entire planning horizon

$\boldsymbol{q}$ = production vector for the entire planning horizon, $\boldsymbol{q} = \{q_1, q_2, \dots, q_T\}$

$\boldsymbol{\zeta}$= Demand vector for the entire planning horizon, $\boldsymbol{\zeta} = \{\zeta_1, \zeta_2, \dots, \zeta_T\}$

I_t^U= Storage capacity for period t

P_t^U= Production capacity for period t

α = A threshold that the profit $\Pi(\boldsymbol{q}, \boldsymbol{\zeta})$ is greater or equal to

β = The degree of risk-aversion of the decision-maker, $\beta \in (0, 1]$

ω = a constant which CVaR is less than or equal to.

Energy-aware production planning is a stochastic optimization problem with probabilistic constraints. Let us consider an industrial system where demand is random and the decision on production rate has to be made before the demand is realized. The objective is to minimize the expected loss and restrict the risks of loss exceeding a certain level. The following assumptions are made:

- The Planning horizon is finite.
- Cost factors are deterministic and assumed to be constant over the planning horizon except for electricity cost coefficient.
- For the purpose of model generality, the demand, shortage and production quantities are continuous.

- Shortage with full backordering is allowed.
- Inventory level at the beginning of the planning period is equal to zero.

The length of each planning period is considered to be an hour. The inventory level is reviewed periodically to determine quantity to be produced in the next period in order to meet the demand in that period. As depicted in Figure 2.3, the inventory level, I_t, is checked at the beginning of each time period $t \in \{1,\ldots,N\}$, and depending on demand, q_t is produced to replenish the inventory. The demand for the period, ζ_t, is realized at the end of each period. The portion of unsatisfied demand (shortage/backorder) in period t is represented by b_t and is backordered in the following periods. The inventory level at the end of each period is I_t, and is given by:

$$I_t = I_{t-1} + q_t - \zeta_t, \quad \forall t \in T \tag{2.2}$$

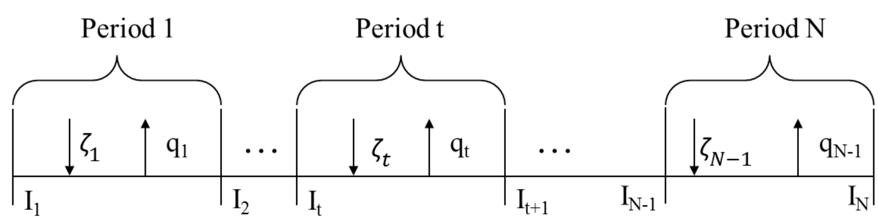


Figure 2.3: The inventory dynamics in the planning horizon

Production cost, denoted by c_t Consists of the labor and raw material cost per unit produced. In the event of stock-out the owners encounter shortage or backorder cost of b_t. Moreover, excess inventory at the end of each period, is subject to the holding cost of h_t. Lastly, the product is sold to the customers at the unit price s_t. Hourly energy consumption (E_t measured in [kWh/q_t]) is calculated as a function of the q_t using the "Energy-Performance" Profile:

$$E_t = \text{Ȩ}(q_t) \tag{2.3}$$

Here, the market demand is assumed to be a random variable denoted by ζ(.), where ζ: Ω →Ξ ⊂ ℝ is defined on a probability space (Ω, $\mathcal{F}$, *P*) with a density function *p(.)* and cumulative distribution function *P(.)*. Let total profit realized during each time period be $\pi_t(q_t, \zeta_t)$ when the demand is ζ_t:

$$\pi_t(q_t, \zeta_t) = p_t min\{I_t + q_t, \zeta_t\} - h_t max\{I_{t+1}, 0\} - b_t max\{-I_{t+1}, 0\} - c_t q_t - E_t e_t q_t \tag{2.4}$$

Hence the total profit over the *N* time periods will be:

$$\boldsymbol{\Pi}(\boldsymbol{q}, \boldsymbol{\zeta}) = \sum_{t=1}^{N} \pi_t(q_t, \zeta_t) \tag{2.5}$$

Our focus here is the loss function, therefore we consider:

$$\boldsymbol{J}(\boldsymbol{q}, \boldsymbol{\zeta}) \coloneqq -\boldsymbol{\Pi}(\boldsymbol{q}, \boldsymbol{\zeta}) \tag{2.6}$$

When $J(\boldsymbol{q}, \boldsymbol{\zeta}) < 0$, the process owner obtains a profit of $-J(\boldsymbol{q}, \boldsymbol{\zeta})$. The decision problem is to find the optimal production quantity to minimize the total loss in such way to reduce the energy costs associated with the production process. In other words, optimally shift the energy intensive production plan to time periods with lower electricity cost to reduce energy cost while satisfying service level and production constraints. The constraints are as follows:

The inventory levels are constrained by the storage capacities (I_t^U):

$$0 \le I_t \le I_t^U \quad \forall t \in \{1, \dots, T\} \tag{2.7}$$

Moreover, the production amount in each period cannot exceed the limit specified by the production capacity (P_t^U):

$$0 \leq q_t \leq P_t^U \quad \forall t \in \{1, \dots, T\} \tag{2.8}$$

Conditional Value at Risk (CVaR) is used here as an appropriate risk measure, which is defined as the expected value of tail distributions of losses. For a risk-averse owner the β-level CVaR is the expected loss, conditioned on the loss being lower than the β-level VaR over a given period. In the case of loss function here, the β-level VaR can be defined using the probability of total loss, $J(\boldsymbol{q}, \boldsymbol{\zeta})$, that is less than or equal to a threshold α:

$$\varphi_\beta\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big) = min\{\alpha \in \mathbb{R} | \mathbb{P}[J(\boldsymbol{q}, \boldsymbol{\zeta}) \leq \alpha] \geq \beta\} \tag{2.9}$$

The quantity $\varphi_\beta\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big)$, is the VaR which is the β-lower quantile of the loss function, where the parameter β is the prescribed confidence level and is typically set at %5. Using Rockafellar et al. (2002)'s definition, CVaR is defined as the expected value of $J(q, \zeta)$ when $J(\boldsymbol{q}, \boldsymbol{\zeta}) \leq \varphi_\beta\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big)$[31].

Define $\phi\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big) = [expectation\ of\ \beta - tail\ distribution\ of\ J(\boldsymbol{q}, \boldsymbol{\zeta})]$. Assuming demand has a density function *p(ζ)*, the CVaR can be written as:

$$\phi\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big) = \frac{1}{1-\beta} \int_{J(\boldsymbol{q}, \boldsymbol{\zeta}) \geq \varphi_\beta(q)} J(\boldsymbol{q}, \boldsymbol{\zeta}) p(\zeta) d\zeta \tag{2.10}$$

It is proved that $\phi\big(J(\boldsymbol{q}, \boldsymbol{\zeta})\big)$, can be defined by Krokhmal et al. (2002) [32]:

$$\phi(J(\boldsymbol{q}, \boldsymbol{\zeta})) = \min_{\alpha \in R} \left(\alpha + \frac{1}{1-\beta} E[(J(\boldsymbol{q}, \boldsymbol{\zeta}) - \alpha)^+] \right) \tag{2.11}$$

Where $[a]^+$ denotes the max-function *max{a,0}*. Given:

$$F_\beta(q,\alpha) = \alpha + \frac{1}{1-\beta} E[(J(\boldsymbol{q},\boldsymbol{\zeta}) - \alpha)^+] \tag{2.12}$$

In this problem, the risk constraint ensures that the mean values of the worst β % losses are limited by some value ω, chosen by the owner of industrial process. Hence, the optimization problem can be written as:

$$\min_{q \in Q} E[J(\boldsymbol{q},\boldsymbol{\zeta})] \tag{2.13}$$

$$s.t. \qquad \min_{\alpha \in R} F_\beta(q,\alpha) \le \omega$$

$$0 \le I_t \le I_t^U \quad \forall t \in \{1, \dots, T\}$$

$$0 \le q_t \le P_t^U \quad \forall t \in \{1, \dots, T\}$$

2.4. Solution Approach

Scenario generation approach may be used to solve the optimization problem presented in the previous section. The solution approach is broken down into two steps. First, Monte Carlo simulation is used to create scenarios and generate hourly demand and electricity price random variables. Then we use these random variables to find the optimal inventory strategy using large-scale optimization (MINLP) that seeks to minimize loss function subject to minimized tail risk. When using Monte Carlo to simulate the distribution the CVaR equation reduces to a discrete sum; therefore, Equation (2.12) is re-written as:

$$F_\beta(q,\alpha) = \alpha + \frac{1}{n(1-\beta)}\sum_{i=1}^{n}[(J(\boldsymbol{q},\boldsymbol{\zeta}) - \alpha)^+] \tag{2.14}$$

Minimizing this function minimizes the CVaR. Krokhmal et al. (2002) suggest dropping the minimization over α in the constraint in Equation (2.13) [31]. Therefore, we rewrite the risk constraint as follows:

$$\alpha + \frac{1}{n(1-\beta)}\sum_{i=1}^{n}[(J(\boldsymbol{q},\boldsymbol{\zeta}) - \alpha)^+] \leq \mu \tag{2.15}$$

The constraint in (2.15) is not exactly a CVaR constraint, but rather a CVaR-like constraint. This optimization problem can be solved after linearizing the constraint as a MILP using commercial software such as LINGO.

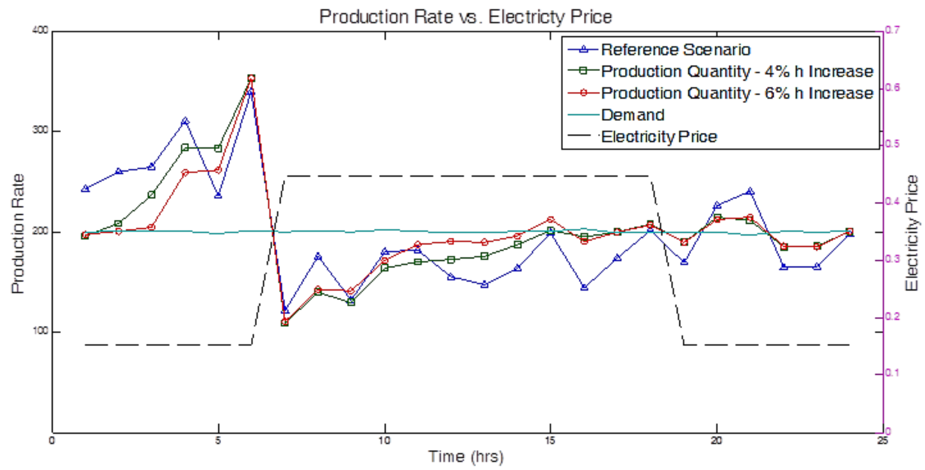
2.5. Sensitivity Analysis and Validation

In this section the impact of some of the most important parameters on the production planning optimization is evaluated for validation and sensitivity analysis purposes. Multiple designs of experiment were set up, each with different combination of parameters and the optimization model was run for each input combination and the outcomes were compared.

2.5.1. Impact of Holding Cost Coefficient

The first set of sensitivity analysis scenarios investigates the impact of holding cost coefficient on the output of the optimization model. A reference case is considered where the electricity price changes in a 24 hour period between the two rates and demand have low volatility. All cost coefficients are kept constant between the scenarios except for the holding cost coefficient, which is changed by 4% and 6%.

a) Production Rate vs. Electricity Price



b) Inventory Level vs. Electricity Price

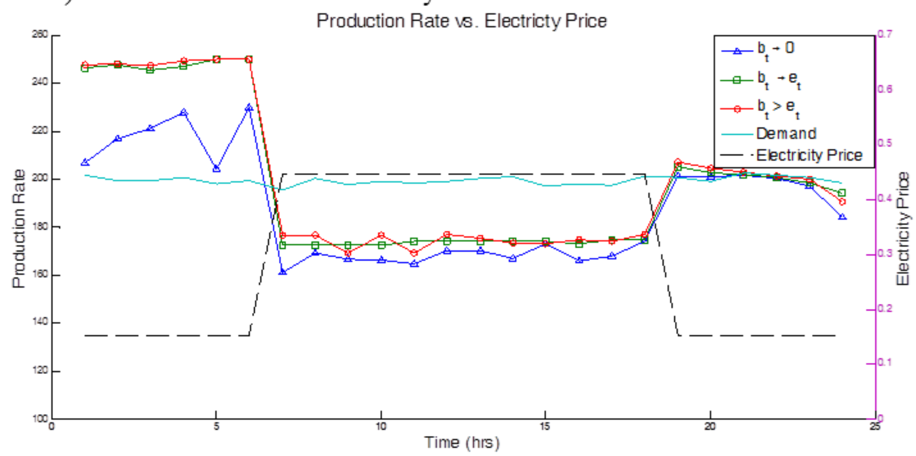
Figure 2.4: (a) Production Rate (b) Inventory Level vs. Electricity Price–Holding Cost Coefficients scenarios

As demonstrated in Figure 2.4, in order to avoid substantial electricity costs, the production rate decreases during hours with higher electricity price and the level of inventory increases just before and during these time periods. This behavior is common in all the scenarios; however, the higher the holding cost coefficient, the lower the corresponding scenario's inventory level would be.

2.5.2. Impact of Backorder Cost Coefficient

The second set of validation scenarios aims at evaluating the impact of backorder cost coefficients.

a) Production Rate vs. Electricity Price



b) Inventory Level vs. Electricity Price

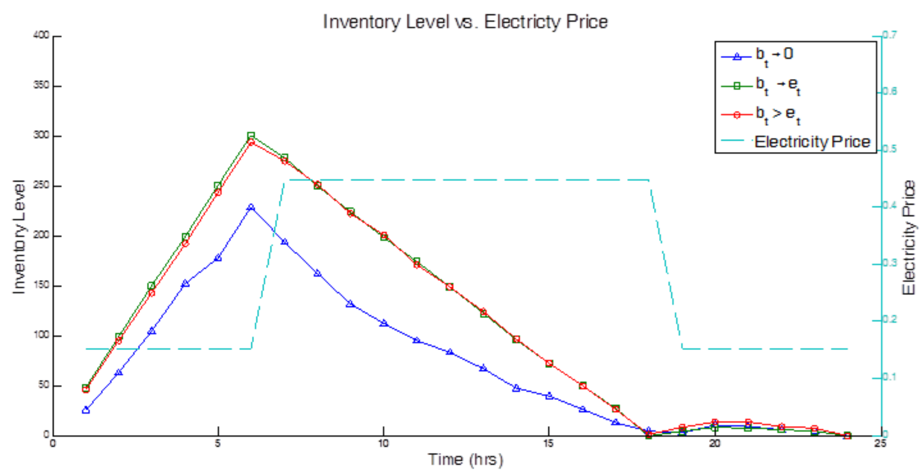


Figure 2.5: (a) Production Rate (b) Inventory Level vs. Electricity Price–Backorder Cost Coefficients scenarios

Similar to previous scenarios, electricity price (e_t) fluctuates with two rates. The higher rate of electricity price dominates the production cost coefficient (p_t) by 80%. However, p_t dominates lower rate of electricity price by 40%; Moreover, both production cost and electricity cost coefficients dominate the holding cost coefficient (h_t) considerably; hence, it is more desirable to produce and stock the inventory during periods with lower rates of electricity price. The impact of backorder penalty is examined and the results are summarized in Figure 2.5. It can be seen how the production rate is lowest throughout the time period for the case of no backorder penalty ($b_t \cong 0$) to minimize the total loss while satisfying service level constraints. As, b_t rises ($b_t \cong e_t$ & $b_t > e_t$), the production rate increases to avoid shortage.

2.5.3. Impact of Energy-Performance Profile

In this section we investigate how the variations in "Energy-Performance" profile is likely to impact the decision making using the optimization model introduced in section 2.3. This is particularly important when making decisions about modifying an existing control strategy that governs an industrial system in order to achieve energy saving. Changes in the control strategy obviously impact the "Energy-Performance" profile which in turn modifies the production planning. An industrial process is considered in which specific energy consumption changes linearly with the throughput rate. Cost coefficients are proportionally distributed and none of these coefficients dominate the others. In order to evaluate how the production plan is likely to change according to the modification in the "Energy-Performance" curve, the slope is increased by %1.5 and %3.5, while all other cost coefficients and service level constraints remain constant, as depicted in Figure 2.6. As expected, the daily production volume declines when switching from case 1 to case 3, so as to reduce energy consumption and minimize the total loss, while maintaining within demand requirement constraints.

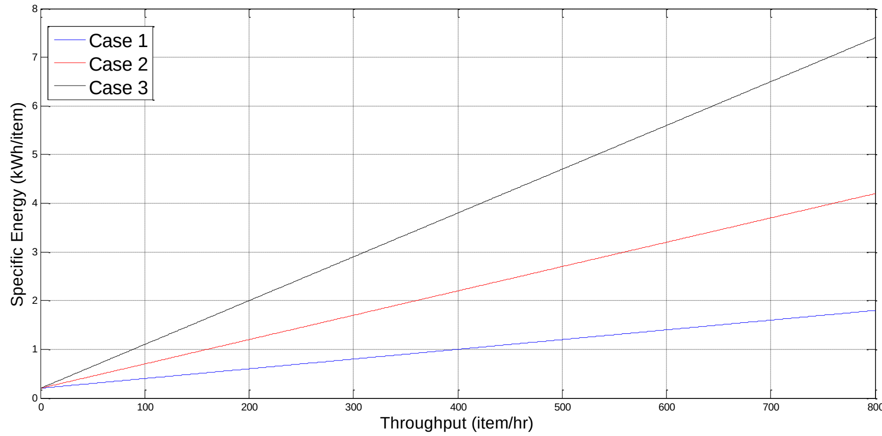


Figure 2.6: "Energy-Performance" Profiles

Figure 2.7 presents the average hourly energy consumption for the three cases studies here. As expected the average hourly and total energy consumption in case 2 and 3 rises by %8.5 and %78 respectively when compared to case 1. The total loss values are also considerably impacted by changes in the "Energy-Performance" patterns. This is mainly due to higher total energy costs per unit produced. The average loss in cases 2 and 3 shows an approximate%5 and % 21 increases from losses in case 1.

2.6. Experiments

With electric power industry's transition toward smarter grid advancement, many utility companies are offering new tariff plans in order to increase the elasticity of electricity consumers and moderate the extreme demand variation [33]. However, manufacturing customers' participation in such programs is subject to how economically sound the offered pricing schemes are. In this section, the optimization model presented earlier is used to evaluate the impact of distinct electricity pricing schemes on the production plan for the case of a single machine operation as well as a multiple machine industrial process.

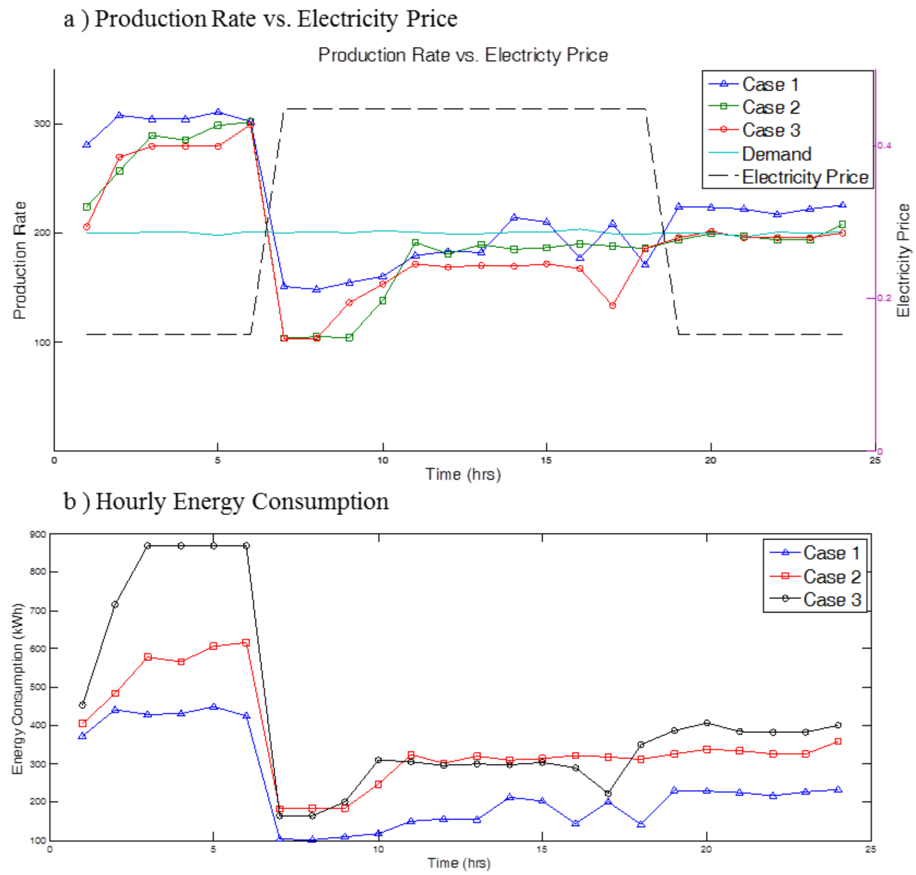


Figure 2.7: (a) Production Rate vs. Electricity Price (b) Hourly Energy Consumption – “Energy-Performance” Scenarios

Two time-varying electricity price plans are addressed here: (1*)* Time-of-Use (TOU) rates have different per unit prices ($/kWh) for usage during different block of time. The TOU rates analyzed in this section have two prices for peak and off-peak periods. (2) Real-time pricing (RTP) or Spot price scheme, in which rates vary continuously in a way that directly reflects the wholesale price of electricity rather than a pre-set price. The optimization model is formulated as a linear programming, solved using commercially available solver (i.e. LINGO) and is used to answer which of the two pricing incentives offered is economically sound and achieve savings in electricity cost without compromising the throughput. The risk-aware decision maker also intends to restrict the 5% (i.e. β=0.95) of worst losses, according to the CVaR risk constraint. While the model can incorporate any probability distribution type for demand and electricity price variables, the generation of scenarios poses limitations on how much of these distributions can actually be experienced in a typical industrial environment; therefore, scenario generation is performed using the volatile hourly electricity pricing data on a day-ahead basis from actual historical data. Moreover, the hourly demand comes from dynamic small/medium industrial load profiles [34]. Let us consider the case of a single machine process first in which discrete loading is applied, such as a bending operation. The typical production modes of such a machine stand-out as: the work-mode, the stand-by and the OFF-mode. When in stand-by, the machine remains in idle operation, but still consumes energy. Santos et al. (2011) used Equation (2.1) to calculate the specific process energy as a function of the throughput [35]. For discrete loading operations in this case, the process rate ($\dot{\mathbf{\upsilon}}$) is described as a function of the frequency of production cycles. Assuming the cycle time to be an hour, we have used the function reported by Santos et al. to define the "Energy-Performance" curve to be used in the production planning optimization as illustrated in Figure 2.8. The day-ahead production plan for the case of a single machine based on a 3-year electricity price and load profile data is illustrated for RTP and TOU pricing in Figure 2.9 and Figure 2.10 respectively. As it can be observed in Figure 2.9, during periods with lower electricity rates, the production volume rises to avoid substantial energy costs as well as stock outs during peak electricity price periods.

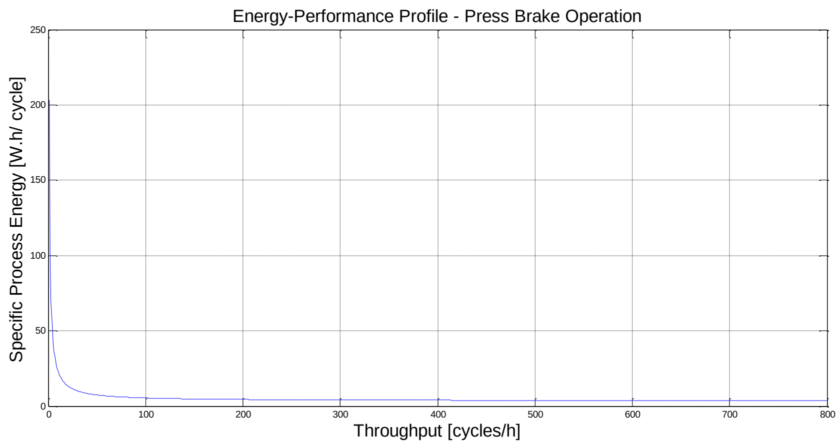


Figure 2.8: “Energy-Performance” for a Single Machine during Bending as a Function of Throughput

The inventory level is at its peak, just before the house with higher electricity price (i.e. t=6). Although the production rate seems to increase during periods with lower electricity price, demand volatility, holding costs as well as risk constraints limit substantial increases in production rate during $t \in [10,20]$ hours.

Next, let us experiment the TOU pricing in which electricity rate takes a peak and off peak rate depending on the time of the day. As displayed in Figure 2.10, the first production period has a lower energy price followed by a 12 hour peak price and the last few hours are subject to off-peak rates. In the case of a single machining operation, the production rate seems to have less stochasticity when compared to the previous pricing scheme due to lower volatility in electricity prices.

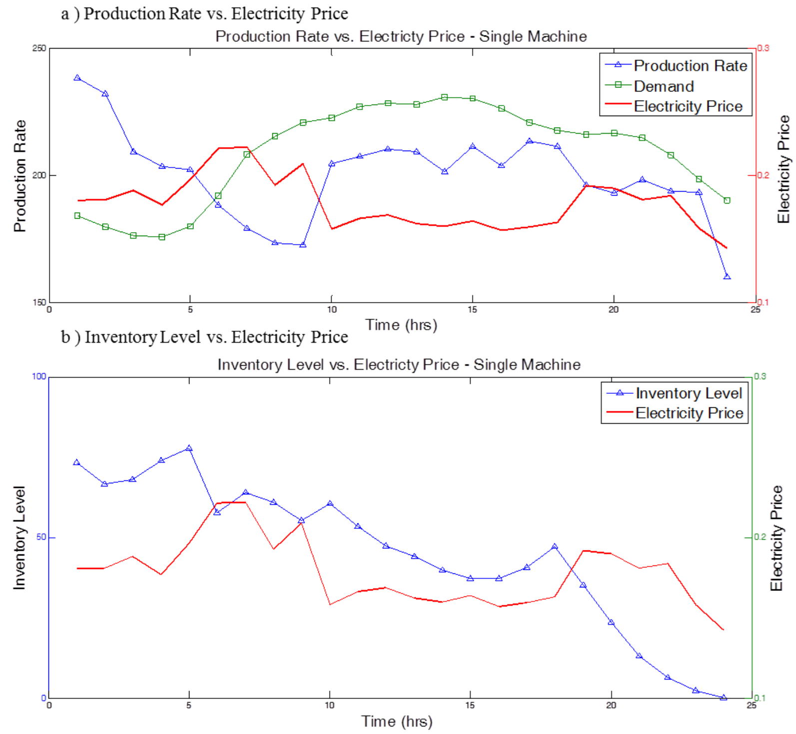


Figure 2.9: (a) Production Rate (b) Inventory Level vs. Electricity Price - Case of a Single Machine – Real Time Electricity Pricing Scheme

It is further observed that the inventory level reaches the peak as we get to peak price times, followed by a steady drop during the peak price period. This is explained by growing demand in this time frame and limits posed by risk and service level constraints. The optimal results for the two pricing schemes suggest an increase in both total loss and the average losses in the worst %5 of the loss distribution (CVaR), when switching from TOU to RTP electricity pricing schemes. These results suggest that production planning under former pricing schemes is potentially more economically sound compared to the alternative and provides the process owner with an annual savings of as much as $12500 in energy expenses.

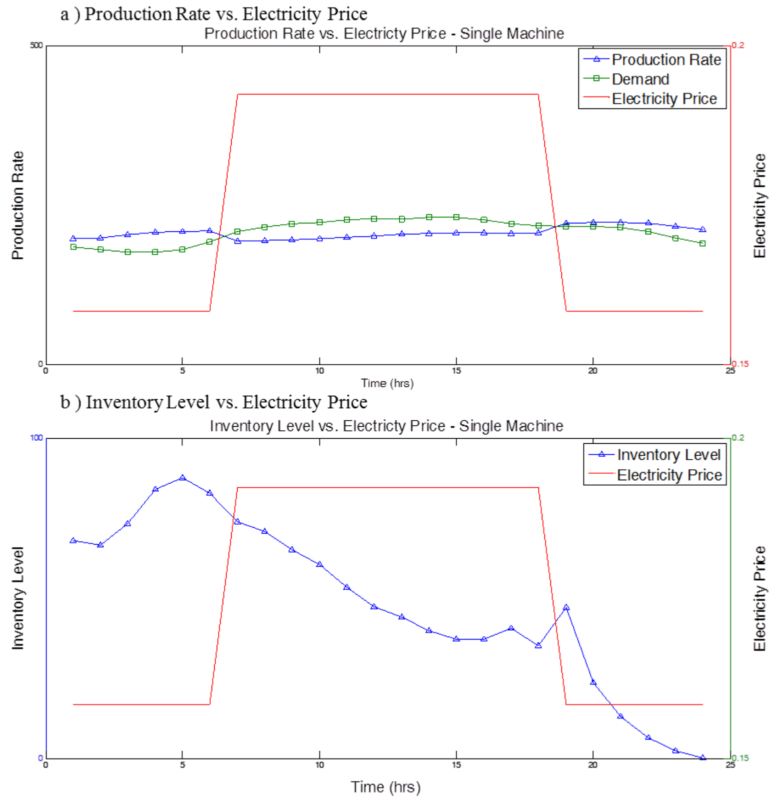


Figure 2.10: (a) Production Rate (b) Inventory Level vs. Electricity Price - Case of a Single Machine – Time of Use Electricity Pricing Scheme

Let us investigate the two electricity pricing schemes for the production planning of a second industrial process which consists of multiple machining operations and has the "Energy-Performance" pattern illustrated in Figure 2.11 below. According to this "Energy-Performance" profile, as the total throughput in the industrial process increases, the amount of energy per unit produced also rises in a linear fashion.

As depicted in Figure 2.12 and Figure 2.13, similar to the case of a single machine, the process rate and inventory level rise during periods with lower electricity rates in order to avoid shortage and also cut the excess energy costs.

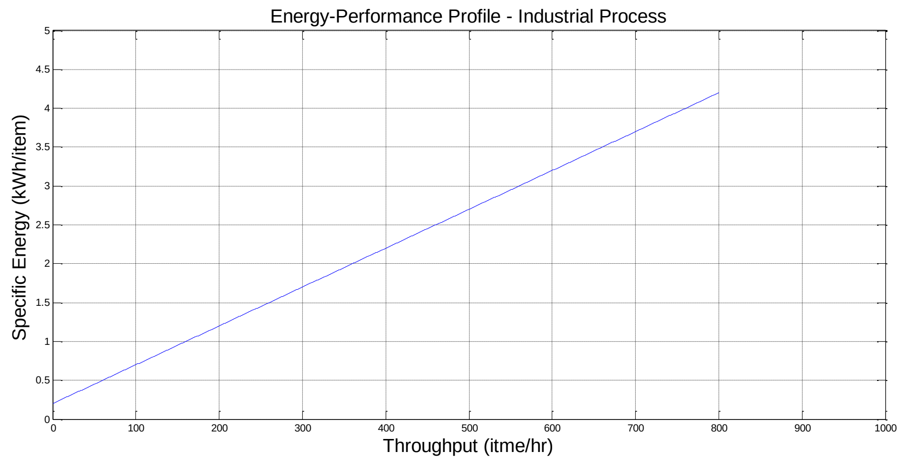
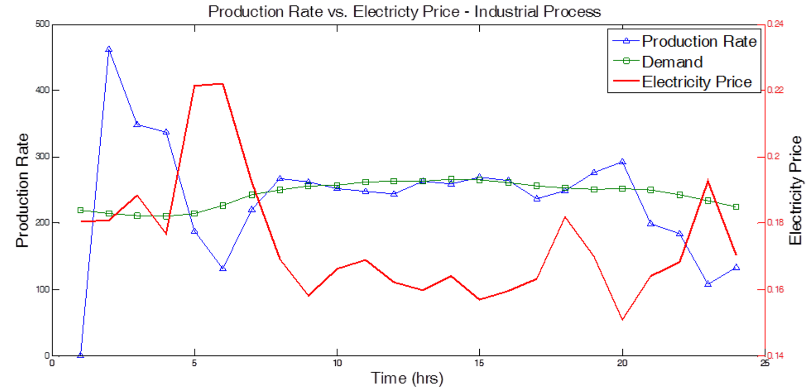


Figure 2.11: “Energy-Performance” for a Multiple Machine Process as a Function of Throughput

Both production and inventory levels are relatively more volatile under the TOU pricing scheme and reach up to production and inventory capacities just before the peak pricing period. This is mainly dictated by the “Energy-Performance” profile which indicates a substantial increase in energy consumption for higher throughput values; therefore, although producing in larger numbers increases the energy consumption, this cost is compensated for by the lower rate of electricity price during off-peak periods. Hence, in this case it is beneficiary for the process owner to produce and stock as much as possible during periods with higher rates in order to avoid stock out due to high rates of electricity price in peak periods.

Similar to the results obtained in the case of a single machine, optimization results favor production planning using TOU profile. The manufacturer can obtain a 6% daily profit gain, equal to as much as $70,000 annual energy cost savings, using TOU pricing when compared to RTP pricing scheme.

a) Production Rate vs. Electricity Price



b) Inventory Level vs. Electricity Price

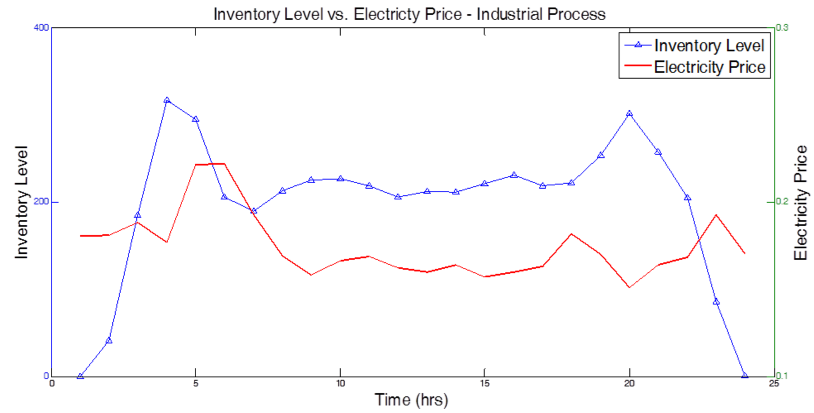


Figure 2.12: (a) Production Rate (b) Inventory Level vs. Electricity Price - Case of a Multiple Machines – Real Time Electricity Pricing Scheme

The aforementioned day-ahead optimal production plan reports the decision making for a risk averse manufacturer (i.e. β=0.95). In order to examine how these results are likely to change according to the manufacturers' risk-averseness, the two pricing schemes were run for a risk taker manufacturer (i.e. β=0. 3[1]) for both cases of single and multiple machine operations, and the results were compared.

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[1] The decision maker intends to limit the expected value for %70 of worst losses, by a certain predefined value.

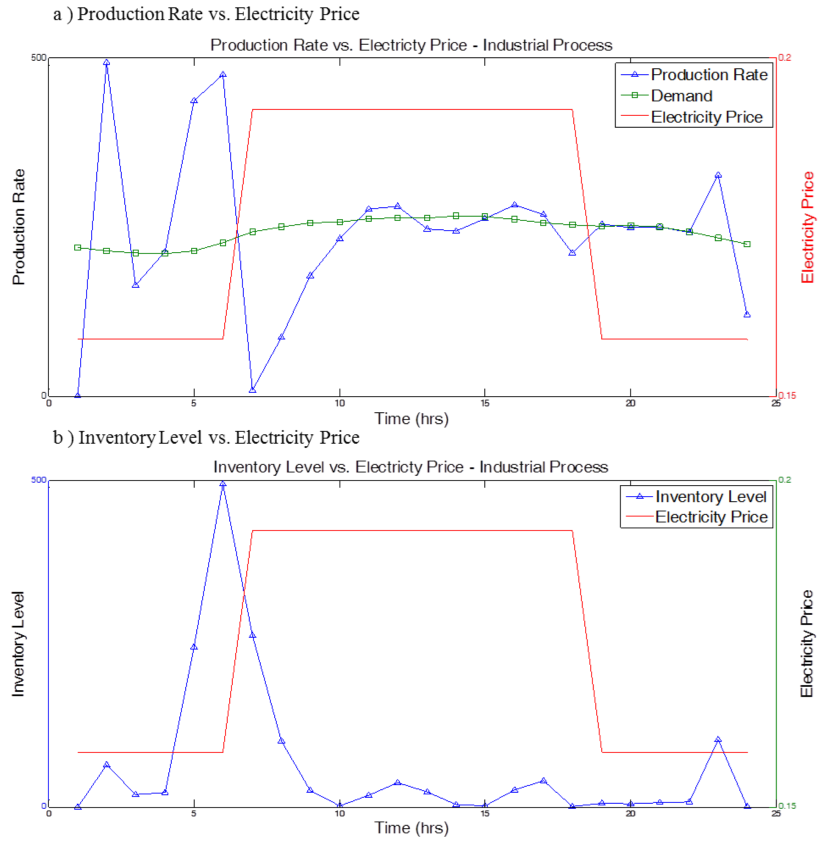

Figure 2.13: (a) Production Rate (b) Inventory Level vs. Electricity Price - Case of a Multiple Machines – Time of Use Electricity Pricing Scheme

It is observed that for the risk taker owner of a single machine operation, the hourly production rate increases by as much as %19 and %26 when adopting RTP and TOU pricing schemes respectively.

However, for the multiple machine operation, the decrease in manufacturers' risk-averseness leads into negligible changes in the optimal hourly production rate, which is explained by the "Energy-Performance" measure in Figure 2.11 as follows. Although the increase in β parameter allows for higher production rates, the substantial increase in energy consumption for higher levels of throughput cannot be compensated for with the revenue obtained from additional production; thus, the optimal hourly production reveals a negligible sensitivity to β parameter in this case.

Similar to the previous case of a risk-averse manufacturer, switching from RTP to TOU pricing suggests a profit gain in both single and multiple machine processes. Moreover, compared to the scenario with β=0.95, the risk taker process owner of a single machine operation, may potentially save as much as %20 and %25 in total losses using RTP and TOU pricing schemes respectively. As expected, such savings would be lower for the multiple machine operation (%3 and %7 for RTP and TOU pricing, respectively) due to relatively lower change in the production rate. The average production and inventory levels as well as The loss and CVaR values for single and multiple machines optimal planning under both pricing schemes are included in the appendix A.

2.7. Conclusion

In this chapter we have expanded the conventional optimal production planning by introducing a two-dimensional measure, namely “Energy-Performance”, into the modelling process. The definition of “Energy-Performance” is borrowed from “Specific Energy” at machine level, which is the energy used per single product or a certain number of pieces. Expanding to multiple machine processes, “Specific Energy” calculation may be used to define the “Energy-Performance” profile as a function of process throughput. By incorporating this measure, the production planning will explicitly include physics-based requirements, demand pattern as well as a host of process and machinery parameters. We have formulated the problem as a MILP and introduced risk-averse constraints to ensure profitability of the production plan.

Sensitivity of the optimization problem to a set of parameters, namely cost coefficients and variations in the “Energy-Performance” curve, was investigated through several experiments. We have further argued that one of the applications of the presented optimization model is energy-aware production planning according to various electricity pricing schemes. Moreover, as an application of the optimization model, an energy-aware production plan is presented in which various electricity pricing schemes are incorporated. This application was demonstrated for a case of a single machining operation as well as a multiple machine industrial process. The illustrative example results suggest that switching to a “Time of Use” pricing scheme seem to be economically sound for both single and multiple machine industrial processes and lead to lower total economic loss as well as lower risk values.

Chapter 3

3. Business Value-Driven Asset Management for Building Energy Efficiency Optimization

3.1. Introduction

With almost 97 quads consumptions, buildings account for approximately 41 percent of the primary energy consumption in the U.S. in 2015 [36]. Energy used by commercial and industrial buildings is responsible for about $200 billion in annual costs and creates nearly 50 percent of national emissions of greenhouse gases (GHGs) that contribute to global climate change. Moreover, within an industrial plant, facility and technical services (lighting, heating, cooling, air conditioning, office equipment, computers, etc.) which are responsible for maintaining the required conditions for “industrial process”, constitutes an important fraction of the total energy use. Energy reduction and efficiency practices in building facilities range from building design and plant-wide energy audits [37], to energy reduction in lighting and HVAC (Heating, Ventilation and Air Conditioning) systems as the most important components of technical services. Liu et al. (2013) present an energy efficient building design for an industrial plant to minimize the annual energy cost taking into account production scheduling and uncertainties such as weather conditions and energy prices while estimating the performance of the design [38]. Building energy management systems (BEMS) which control and monitor the building’s mechanical and electrical equipment such as ventilation, lighting, power systems, fire and security systems have also been used extensively for energy efficiency in facilities.

In recent years due to intensification of energy consumption in HVAC systems, numerous studies have focused on improving performance and energy efficiency of such systems. These practices consist of optimal control strategies such as reset control, setback control, improves start-stop times and occupied time adaptive control as well as optimal configuration and component level energy efficiency improvements. Note that most researched focus on evaluation of temperature and humidity-based control systems [39-41]. For instance, Huang et al, investigated five energy management control functions, and evaluated using a variable air volume heating, ventilating and air conditioning, VAV-HVAC. Their result suggests that the optimal set point strategy is very useful in achieving energy efficient operation of HVAC systems [42]. A decision support model is presented by Doukas et al. (2007) which takes advantage of rule sets based on a typical building energy management system. This proposed decision support system is set to optimize building's energy operation, according to internal conditions and comfort requirements [43]. A number of scholars adopt simulation approaches for HVAC optimization and energy management. Fong et al. (2006) present a simulation-evolutionary program coupling approach for effective energy management of HVAC system [44]. An automated control for a thermally-activated building system is investigated in the work by Gwerder et al. (2008) to optimally switch between heating and cooling [45].

While the aforementioned energy optimization approaches are certainly effective in achieving energy savings, most buildings are significantly net energy positive and consume far more energy compared to their optimal design and operation conditions. This condition specially worsens as the age of the buildings and their equipment increase.

This is mainly because in the absence of appropriate maintenance practices, a building designed and commissioned for "optimal performance" starts fading fast from energy efficient to energy intensive, immediately following the start of its service. Thus, asset management techniques and optimal equipment maintenance planning can potentially lead into substantial energy savings in building facilities. However, limited attention has been drawn to energy waste and performance degradation due to the lack of good state of maintenance practices and few studies have been conducted on the energy efficiency part of an asset management project. The benefits of combining asset management and energy management, including monetary savings, increased equipment reliability, reduced production cost and improved decision-making is addressed in the work by Chin et al. (2010) [46]. However, no mechanism is introduced to incorporate such energy management dimensions into current asset management practices. Wang et al. (2015) discusses a maintenance plan optimization problem for the energy efficiency purpose in a building energy efficiency retrofitting context. In their work they propose a corrective maintenance planning approach, where the corrective maintenance for malfunctioning retrofitted items in a building is involved [47]. While the suggested modelling approach is certainly a considerable improvement to a retrofitting project, there is still room for a considerable added value in terms of energy and cost savings by incorporating an effective preventive maintenance regime into an existing building asset management practice. Commercial asset management systems (e.g., IBM Maximo, TRIRIGA, etc.) have also been extensively popular among facility managers and real estate executives to manage their assets and reduce operational and energy costs [48].

In this chapter, we integrate the existing asset management and reliability theory with building energy simulation technology to develop effective and optimal maintenance strategies for the purpose of reducing energy footprint of buildings while ensuring that building performance and business objectives are met. The optimality criteria take into account not only the building's energy consumption, but also the "value" that the building assets generate with respect to building business objectives. An energy efficient asset with minimal stoppages due to failures or replacements, coupled with minimal business value loss would certainly generate high asset values. While the theory of reliability and asset maintenance is largely borrowed from the literature, the integration of these models with building energy simulation has not been addressed before. Moreover, the concept of directly integrating building business objectives into energy and performance optimization is an enhancement to the current asset management practices where penalties are assigned only when comfort constraints are violated [49]. The asset management methodology presented here is the foundation for a technology, Building Energy Asset Management (BEAM), developed by Rutgers State University of New Jersey. Note that for illustration purposes we focus solely HVAC assets and demonstrate the aforementioned models for components of such assets.

This chapter outlines as follows: a brief overview of building energy simulation using EnergyPlus simulation packages is given in the next section. In section 3.2, we demonstrate a methodology, Business Value Model (BVM), to compute the building assets' value derived from its business objectives. Next, a computationally efficient optimization algorithm is presented integrating building business and comfort requirements with maintenance planning to achieve energy efficiency. Finally, we demonstrate the models through case studies and argue that while the maintenance plans seem intuitive, especially by experts, the details of these plans together with cost factors that are broken down into energy, maintenance and penalty cost, can significantly help achieve energy and cost savings.

3.2. Building Energy Computation and Co-simulation Approach

U.S. Department of Energy's EnergyPlus simulation package is used to simulate building energy consumption. An application of EnergyPlus is configured according to the specifics of building enclosure, heating/cooling (HVAC) equipment, lighting, and average occupancy characteristics. Given weather input data, the EnergyPlus model, then generates a deterministic set of outputs on energy consumption of building assets. The stochasticity of asset failures can be programmed in a separate platform (i.e. MATLAB). The communication between the two platforms is accomplished by a MATLAB script package, MLE+ [50]. The MLE+ co-simulation is written in a script language and, in addition to providing input/output channel between the two applications, it synchronizes their executions with a common discrete time step. At each time step, the variables corresponding to building thermal dynamics and performance computed by EnergyPlus are read from EnergyPlus through an "External Interface". These variables are then passed to the core engine and used by "Asset Efficiency Degradation", "Asset Reliability", and "Maintenance Optimization" functions. The energy transfer or conversion efficiencies of assets are calculated based on their loads (instantaneous and cumulated). Random failure events are generated based on lifetime probability distributions defined by asset reliability models. The asset efficiency measures and availability indicators are then "injected" back to EnergyPlus for the next time step simulation. Table 3.1 lists the notations used throughout the rest of this chapter and their explanation.

Table 3.1: Nomenclature

(T;k;l)	Maintenance policy, *k*= maintenance type; *l* =freq.; *T*=season
$x_{i,Tkl}$	Binary decision variable
X	Vector of Maintenance policy
$S(.)$	Total building energy consumption
$C(.)$	Total cost of maintenance & penalty
U	Control variable(s) (heating & cooling set point
Φ	Random load, function of weather & operation factors (e.g. occupancy)
$\omega(\varphi, t)$	Random failure event at time t, function of load
$g(X)$	Total preplanned maintenance cost
$h(X, \omega(\varphi, t))$	Total unplanned reactive maintenance cost
$p(X, \omega(\varphi, t))$	Total penalty cost due to asset failures
$EPI_i(X, \omega(\varphi, t))$	Asset *i*'s energy performance improvement due policy X
$CRR_{i,Tkl}(.)$	Reduction in unplanned cost as a result of maintenance option *(T;k,l)* on asset *i*
$CPR_{i,Tkl}(.)$	Penalty cost reduction as a result of maintenance option *(T;k,l)* on asset *i*
$CR_{Base_{iT}}(.)$	Unplanned maintenance cost for base maintenance option on asset *i* in season *T*

B_{limit}	Annual budget limit
$(N(\omega(\varphi,t))_{Base})_i$	Number of failures for asset *i* in base maintenance option
$(N(\omega(\varphi,t))_{Tkl})_i$	Number of failures in *(T;k,l)* for asset *i*
EW	Energy weight matrix
DG_T	Vector of average seasonal degradation of assets in season T
DG_{iT}	Average seasonal degradation of asset *i* in season T (element *i* of DG_T)
BVM_i	Penalty per failure of asset *i*
Rf	Restoration factor
$(C\_rpr)_i$	Repair cost for asset *i*
$(C\_rpl)_i$	Replacement cost for asset *i*
$CP_{Base_{Ti}}(\omega(\varphi,t))$	Penalty cost for base option on asset i in season T
$CPR_{i,Tkl}(\omega(\varphi,t))$	Reduction in penalty cost due to option *(T;k,l)* on asset *i*

3.3. Building Value Model (BVM)

The priorities of the maintenance actions and budget appropriation are essential aspects of asset management practices to ensure reliable and efficient performance of assets and to provide continuous building functions without unplanned interruption. The value-modelling approach introduced here, identifies the business value of physical assets and define the criticality of those assets with respect to a building's purpose and functionality. Business value is defined in terms of economic loss due to failure or performance degradation of an asset. Assets with higher business values are considered more critical and thus have higher priority for maintenance planning. Such business values can also be used as appropriate Key Performance Indicators (KPI) in other energy efficiency practices within the building facility as explained in Chapter 4. Examples of physical assets considered here are HVAC components: namely, centrifugal water cooled chiller, air handler's supply and return fans, boilers and heat exchangers.

Economic consequences of failure/performance degradation of building assets cover easy to measure outcomes, such as replacement/repair costs, as well as outcomes that are not easily quantifiable, such as building zones' functionality loss, occupant dissatisfaction, and productivity loss. BVM not only takes into account both such consequences, but also, allows for seasonality considerations in the asset business value calculations. Seasonality is defined based on weather conditions (i.e. Cooling vs. heating seasons) as well as building operation schedule and occupancy patterns (i.e. Periods of intensive/peak occupation and usage). The duration and timing of the cooling and heating seasons for a particular building is generally determined by its geographic location.

Depending on the type of "Functional Tasks" performed in various building zones, two distinct methods may be used to calculate the business value of assets serving each type of zone. The following steps are taken:

1. Building zones are categorized based on the type of "Functional Tasks" performed in them as follows: a) zones that support consistent "Task-related" functions such as office spaces and zones housing the labor tasks b) zones with "Non-task-related" functions such as common areas and hallways.

2. The assets' "Business Value" is defined by the economic consequence of losing Assets serving each zoning category during cooling and heating seasons at peak and off-peak usage periods.
3. For assets that are shared among multiple zones, economic loss accounts for all the types of zones that are served by that asset.

3.3.1. Asset Business Values for Task-related Functions

For zones that involve "Task-related" functions, asset business value can be estimated using the percentage of the occupants' performance (i.e. "Productivity") loss due to asset degradation/failure. Here we focus on degradation and the probability of failure of HVAC components. At the design stage, performance characteristics of HVAC components are calculated in order to ensure that Indoor Air Quality (IAQ) requirements are met. Kosonen et al. (2004) show that task related performance is significantly correlated with the human perception of thermal environment and that such perception, in turn, is dependent on temperature [51]. Any deviation from the optimum performance of HVAC components will result in deterioration of IAQ and loss of thermal comfort, with a resulting loss of occupant productivity. According to the ASHREA standard for "Thermal Environmental Conditions for Human Occupancy" (ASHRAE standard 55-2012) [52], thermal comfort is a condition of mind, which expresses satisfaction with thermal environment, assessed by subjective evaluation (i.e. Thermal sensation vote). It is a conscious feeling commonly graded into the categories, cold, cool, slightly cool, neutral, slightly warm, warm, and hot; and is related to the thermal balance of each individual human body considered as a whole. This balance is influenced by a number of physical and environmental parameters, namely the body's metabolic heat production, physical activity, clothing, air temperature, mean radiant temperature, air velocity and air humidity [52]. Thermal comfort can be estimated by a Predicted Mean Vote (PMV) index introduced by Fanger which is an index to predict the mean value of the votes of a large group of people on the 7-point thermal sensation scale ranging from -3 (very cold) to +3 (very hot) [53]. ISO-7730 [54] and ASHREA provide algorithms to calculate PMV as a function of the parameters discussed earlier in this section. Suggested acceptable PMV limits in workplaces are within the range of -0.5 and 0. We use the PMV index to quantify the thermal discomfort, caused by elevated or decreased air temperature, as a result of asset failure. It is assumed that the mean radiant temperature is equal to the air temperature [55]. Such temperature data may be extracted from temperature sensors. If physical temperature sensors are not economically viable, data can be collected using a building energy simulation tool such as DOE's EnergyPlus simulation package. It is further assumed that asset failure has negligible impact on the air velocity and humidity. Physical activity and building occupants' clothing parameters are defined according to the type of activities performed and type of clothing worn. PMV is then used to define a quantitative relationship between occupants' performance (i.e. "Productivity") and thermal environment by means of regression analysis as discussed in the works of scholars namely Fanger and Gagge et al. (1972) (1986) [53][56]. This relationship is as follows:

$$PL = b_0 + b_1 PMV + b_2 PMV^2 + b_3 PMV^3 + b_4 PMV^4 + b_5 PMV^5 + b_6 PMV^6 \tag{3.1}$$

Where PL in Equation (3.1) is the loss in percent of employee performance and $\mathrm{b}_0 - \mathrm{b}_6$ are regression coefficients that can be obtained by experimental data sampling.

Occupants' income or income contribution is then used to derive a monetary value for the loss of an asset, due to productivity loss of building occupants for the duration of asset unavailability. The rationale for using salary is that employees are hired to earn money for their company, and when their performance decreases the income of the company decreases; thus loss of employees' productivity can be used as a proxy with which to estimate the economic consequence of an assets' loss and/or failure.

3.3.2. Asset Business Values for Non-Task-Related Functions

For zones where "Non-task-related" functions are performed, loss of an asset leads to measurable as well as intangible and "difficult-to-quantify" consequences such as occupant dissatisfaction or zone functionality loss. These intangible consequences can be considered in Business Value calculations on the basis of their contribution to the total economic consequence of assets' loss. This economic value is inferred from management judgment. A modification of Analytical Hierarchy Process (AHP) introduced by Boucher et al. (2007) [57] can be used to capture the economic contribution of such intangible consequences as assessed by the building or facility management. Consider the three-level hierarchy structure in Figure 3.1. The first level is the overall objective of the problem to be solved by AHP. The bottom level is the list of assets serving the zone under study to be evaluated through the AHP methodology. The second level is a list of criteria that is used to compare assets in terms of their criticality to the zone under study. Note that the criteria in level two represent measurable and "difficult-to-quantify" consequences of failure of assets.

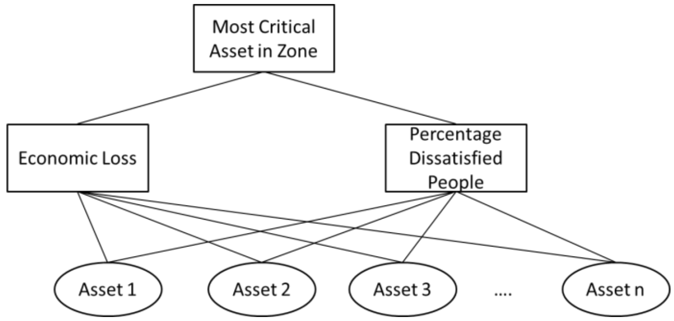

Figure 3.1: Three Level Hierarchy for Asset Criticality

The first criterion in level two of the hierarchy is the quantifiable economic consequence of asset failure. For instance, in conference rooms or auditorium zones, this economic consequence includes the average business value of an event that would be lost due to an asset failure. However, the value of the second criterion (i.e. The percentage of dissatisfied people in the zone) is measured in percentage terms using the Predicted Percentage of People Dissatisfied (PPD) index [53]. PPD index is an indication of the percentage of people who could be expected to complain about the thermal quality of a given indoor environment. It is based on the assumption that people voting +2, +3, -2, or -3 on the thermal sensation scale are dissatisfied, and the simplification that PPD is symmetric around a neutral PMV [52]. Note that temperature fluctuations in a zone happen due to asset's unavailability/degradation. PPD criterion also has economic value; however, this monetary value is not easily measurable. For Assets serving zones with "Non-task-related" functions, Business Value" is estimated as follows:

1. The economic consequence of loss of business due to asset failure is measured in dollar terms.
2. The percentage of thermally dissatisfied people is estimated using the PPD index as a function of PMV according to Equation (3.2).

$$PPD = 100 - 95\exp(-0.03353PMV^4 - 0.2179PMV^2) \tag{3.2}$$

For each asset, a judgmental evaluation using an inverse of the traditional AHP method is applied to compute the contribution of the thermally dissatisfied people to the total economic consequence of asset failure. In this way, the model converts the levels of the criterion to a monetary scale. A brief review of this process, based on a method introduced by Boucher et al. (2007) [57] is included in the appendix B.

3.4. Business Value Model - Case Study

For illustration purposes, we will use an example model, "5-ZoneAir-Cooled.imf" which comes with the EnergyPlus installation. This model simulates a simple 5-zone building, with single floor and 5000 sq. ft. conditioned area. The HVAC system includes a variable air volume system, a hot water boiler, and an electric compression chiller with air-cooled condenser. The building simulation was executed over a period using USA_CA_San.Francisco.Intl.AP.724940_TMY3 weather file (National Solar Radiation Data Base). This building is used for recreational services and consists of an auditorium and a ballroom for public and private events as well as 3 office spaces for planning and organizing such events. Assuming one day of asset unavailability upon failure, indoor air temperature fluctuations is derived from simulation runs and is summarized in Table 1. Kosonan et al. (2004) investigated the productivity gain/loss due to changes in thermal comfort and delivered productivity as a polynomial function of PMV for a variety a number of office-related tasks [51]:

$$\begin{aligned} PL = {} & 1.5928PMV^5 - 1.5526PMV^4 - 10.401PMV^3 \\ & + 19.226PMV^2 + 13.389PMV + 1.8763 \end{aligned} \tag{3.3}$$

In this chapter, we have used the PMV values and Equation (3.3) to calculate the occupant productivity loss (PL) upon failure of assets serving office space zones. These values are then compared with the situation where assets are available. According to results in Table 3.2, the productivity loss attributable to thermal discomfort increases from %1.4 to %4.85 per employee due to chiller unavailability.

Table 3.2: Seasonal Average Temperature, PMV and PL for Asset Availability and Unavailability by Asset

Chiller (cooling season)	**Available**	**Unavailable**
Temperature (℃)	23.75	26.45
PMV	-0.52	0.18
PL(%)	1.4	4.85
Economic Loss Per Employee ($)	280	970
Boiler (heating season)	**Available**	**Unavailable**
Temperature(℃)	20.95	20.34
PMV	-0.45	-0.60
PL(%)	0.6	2.7
Economic Loss Per Employee ($)	120	538
Supply Fan (cooling season)	**Available**	**Unavailable**
Temperature(℃)	23.75	26.70
PMV	-0.52	0.40
PL(%)	1.4	9.62
Economic Loss Per Employee ($)	280	1924
Supply Fan (heating season)	**Available**	**Unavailable**
Temperature(℃)	20.95	20.69
PMV	-0.45	-0.52
PL(%)	0.6	1.4
Economic Loss Per Employee ($)	120	280

Assuming a $100 average daily income contribution (per employee), the cost of productivity loss increases from $140 to $485 when chiller is unavailable; therefore the economic loss per failure for chiller is estimated to be $345 per employee and $3450 for total zones population[2]. Economic loss per failure for the assets serving office zones in the case study are summarized in Table 3.3 below. It is worth to mention that the chiller and boiler are operational only during cooling and heating seasons respectively. Air handler's supply fan is operational during heating and cooling seasons. Moreover, since these zones have fixed annual office hours (9:00AM-5:00PM), it is reasonable to consider equal economic loss due to employee productivity decrease in cooling/heating peak and off-peak usage seasons

Table 3.3: Seasonal Economic Loss per Asset Failure for Office Space Zones

Asset	Economic loss per failure ($)
Chiller (cooling season)	34,50
Boiler (heating season)	20,90
Supply Fan (cooling season)	82,20
Supply Fan (heating season)	8,00

Next, business value for assets serving auditorium and ballroom zones, is quantified using methods described in section 3.3.2 and summarized in Table 3.4.

For an asset serving multiple zones, given the contribution of having "dissatisfied people", to the economic consequence of asset loss, total "Economic Consequence" of asset failure is obtained according to Equation (3.4):

$$TEC_i = \sum_{z_j} TEC_i^{z_j} \tag{3.4}$$

Where $TEC_i^{z_j}$ in Equation (3.4) is the economic consequence of failure of the asset in zone j. For instance in our case study, the chiller, boiler and supply fan serve the

[2] Total zones' population is assumed to be 10 people.

ballroom and auditorium, thus total "Economic Consequence" of each asset failure should be summed over both zones.

Table 3.4: Seasonal Values for Failure Consequences for Assets Serving Ballroom (top), Auditorium (bottom)

Season	**Cooling Peak**		**Cooling Off-Peak**		**Heating Peak**		**Heating Off-Peak**	
Consequence	Chiller	AHU	Chiller	AHU	Boiler	AHU	Boiler	AHU
Business Value Loss	10000	10000	3000	3000	14000	14000	40000	4000
PPD (%)	7.15	8.35	7.15	8.35	12.5	10.65	12.5	10.65
Season	**Cooling Peak**		**Cooling Off-Peak**		**Heating Peak**		**Heating Off-Peak**	
Consequence	Chiller	AHU	Chiller	AHU	Boiler	AHU	Boiler	AHU
Business Value Loss	7000	7000	2000	2000	8000	8000	2000	2000
PPD (%)	5.1	7.0	5.1	7.0	10.6	8.3	10.6	8.3

Table 3.5 summarizes this result for ballroom and auditorium. Details on $TEC_i^{z_j}$ calculations using inverse of AHP method, is included in the appendix B.

For assets serving both Task-related and Non-task-related zones, "Business Value" is obtained by adding up the economic consequence of an asset's failure in all corresponding zones as presented in Table 3.6. In the case of our illustrative example, the business value of the three assets is calculated by summing the economic consequence of asset failure for offices as well as for the ballroom and auditorium (Table 3.6).

Table 3.5: Economic Consequence of Asset Failures in Non-task related Zones (Auditorium and Ballroom)

Asset	Cooling Peak Economic Consequence ($)	Cooling Off-Peak Economic Consequence($)	Heating Peak Economic Consequence($)	Heating Off-Peak Economic Consequence($)
Chiller	68,000	3,0000	0	0
Boiler	0	0	66,000	30,000
Supply Fan	51,000	25,000	88,000	36,000

It can be seen that the air handler's supply fan serving the 5-zone recreational building, has the highest "Business Value" in the cooling peak season and thus needs to have the highest priority for Preventive maintenance scheduling.

Table 3.6: Asset Business Value

Asset	Cooling Peak	Cooling Off-Peak	Heating Peak	Heating Off-Peak
Chiller	102,500	64,500	0	0
Boiler	0	0	86,900	50900
Supply Fan	133,200	107,200	96,000	44,000

3.5. Asset Reliability Model

In this section, the asset reliability and optimal maintenance planning formulation is presented. The probability of failure of an asset within time interval $(t, t + \Delta t)$, commonly referred to by hazard rate function, is given by Equation (3.5):

$$P\ \{Failure\ in\ (t, t + \Delta t) | No\ failure\ before\ t\} = h(t) \times \Delta t$$
$$= f(t)/R(t) \times \Delta t \tag{3.5}$$

Δt defines the length of discrete time steps that synchronizes MLE+ co-simulation. The hazard rate functions follow a bathtub curve where the rates are conditioned on the assets' stage in life, namely, BOL (Beginning of Life), MOL (Middle of Life), and EOL (End of Life). The use of the bathtub curve for HVAC equipment and its electrical and mechanical components is common in the literature [59]. Furthermore, it has been a common practice to approximate the corresponding lifetime distribution by a Weibull function consisting of three parameters: β (shape parameter also known as Weibull slope), η (scale parameter) and γ (start location or location parameter which generally equals to 0). Parameter $\beta < 1$ implies infant mortality while $\beta = 1$ implies random failures, $1 < \beta < 4$ implies early wear out and $\beta > 4$ is considered as end of life rate. We assume $(\gamma = 0)$ and use the empirical data provided by Barringer et al. [59] to estimate the default values for our model. It is important to note that asset's useful life can be extended by the care and maintenance that it receives. In other words, asset's age restores to an earlier stage depending on the type of maintenance actions it receives. We assign a "Restoration Factor" ($rf \in [0,1]$) to each maintenance action which implies the percentage to which a component is restored upon successful application of the maintenance action (i.e. Maintenance effectiveness). Therefore, at any point in an asset's life, it will have a real age and an effective age, with the latter one depending on the to-date maintenance actions. It is further assumed that a relationship can be drawn between asset's real age and effective age depending on these maintenance routines. We use the results from Hendron et al. (2006) [60]:

$$(A_{Eff_0})_i = \log\left({CI_i}/_{100}\right)/\log(M_i) \tag{3.6}$$

Where for asset i , $(A_{Eff_0})_i$ is the initial asset effective age, M_i is the constant defined according to the type of maintenance and degradation function; CI_i is the "Condition Index" ($CI_i \in [0,1]$). Normally, $CI_i \in [88,100]$ refers to excellent condition while $CI_i \in [0,10]$ indicates a failed condition. Here, we extend the definition of CI to also include asset's energy efficiency; to be more specific CI_i represents the ratio of nominal (expected) power to the actual power consumptions. Note that historical data or near real time data collected using a monitoring scheme may be used to measure CI_i parameter.

Asset effective age (in hours) at each time step h, is then quantified according to Equation (3.7) [61-63]:

$$A_{Eff_i}(h+1) = (A_{Eff_i}(h) + PLR) \times \left(1 - rf_{(Tkl)_i}\right) \tag{3.7}$$

Where k, l and T are indices for maintenance type, maintenance frequency, and the season respectively. Moreover, $rf_{(Tkl)_i}$ is defined based on the type of maintenance action on asset i; (i.e. $rf_{(Tkl)_i} = 0$ if no maintenance is applied for period T). $PLR \in (0,1)$ is the Part Load Ratio of the asset for a specific time interval $[h, h+1]$. The asset loads or PLRs are derived from the EnergyPlus simulation runs. Figure 3.2 illustrates a scenario where an asset's effective age is shifted twice, according to two maintenance actions that were applied to the asset at the ages of a_1 and a_2, with each shift defined by an appropriate restoration factor $\left(rf_{(Tkl)_i}\right)$. Keeping the real age of an asset fixed, the effective age improves by the maintenance actions as shown in Figure 3.2.

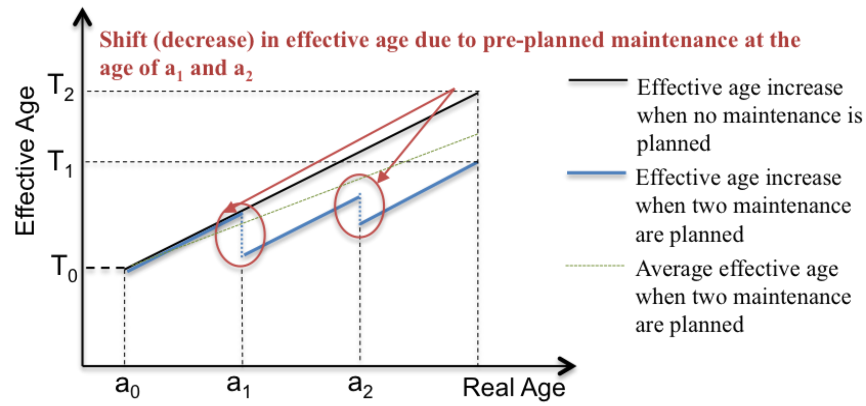

Figure 3.2: Effective age shift with pre-planned maintenance

These shifts are approximated by an average smooth function over asset real life as presented in Figure 3.2. Given a history of maintenance actions for a given asset, the corresponding improvement factors ($(A_{Eff_0})_i$), and CI, can be estimated using Equation (3.6).

3.6. Building Energy Optimization

The maintenance planning problem in this chapter is a cost minimization problem, with three main cost elements, namely maintenance cost, penalty cost obtained from BVM, and asset energy cost. Each maintenance action has a fixed cost and a variable cost coefficient. The variable term depends on the time duration and hourly labor cost required to perform the maintenance action. Finally, asset energy cost coefficient also includes a fixed and variable term relevant to the type of energy used (e.g., electric energy and natural gas). We formulate the above cost minimization problem as a multi-objective stochastic optimization problem (MOSOP) with a trade-off between capital expenditures and energy savings. The objective is to compute the decision vector denoted by $X = \{x_{i,Tkl};\ \forall T, \forall i, \forall k, \forall l\}$ which minimizes a two-dimensional objective function, $z(X^{*}) = \{S(.), C(.)\}$, where $S(.)$ and $C(.)$ represent the Total Building Energy Consumption and the Total Cost of Maintenance and Penalty respectively. $x_{i,Tkl}$ is a binary decision variable ($x_{i,Tkl} = 1$ if the maintenance option (T;k, l) applies to asset i, and otherwise $x_{i,Tkl} = 0$). Without loss of generality, we assume that the set of maintenance types is limited to (1) Reactive maintenance upon failure, (2) clock-based preventive maintenance type 1, (3) clock-based preventive maintenance type 2 and (4) clock-based preventive maintenance type 3$\}$.

The stochastic elements of the problem are the Load (φ) on assets (e.g., chiller's part load ratio, supply fan's flow), and asset failure events represented by $(\omega(\varphi, t))$. The random load is a function of weather & operation factors (e.g. Occupancy) and can be simulated based on building configurations, operation and controls, as well as weather conditions. Failure events are defined by asset lifetime distributions, with bathtub hazard rates and Weibull functions. The following constraints are considered: (1) For a given season T, all possible maintenance policy sets (k, l) on asset i are mutually exclusive as presented by Equation (3.10). (2) For a given planning period, the total maintenance budget has an upper limit (Equation (3.11)). The MOSOP formulation is formulated as:

$$\min_{X}\{S(X, \varphi, u, \omega(\varphi, t))\} \tag{3.8}$$

$$\min_{X}\{C\big(X, \omega(\varphi, t)\big) = g(X) + h\big(X, \omega(\varphi, t)\big) + p\big(X, \omega(\varphi, t)\big)\} \tag{3.9}$$

Subject to:

$$\sum_{k=i}^{m}\sum_{l=1}^{s} x_{i,Tkl} \leq 1 \qquad \forall T, \forall i \tag{3.10}$$

$$g(X) + h\big(X, \omega(\varphi, t)\big) \leq B_{limit} \tag{3.11}$$

Where $h\big(X, \omega(\varphi, t)\big)$ and $p\big(X, \omega(\varphi, t)\big)$ represents the Total Unplanned Reactive Maintenance Cost and the Total Penalty Cost Due to Asset Failures respectively and B_{limit} is the Annual Budget Limit. Computation of $S(X, \varphi, u, \omega(\varphi, t)))$ requires detailed understanding of interactions between building assets (e.g., HVAC system), weather and operational factors, building control, fault and failure events at asset levels. In the absence of any analytical form, and assuming that there is a positive correlation between asset maintenance and energy consumption, we make the following approximation in Equation (3.12):

$$\begin{gathered} \min\{S(X, \omega(\varphi, t), u, \varphi)\} \approx \max\left\{\sum_i EPI_i\left(X, \omega(\varphi, t)\right)\right\} = \\ Max\{\sum_{T=1}^{2} \sum_{i=1}^{n} \sum_{k=1}^{m} \sum_{l=1}^{s} x_{i,Tkl}\} \end{gathered} \tag{3.12}$$

Where $EPI_i(X, \omega(\varphi, t))$ is the asset i's energy performance improvement due policy X. Without loss of generality, we assume that a year is divided into two seasons, namely heating and cooling seasons. The above approximation equates energy savings to energy performance improvement, which is controlled by practicing appropriate maintenance policies. Note that $C[X, \omega(\varphi, t)]$ includes three parts: (1) cost $g(X)$ of pre-planned maintenance actions; (2) cost $h[X, \omega(\varphi, t)]$ of unplanned reactive maintenance upon asset failure; and (3) a penalty cost proportional to the asset's business value denoted by $p[X, \omega(\varphi, t)]$. Following relationships hold:

$$h[X, \omega(\varphi, t)] = \tag{3.13}$$

$$\sum_{T=1}^{2}\sum_{i=1}^{n} CR_{Base_{Ti}}[\omega(\varphi,t)] - \sum_{T=1}^{2}\sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[CRR_{i,Tkl}[\omega(\varphi,t)] \times x_{Tikl}\right]$$

Where :

$$g(X) = \sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[CPA_{i,Tkl} \times x_{i,Tkl}\right] \tag{3.14}$$

$$CR_{Base_{Ti}}[\omega(\varphi,t)] = N[(\omega(\varphi,t))_{\ Base}]_{Ti} \times \left[(C_{rpr})_i + \ (C_{rpl})_i\right]/2 \tag{3.15}$$

$$CRR_{i,Tkl}[\omega(\varphi,t)] \tag{3.16}$$

$$= [N[(\omega(\varphi,t))_{\ Base}]_{Ti} - N[(\omega(\varphi,t))_{Tkl}]_i] \times \left[(C_{rpr})_i + \ (C_{rpl})_i\right]/2$$

Note that in this study, base option (CR_{Base}) is used as a reference policy and all maintenance policy options are compared to this option in terms of cost and performance. Reduction in unplanned maintenance cost on asset i as a result of a pre-planned maintenance option $(T; k, l)$ is due to reduction in number of failures compared to base option. Cost of reactive maintenance action can be approximated using average cost of asset repair and replace as denoted in Equation (3.15) and (3.16). The total penalty due to asset failure, $p[X, \omega(\varphi,t)]$ is defined according to Equation (3.17):

$$p[X, \omega(\varphi,t)]$$

$$= \sum_{T=i}^{2}\sum_{i=1}^{n} CP_{Base_{Ti}}[\omega(\varphi,t)] - \sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[CPR_{i,Tkl}[\omega(\varphi,t)] \times x_{i,Tkl}\right] \tag{3.17}$$

Where,

$$CP_{Base_{Ti}}[\omega(\varphi,t)] = N[(\omega(\varphi,t)_{\ Base}]_{Ti} \times (BVM)_i \tag{3.18}$$

$$CPR_{i,Tkl}[\omega(\varphi,t)] = [N[\omega(\varphi,t)_{\ Base}]_{Ti} - N[\omega(\varphi,t)_{Tkl}]_i] \times (BVM)_i \tag{3.19}$$

Penalty cost $p[X, \omega(\varphi, t)]$ due to asset failure is quantified in the same fashion as Equation (3.15) using the base option as reference point. Again, reduction in penalty cost due to asset failure is quantified in Equation (3.19) using reduction in total number of asset failures in comparison to the base option.

3.7. Solution Approach

Due to extensive computational time required by a single EnergyPlus run (to simulate a planning period of several years), we ought to institute an efficient solution methodology to minimize the number of runs. First, we assume that three distinct stochastic patterns generate random loads in the building. These patterns normally depend on weather and occupancy, but here only weather variations are considered. These patterns, respectively, generate two extreme and most likely operating conditions for the building EnergyPlus simulations within a given season. For each pattern the MOSOP coefficients (i.e. $CR_{Base_{Ti}}[\omega(\varphi,t)]$ and $CRR_{i,Tkl}[\omega(\varphi,t)]$). A few more runs are also required to compare the set of non-dominated solutions of the optimization problem. A feasible solution to the above MOSOP is efficient (non-dominated and Pareto optimal) if no other feasible solution is at least as good for every objective function. The set of all efficient points in a multi objective problem is known as the efficient frontier. Regardless of how objective functions are prioritized, the optimal solution must be selected from the efficient frontier. There are various solution strategies to solve the above MOSOP, namely, multi objective linear programming, preemptive optimization, weighted sum and goal programming. In this thesis the weighted sum approach is chosen since it is computationally less complex and can be used for practical applications. The goal of the weighted sum approach is to find a set of solutions that are non-dominated [64]. More details on this approach is included in the appendix C. Suppose that the most likely sample path for load φ' is realized. Therefore, the only stochastic variable in the optimization problem is a asset failure (i.e. $\omega(\varphi', t)$), which is governed by Weibull distribution. Let $E_\omega(.)$ be the expected value function defined over events $\omega(\varphi', t)$. Then MOSOP reduces to:

$$\max_X \sum_i E_\omega(EPI_i\,[X, \omega(\varphi', t)]) = \max_x \sum_{T=1}^{2} \sum_{i=1}^{n} \sum_{k=1}^{m} \sum_{l=1}^{s} x_{i,Tkl} \tag{3.20}$$

$$\min_X E_\omega(C[X, \omega(\varphi', t)]) = \min_X g(X) + E_\omega(h[X, \omega(\varphi', t)]) \tag{3.21}$$
$$+ E_\omega(p[X, \omega(\varphi', t)]$$

Subject to,

$$\sum_{k=i}^{m} \sum_{l=1}^{s} x_{i,Tkl} \leq 1 \qquad \forall T, \forall i \tag{3.22}$$

$$g(X) + E_\omega(h[X, \omega(\varphi', t)]) \leq B_{limit} \tag{3.23}$$

Where,

$$E_\omega(h[X, \omega(\varphi', t)]) = \sum_{T=1}^{2} \sum_{i=1}^{n} CR_{Base_{Ti}} - \sum_{T=1}^{2} \sum_{i=1}^{n} \sum_{k=1}^{m} \sum_{l=1}^{s} [CRR_{i,Tkl} \times x_{i,Tkl}] \tag{3.24}$$

$$CR_{Base_{Ti}}[\omega(\varphi', t)] = E_\omega(N[\omega(\varphi', t)\ _{Base}]_{Ti}) \times [(C_{rpr})_i + (C_{rpl})_i]/2 \tag{3.25}$$

And $E_\omega(N[\omega(\varphi', t)\ _{Base}]_{Ti})$ is the expected number of failures for asset i under “Base maintenance option” when the load pattern is given by φ'; thus we have:

$$E_\omega(N[\omega(\varphi',t)\ _{Base}]_{Ti}) = \int_{T0_i}^{T\_Base_i} [\lambda(\omega(\varphi',t))]_i dt \tag{3.26}$$

$$CRR_{i,Tkl}= \tag{3.27}$$

$$[E_\omega(N[\omega(\varphi',t)\ _{Base}]_{Ti}) - E_\omega(N[(\omega(\varphi',t))_{Tkl}]_i)]\ \times \left[(C_{rpr})_i +\ (C_{rpl})_i\right]/2$$

where $E_\omega(N[(\omega(\varphi',t))_{Tkl}]_i)$ is the expected number of failures for asset i under ($T;k,l$) option and is given by:

$$E_\omega(N[(\omega(\varphi',t))_{Tkl}]_i) = \int_{T0_i}^{T_{i,Tkl}} [\lambda(\omega(\varphi',t))]_i dt \tag{3.28}$$

$E_\omega(p[X,\omega(\varphi',t)]$ is calculated according to:

$$E_\omega(p[X,\omega(\varphi',t)] = \sum_{T=i}^{2}\sum_{i=1}^{n} CP\_Base_{Ti}\ - \sum_{T}^{2}\sum_{i}^{n}\sum_{k}^{m}\sum_{l}^{s}\left[CPR_{i,Tkl} \times x_{i,Tkl}\right] \tag{3.29}$$

$$CP\_Base_{Ti} = E_\omega(N[\omega(\varphi',t)\ _{Base}]_{Ti}) \times (BVM)_i \tag{3.30}$$

$$CPR_{Tikl} = [E_\omega(N[\omega(\varphi',t)\ _{Base}]_{Ti}) - E_\omega(N[(\omega(\varphi',t))_{Tkl}]_i)] \times (BVM)_i \tag{3.31}$$

Thus the first objective in Equation (3.20) can be re-written as:

$$\max_X \sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s} x_{i,Tkl} \tag{3.32}$$

It is assumed that reactive maintenance actions are mandatory upon failure of an asset. A reactive action can include repair or replacement of the failed asset depending on its *CI* at the time of failure. Therefore, the second objective in Equation (3.21) can be re-written as shown in Equation (3.33):

$$\min_{X} E_{\omega}\left(C\big(X, \omega(\varphi', t)\big)\right)$$

$$\approx \min_{X} \sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[\left(CPA_{i,Tkl} \times x_{i,Tkl}\right) - \left(CPR_{i,Tkl} + CRR_{i,Tkl}\right) \times x_{i,Tkl}\right] \tag{3.33}$$

The total cost of asset maintenance, including unplanned and preplanned cost cannot exceed the total budget limit (B_{limit}). Cost Coefficients of the optimization problem can be quantified offline using the assets' failure rate; therefore we can rewrite constraint in Equation (3.23) as:

$$\sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[\left(CPA_{Tikl}\right) \times x_{i,Tkl}\right]$$

$$+\sum_{T=i}^{2}\sum_{i=1}^{n} CR\_Base_{Ti} - \sum_{T=1}^{2}\sum_{i=1}^{n}\sum_{k=1}^{m}\sum_{l=1}^{s}\left[CRR_{i,Tkl} \times x_{i,Tkl}\right] \leq B_{limit} \tag{3.34}$$

After solving the problem for the most likely operating condition the optimization problem needs to be solved for the other two extreme conditions. The final result for the discussed optimization problem is defined as the combination of the three solutions. For continuous variable stochastic problem usually the final solution is the weighted average. Note that the weights in this linear combination are the probability of occurrence for each operating condition [64].

3.8. Validation and Sensitivity Analysis

Using bathtub curves and Weibull distributions, for modeling the hazard rate functions and time to failure of mechanical components, respectively, has been extensively practiced in the reliability literature. The parameters for these models can be estimated from manufacturers' or field data. The concept of asset effective age and degradation in this chapter was adopted from asset management practices. Furthermore, it is general common sense that proper and timely maintenance of assets, improve asset performance and reliability. And commonly speaking, an asset performance improvement leads to a reduction in its energy consumption; or in the worst case the energy consumption remains flat with improvements in performance. Numerical validation of these effects is beyond the scope of this work. According to the energy modelling protocol established by ASHRAE Standard 90.1-2010 [66] used in LEED (Leadership in Energy & Environmental Design) [67], building energy simulations (using EnergyPlus or similar software packages) are increasingly becoming common practice in the industry for new buildings. Such simulation models are normally calibrated with building's monthly utility bills. Thus, depending on the model granularity and accuracy of weather input files, these simulations are able to provide reasonable energy forecasts for buildings.

The optimization approach introduced in this chapter is not exact and requires validation. Since there is no closed form solution for our performance and energy measures, a brute force validation approach is taken in which the "optimal" solution is compared to a set of What-If scenarios. Each such scenario presents a feasible solution and is run for a number of replications (to imitate random variations in failures). But the weather and occupancy patterns are kept at most likely values; (i.e. Load φ is kept at "Most Likely" value). Extensions to other weather and occupancy scenarios are straightforward. Using EnergyPlus's "5-ZoneAir-Cooled.imf" example model introduced in section 3.3, we perform a sensitivity analysis to test the performance of the optimization model introduced. The following set of maintenance options was used:

1. Clock-based Preventive Maintenance type 1, Frequency = 3 months
2. Clock-based Preventive Maintenance type 1, Frequency = 6 months
3. Clock-based Preventive Maintenance type 2, Frequency = 3 months
4. Clock-based Preventive Maintenance type 2, Frequency = 6 months
5. Clock-based Preventive Maintenance type 3, Frequency = 3 months
6. Clock-based Preventive Maintenance type 3, Frequency = 6 months

To form the "What-If" scenarios, each combination of the aforementioned maintenance options is run for enough number of replications to ensure sufficient coverage of random variations. Failure events are generated from asset specific Weibull distributions [58]. Energy prices used in the case studies are summarized in Table 3.7 and the "What-If" scenarios used for validation are summarized in the appendix D.

Table 3.7: Local Energy Costs[3]

Energy Type	Price
Electricity	0.207 $ per kWh
Natural Gas	1.14 per thermal unit

[3] Prices are based on local prices in San Francisco (2013)

3.9. Penalty Cost Impact

In the first set of illustrative cases we intend to: (1) compare the results obtained from our optimization with the results from "What-If" scenarios; (2) and evaluate the impact of penalty costs on the optimal solution. It is assumed that electric compression chiller, hot water boiler and supply fan are in their "wear-out" or "End-of Life" stage. Weibull distribution with $\beta > 4$ (shape parameter) is used to predict failure times and initial condition index is set at 20% for all the three assets. It is further assumed that penalty cost per failure of an asset is considerably higher than its maintenance costs. Case 1 optimization takes into account penalty cost (i.e. BVM scores) for asset failures as given in Table 3.8. These penalties are ignored in Case 2. The results indicate that in both cases, the approximate MOSOP optimization methodology yields "optimal" solutions that match the best results from "What-If" scenarios included in the appendix D.

Table 3.8: BVM Sores for Illustrative Case Study

Asset Type	BVM Score
Electric Compression Chiller	188,9334
Hot Water Boiler	70,360
Supply Fan	82,615

In case 1, the optimization approximation output suggests a Preventive Maintenance Clock-based type 3 with 3 months frequency as the optimal strategy for all 3 assets, which matches the best solution from "What-If" analysis. Figure 3.3 shows the total cost breakdown for the 10 "What-if" scenarios in the appendix D. Scenario 6, representing the Preventive Maintenance Clock-based type 3 with 3 months frequency, is the cheapest maintenance combination with zero penalty cost. To evaluate the impact of penalty costs on the "optimal" solution, Case 1 is simulated again without penalty costs (i.e. Case 2). The MOSOP yields the optimal strategy that pertains to: Preventive Maintenance Clock-based type 3 with 3 months frequency for the chiller and 6 months frequency for the hot water boiler and supply fan.

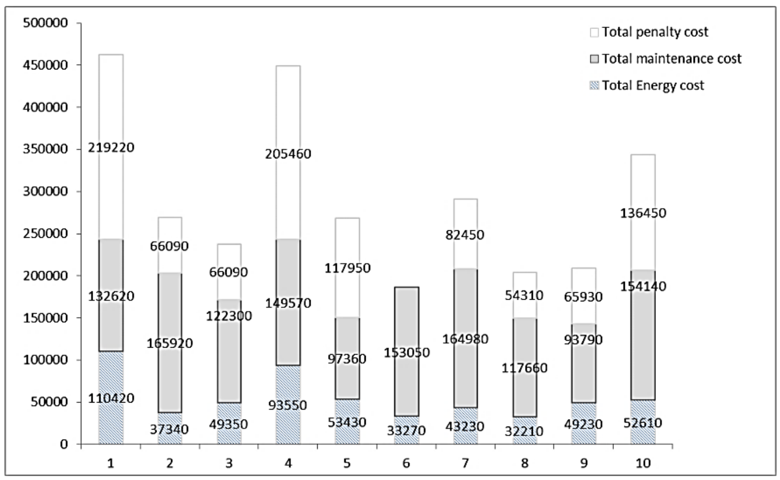

Figure 3.3: "What-if" scenario cost results – Case 1

Scenario based validation (using appendix D) approves the "optimal" strategy as depicted in Figure 3.4 Comparing the results from the above two illustrative cases, it is observed that, in Case 1, a maintenance strategy that pertains to the highest restoration factor (i.e., Preventive Maintenance Clock-based type 3 with low frequency) is favorable to prevent substantial business penalties. However, in the absence of such penalties, as represented by Case 2, the optimal strategy solely depends on maintenance and energy costs; thus, with a limited budget, the "optimal" strategy suggests incorporating maintenances with higher restoration factors for assets with higher rates of energy consumption (i.e. The chiller in this illustrative case).

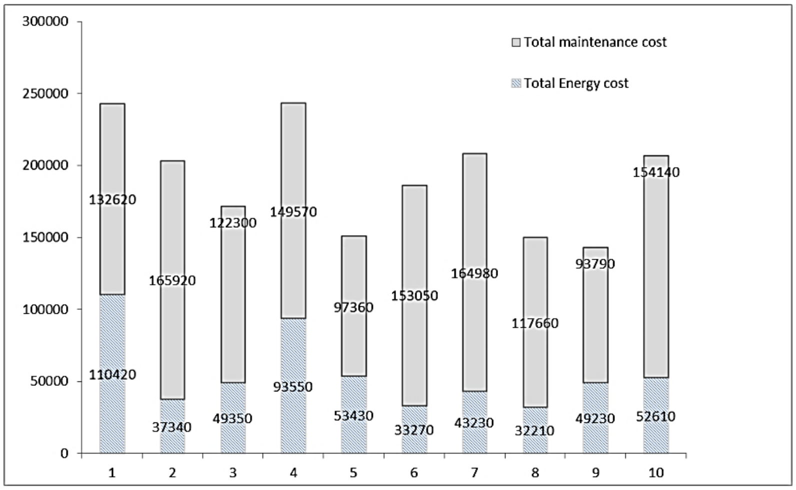

Figure 3.4: "What-if" scenario cost results – Case 2

3.10. Impact of Assets' Age

Next, the impact of assets' age is evaluated in terms of energy and cost savings. The optimization model is run with different asset age combinations and results are compared to the base maintenance option (i.e. Reactive Maintenance). The following cases are evaluated in this section:

1- Assets are in the first 30% of the life cycle (BOL).

2- Assets are in the MOL period (between 30% and 70%)

3- Assets are in the last 30 % of their life (EOL).

Table 3.9 presents the recommended policy as well as energy and total cost saving for each age scenario category mentioned above compared to the base maintenance option. For assets in BOL stage, the recommended policy is "Reactive Maintenance", which matches the base maintenance option. However, as assets age, the necessity for more rigorous maintenance routine arises; hence, for assets in EOL, a Preventive Maintenance with 3 month frequency is suggested as optimal maintenance strategy. Note that when assets are in their MOL, given a limited budget to manage the assets, the focus would be on assets which consume more energy; thus, the chiller would require a Preventive maintenance, while a basic failure-based routine would suffice for the other assets. It is further observed that since the assets in EOL stage have a considerable increase in energy consumption due to degradation, incorporating an effective preventive maintenance would lead into almost 70% savings in the total energy consumption when compared to base maintenance routine.

Table 3.9: Optimization Result in different asset life cycles

Scenario Number	**Recommended Policy**	**Energy Saving (%)**	**Total Cost Saving (%)**
1	Reactive Maintenance for all assets	-	-
2	Chiller: "PM clock, type 3, frequency=6" Boiler and Supply Fan: Reactive Maintenance	26%	56%
3	"PM clock, type 3, frequency =3" for all assets	69%	59%

3.11. Conclusion

With building and technical services' considerable contribution to an industrial facility's energy consumption, any reduction in consumption rate of these services will lead into significant savings in the facility as a whole. In this chapter asset management in a building facility was discussed as a vehicle to achieve such energy reductions. A methodology was introduced to integrate reliability and maintenance modeling with physics-based building energy simulations and through several case studies, it was illustrated that substantial energy savings can be realized through optimal asset maintenance policies. Another major contribution of this chapter was incorporating asset business values into the introduced optimization regime in order to minimize building energy footprints and maximize performance of assets. We developed models to calculate asset business values in terms of economic consequences of their failure/degradation. This Business Value Model not only calculates the measurable consequences of such failures, but also incorporates the "hard-to-quantify" contributions in the business value calculations.

Chapter 4

4. Network Energy Efficiency Optimization in Industrial System

4.1. Introduction

In the area of industrial energy efficiency a number of modelling approaches have appeared embracing one of the two generic perspectives, namely, “industrial facility efficiency” and “industrial process efficiency”. With the former one, most of the existing works focus on reducing the energy consumed by facility’s infrastructure and technical services (e.g. Lighting, heating and cooling) which are responsible for maintaining the required conditions for “industrial process”. In the arena of “industrial facility efficiency”, plant-wide energy audits are extensively used to identify improvement opportunities at the facility level. Kong et al. (2013) give an overview of such audits in Chinese facilities and describes an energy audit aimed at identifying energy conservation opportunities at a paper mill facility in China [68]. Energy reduction in HVAC (Heating, Ventilation and Air Conditioning) systems as one of the most important components of technical services in an industrial facility has been addressed in literature, including methods for determining optimal control strategies such as reset control, setback control, improved start-stop times and occupied time adaptive control [69-73]. Optimal set point configuration and component level energy efficiency improvements are also investigated for HVAC energy reduction [74-76]. Using an optimal equipment maintenance and asset management techniques also leads into energy savings in HVAC system as demonstrated in previous chapter [77].

“Industrial process efficiency” perspective, on the other hand, centers on modeling the energy reduction in industrial equipment, machinery and production system. These models use “operational” and “physics-based” methods to achieve reductions in energy consumption of industrial processes. In this context many scholars discussed operational models to minimize energy usage of equipment in manufacturing organizations through efficient control techniques. These models either focus on changing the state of the industrial machines [78-82], or reduce the idle time in non-bottleneck stations [83]. Efficient scheduling of machinery and production lines has also been addressed extensively in the field of industrial energy efficiency using decision support system tools [84-87]. A number of works also focused on guidelines for energy efficiency through analysis of mechanical components in production processes [88-89].

However, separating industrial processes from facilities which house these processes, lead to fragmented energy policies and competing and conflicting practices. In recent years efforts in the academia and industry have shifted toward integrated energy efficiency in production management and standardization of such practices [90-92]. Such integrated view in energy consumption of a production environment has been addressed in several articles. A number of recent studies propose techniques for energy efficiency in manufacturing through different system scale levels, including product-level, machine-level and plant-level factors [93-95]. These studies incorporate a more holistic viewpoint, categorizing energy consumption of an industrial environment into various sub-systems, and provide models for calculating energy consumption using all the sub-systems defined [96-98]. Whilst the aforementioned researches have highlighted the necessity of an integrated view to investigate the energy efficiency within an industrial environment, they come short of providing a quantitative algorithm to implement such integrated view. In this chapter, we argue that within an industrial system, dynamic interdependencies exist between production systems, equipment and facility's technical services. Such dynamic interdependencies need to be holistically incorporated into energy efficiency analysis and optimization. Energy optimization has to be performed over all activities that contribute to the making of a product [99]. By annotating activities with nodes and flow (of materials and/or energy) between them by connecting arcs, a complex network emerges. Depending on the granularity of the analysis, these nodes can be simple or composite with a sub-network beneath them. In many instances, these nodes are owned by a single entity or business unit. Nodes across a network are interdependent in terms of "Energy Consumption" in such a way that energy reduction in one node might increase/decrease energy consumption in another upstream/downstream node. Consequently, the total energy reduction at a node is the sum of "Direct" and "Indirect" measures; "Direct" energy reduction is the result of applying an energy saving solution in the node itself, whereas "Indirect" reduction is the impact of implementing a saving solution to other nodes of the network. By the same token, nodes have "Performance" interdependencies; therefore, energy reduction in one node might actually improve or degrade the performance in another node, as measured in terms of appropriate Key Performance Indicators (KPIs). We intend to formalize industrial energy efficiency as a network optimization problem that helps achieve energy efficiency by determining the amount of energy reduction plausible for each node of the network. We present an innovative framework to model and effectively capture the dynamic interdependencies between components of an industrial system, in terms of "Energy Consumption" and

"Performance". The conceptual framework and optimization model are generic, but calculation details are application dependent. Therefore, we will use an illustrative example for demonstration purposes. The remainder of this chapter is outlined as follows: The network optimization problem is formulated next and general assumptions are stated. In section 4.3, using a manufacturing system as an illustrative case, "Performance" and "Energy Consumption" interdependencies are identified and quantified. Given a set of feasible energy saving solutions for the illustrative case, the network optimization is analyzed and solved in section 4.4, followed by conclusions and closing discussions. Table 4.1 lists the notations used throughout the rest of this chapter.

Table 4.1: Nomenclature

x_j	Direct energy reduction in node j stemmed from energy saving solution S_j'
PER_j	Maximum 'Potential Energy Reduction' in node j (kWh), $PER_j \in \mathbb{R} \geq 0$
PRF_j	Current Performance at node j (before energy reduction solution) in terms of
v_j	Economic value generated per unit energy reduction at node j ($/kWh),
c_j	Cost of each unit energy reduction at node j ($/kWh), $c_j \in \mathbb{R} \geq 0$
ESR	Total 'Energy Saving' requirement at network (kWh), $ESR \in \mathbb{R} \geq 0$
B	Total economic budget for energy reduction at network ($), $B \in \mathbb{R} \geq 0$
β_j	Economic budget for energy saving solution at node j($), $\beta_j \in \mathbb{R} \geq 0$
p_j	Penalty per unit energy increase at node j ($/kWh), $p_j \in \mathbb{R} \geq 0$
r_j	Economic reward per unit performance improvement at node j, $r_j \in \mathbb{R} \geq 0$
l_j	Penalty per unit performance degradation at node j, $l_j \in \mathbb{R} \geq 0$
δ_{ij}	"Energy" Dependency: Energy reduction/increase in node i per unit energy
ρ_{ij}	"Performance" Dependency: Performance improvement/degradation in node
π_j	Energy consumption of node j in the base scenario(kWh), $E_j \in \mathbb{R} \geq 0$
PM_j	Performance of node j in base scenario, $PM_j \in \mathbb{R} \geq 0$
π_j'	Energy consumption of node j when an energy saving solution is

PM_j' Performance of node j when an energy saving solution is implemented,

4.2. Preliminaries

We consider a generic industrial system, which includes production processes (e.g. Production lines) and a facility (e.g., a building) that houses these processes as depicted in Figure 4.1 A network of interdependent nodes emerges mapping energy consuming activities into nodes and their material or energy dependencies into arcs connecting these nodes. We assume that owner(s) of the above system is (are) determined to reduce the overall energy usage of the system by a certain quantity due to regulatory compliance or, economic and/or marketing incentives. It is also assumed that there are economic incentives for improving energy efficiency in each node, which means an energy reduction at each node result in a reward for owners. Moreover, nodes have specific “Performance” requirements defined in terms of appropriate KPIs; thus, any deviation from such requirement is penalized.

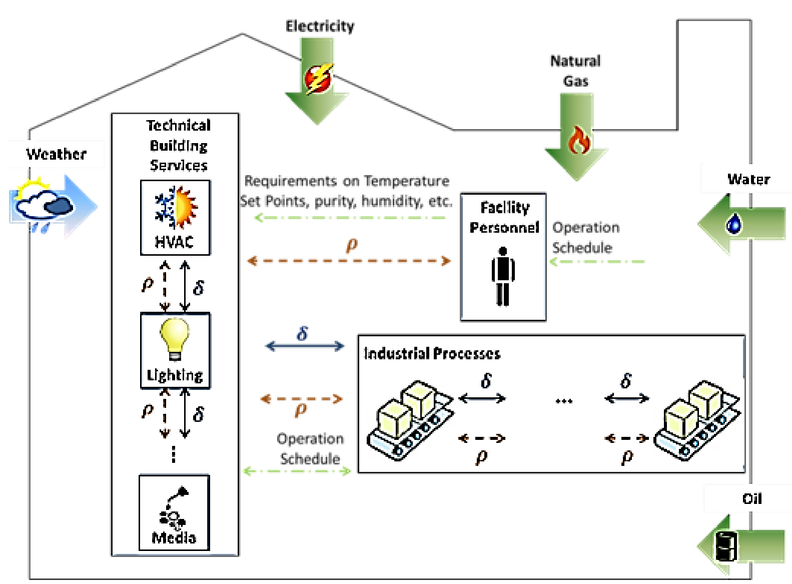

Figure 4.1: An Industrial System as a Network of Interdependent Nodes

As depicted in Figure 4.1, our network is comprised of two composite groups of nodes: (1) Industrial Processes (2) Technical Services in the facility's building. One major task for technical services is to ensure the needed conditions in terms of temperature, humidity and moisture are provided for the industrial process and facility personnel through heating, cooling and air conditioning. Besides, technical services are responsible for providing essential media such as compressed air, steam and cooling water for processes. For illustrative purposes, we assume that the industrial process is a serial production line consisting of three automated machine tools performing machining operations, for example, face milling, drilling and grinding. Also, our focus is on HVAC (Heating, Ventilation and Air Conditioning) system as one of the most important components of technical services in an industrial facility. The components of HVAC system studied here are (1) electric variable speed chiller, (2) hot water boiler and (3) electric supply fan. The industrial process does not have requirements for temperature; thus, interdependencies between machine tools and HVAC nodes are assumed negligible. Moreover, machines are automatic and not manually operated; therefore, no interdependency exists between industrial processes and personnel resources in the facility.

4.3. Problem Statement and Network Formulation

The problem of interest is to determine the share of energy reduction for each node (x_j) in the network. Note that x_j is the 'direct energy reduction' at node j stemmed from energy saving solution imposed on j. As noted earlier, nodes across the network are interdependent in terms of "Energy Consumption" and "Performance". "Energy" dependency between nodes i and j (first order dependency) is denoted by δ_{ij}, where, positive 'Energy' dependency ($\delta_{ij} > 0$) is defined as the amount of energy reduction in node i per unit energy saving in node j. Negative 'Energy' dependency, ($\delta_{ij} < 0$), is the increase in node i's energy consumption, as a result of energy reduction in node j. Similar definitions hold for positive and negative 'Performance' dependency, hereafter denoted by ρ_{ij}. It is worth noting that there might be situations in which a slight increase in energy usage at one node can be compensated for by considerable energy savings in other nodes and thereby resulting in a reduction of the overall network energy. Such consideration is taken into account while determining 'Energy' dependency parameters. For instance, if an increase in energy consumption of node i is tolerable due to high volume of energy saving achieved by putting an energy saving solution at node j, negative energy dependency exists between the two nodes ($\delta_{ij} < 0$). Thus, it is safe to consider that each node's share of energy saving, "Direct" energy reduction, is non-negative (i.e. $x_j \geq 0$). For simplicity, it is assumed that (1) one energy saving solution is applied at a time on each node j and (2) only first order "Energy" and "Performance" dependencies are accounted for, that is, the impact of simultaneous energy saving solutions on multiple nodes is assumed to be negligible.

We assume that the following input data are available: (1) economic reward and penalty data; (2) nodes' minimum "Performance" requirements (η_j); (3) maximum potential energy saving, technically and economically viable for each node (PER_j); and (4) Economic budget at node and network levels. Due to economic incentives for energy use reduction, the energy efficiency optimization problem can be considered as a profit maximization problem; hence, the objective function is the sum of the profits obtained through "Direct" and "Indirect" energy reduction at each node, which is stated as:

$$Max\{f(x) + g(x)\} \tag{4.1}$$

Where $f(x)$ and $g(x)$ are profit functions through "Direct" and "Indirect" measures respectively. We have:

$$f(x) = \sum_{j=1}^{n} (v_j - c_j) x_j \tag{4.2}$$

$$g(x) = \sum_{j=1}^{n} (\sum_{i \neq j=1}^{n} (v_i - p_i)\, \delta_{ij} + \sum_{i \neq j=1}^{n} (r_i - l_i)\, \rho_{ij})\ x_j \tag{4.3}$$

Constraints: As mentioned earlier, it is assumed that the owner of such system has a set of incentives (e.g., compliance requirements, economic and marketing incentives) for network energy savings. Therefore, a minimum energy saving requirement (ESR) needs to be achieved at the network level applying Direct and Indirect energy reduction at individual nodes.

$$\sum_{j=1}^{n} x_j + \sum_{j=1}^{n} \sum_{i \neq j=1}^{n} \delta_{ij} x_j \ \geq ESR \tag{4.4}$$

Reduction in a node's energy usage is subject to technological, physical and economic limitations; therefore, energy saving at a given node cannot exceed the pre-defined maximum potential energy reduction at that node. Moreover, each node's share of energy saving is non-negative.

$$x_i + \sum_{j \neq i=1}^{n} \delta_{ij} x_j \leq PER_i \quad \forall i = 1, \dots, n \tag{4.5}$$

The owner has limited monetary budgets for energy reduction in network and node levels; moreover, penalties due to performance degradation as well as energy increase at any node are deducted from nodes predefined budgets.

$$\sum_{j=1}^{n} c_j x_j + \sum_{j=1}^{n} (|\sum_{i \neq j=1}^{n} I(\delta)_i p_i \delta_{ij}|) x_j + \sum_{j=1}^{n} (|\sum_{i=1}^{n} I(\rho)_i l_i \rho_{ij}|) x_j \leq B \tag{4.6}$$

$$c_i x_i + I(\delta)_i p_i (|\sum_{j \neq i=1}^{n} \delta_{ij} x_j|) + I(\rho)_i l_i (|\sum_{j \neq i=1}^{n} \rho_{ij} x_j|) \leq \beta_i \quad \forall i = 1, \dots, n \tag{4.7}$$

Where,

$$I(\delta)_i = \begin{cases} 0 \; if \; \delta_{ij} \geq 0 \\ 1 \; if \; \delta_{ij} < 0 \end{cases} \quad \forall j = 1, \dots, n$$

$$I(\rho)_i = \begin{cases} 0 \; if \; \rho_{ij} \geq 0 \\ 1 \; if \; \rho_{ij} < 0 \end{cases} \quad \forall j = 1, \dots, n$$

All the nodes across the network are subject to minimum required performance characterization. That is, their performance in terms of appropriate KPI should not degrade below a required threshold as a result of “Direct” or “Indirect” energy saving.

$$\sum\nolimits_{j=1}^{n} \rho_{ij} x_j + PRF_i \geq \eta_i \quad \forall i = 1, \dots, n \tag{4.8}$$

Equation (4.8) underlines a very important relationship between energy and performance. It emphasizes the fact that in real applications, energy reduction strategies can be acceptable only to the extent that they do not disrupt performance requirements. To expand on this idea we introduce what we call “Energy-Performance” curves, which show the direct relationship between energy use and an important KPI of an industrial system (e.g., system throughput rate measured in number of units, number of production batches, or production volume). In practice, “Energy-Performance” curves are quantifiable from historical data, simulations and/or process monitoring. Clearly “Energy-Performance” curve for a given industrial system depends on system control, input and output requirements, and system degradation and, henceforth, on maintenance policies and routines which are practiced within the system.

4.4. Nodes Interdependency Characterization

Energy optimization is contingent on the type of energy saving solutions available at each node. Different energy reduction solutions on nodes lead to distinctive results in terms of nodes energy and consumptions interdependencies. Furthermore, there might be differences in the amount of reduction achieved on a given node through various solutions. In this work a set of common alternatives is chosen for energy saving at nodes in an industrial system.

4.4.1. Energy Saving Solution Alternatives at Nodes

For illustrative purposes, In this chapter, we incorporate a setback control strategy at the HVAC system in which energy saving is achieved by avoiding unnecessary high temperatures and excessive cooling during heating and cooling seasons respectively. In a base case scenario, HVAC components are assumed to have fixed and continuous daily schedule in which chiller and boiler are operational all day during cooling and heating seasons, respectively. With setback control the energy reduction is achieved via shutting down chiller and boiler in off-peak daily shifts. Off-peak shifts start anytime between 8:00 AM and 4:00 PM and last up to 6 hours.

For industrial processes, we set an innovative control solution that manipulates process variables (e.g. Feed, speed, depth-of-cut, and so forth) to determine the industrial operation. More specifically, we define a linear control scheme to reduce the waste of energy due to sudden shifts between operation modes. This will be discussed in more detail later.

4.4.2. "Energy-Performance" Calculations

To carry out the energy optimization, metered or summary data on energy usage and performance characteristics of nodes are required. Salahi et al. (2009) define three metering approaches, namely, physical, virtual and simulated [99]. In physical metering approach, KPIs and energy data are directly obtained from sensors or smart meters. Historical data along with inferential statistical techniques using facility's utility bills, accounting databases, and equipment specification and performance data may be used to derive the virtual metered data. In the absence of meters and historical data, simulation may be used to obtain the required information on energy consumption and node performance. We present a general formulation, which can be supported by one or all of the above data metering approaches. For demonstration purposes, we use simulated metering approach to derive necessary energy consumption and performance data.

4.4.2.1.Industrial Processes: Case of Isolated Machines

For industrial processes, we start from a single isolated machine M_i, where energy π_{M_i}used by the machine over a production shift with duration of T is given as follows:

$$\pi_{M_i} = \int_{t=0}^{T} P_{M_i}(t)dt \tag{4.9}$$

$P_{M_i}(t)$ is the power input to M_i at time t. π_{M_i} is calculated according to machines' operational states and duration of time machine spends in each state. Figure 4.2 shows basic operational states and transitions of a typical machine tool.

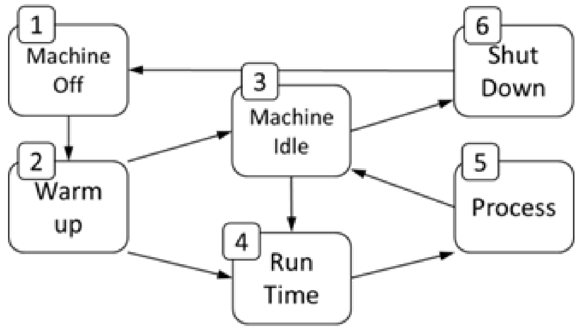

Figure 4.2: Operational States of a Typical Machine Tool

For a machine M_i a production cycle is defined per part or work piece. Let ω_s, $s = 1, \ldots, S$ be a random variable representing the time spent in operational state s. The machine's cycle time (Ω_{M_i}) can thus be estimated by:

$$\Omega_{M_i} = \sum_{s=1}^{S} E(\omega_s) \tag{4.10}$$

Where *E(.)* represents the expected value of the random variable. For random ω_s, the amount of energy consumption in each state, will also be a random variable presented by $\pi_s(\omega_s)$ and can be approximated by $\pi_s\big(E(\omega_s)\big)$. The expected total energy consumed over sampled values of ω_s's can be estimated using:

$$\pi\big(\Omega_{M_i}\big) = \sum_{s=1}^{S} \pi_s\big(E(\omega_s)\big) \tag{4.11}$$

Energy consumption of a multiple-cycle machine, characterized by a sequence of single cycles, is then evaluated by:

$$\Pi_{M_i} = \sum_{k}^{n} \pi\big(\Omega_{M_i}\big)_k = \sum_{k=1}^{n} [\sum_{s=1}^{S} \pi_s(E(\omega_s))]_k \tag{4.12}$$

Given the power profile for states of a machine, Energy consumption can be defined using Equation (4.12). Figure 4.3 below depicts the power profile for a grinding machine.

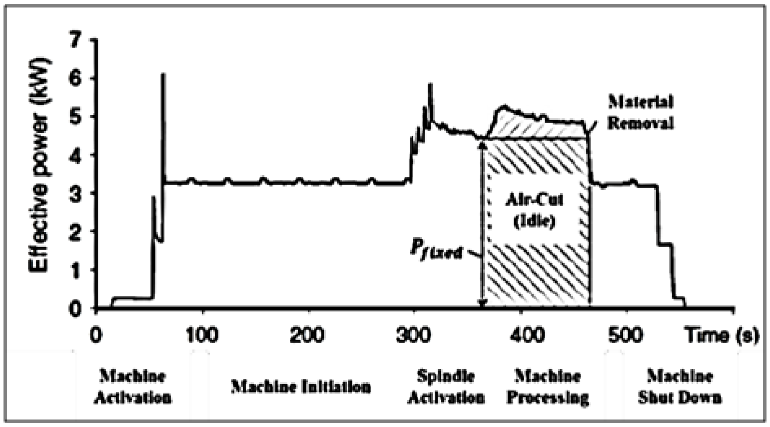

Figure 4.3: Power Profile for a Grinding Machine, derived from [100]

According to Dahmus and Gutowski et al. (2004), processing power (operational state 5 in Figure 4.2), is decomposed into variable and fixed portions. The fixed power is necessary to ensure a functional mode of operation (i.e. Air-cutting which refers to the time when the machine is running without material removal). The variable portion relates to the power consumption for material removal [79]. Energy consumption of machine tools, defined using Equation (4.13), is primarily dictated by workpiece geometry, and Material Removal Rate (MRR) and the duration of time spent in each state. The control solution applied to the machine dictates the time spent in each of the operating states. Diaz et al. (2011), fit the following curve on experimental data collected for “Mori Seiki NV1500 DCG” machine tool’s processing with various piece geometries [101]. $\pi^{Processing}$ in Equation (4.10) represents the energy consumed during the processing state of a machine tool (state 5 in Figure 4.2).

$$\pi^{Processing} = k \times \frac{1}{MRR} + b \tag{4.13}$$

Note that constant k essentially has units of power and b represents steady-state specific energy due to air cutting. Energy consumption profile of various machine tools can effectively highlight the relationship between energy consumption and machining operation's performance (i.e. "Energy-Performance" curve) [79], [88] and [101]. Evidently, as the MRR increases the processing time is reduced. Therefore, the contribution of the constant power demand of the machine tool for the energy per unit processed decreases. However, an increase in MRR demands more power from the machine tool. Figure 4.4 summarizes such relationship for a milling operation and illustrates the energy consumption as a function of MRR. Rate of material removal can be considered as an appropriate KPI for monitoring performance of a machine tool. The "Energy-Performance" profile in Figure 4.4 suggests that energy usage decreases with process time; therefore, choosing appropriate process parameters can minimize process time and lead to energy saving at machine level.

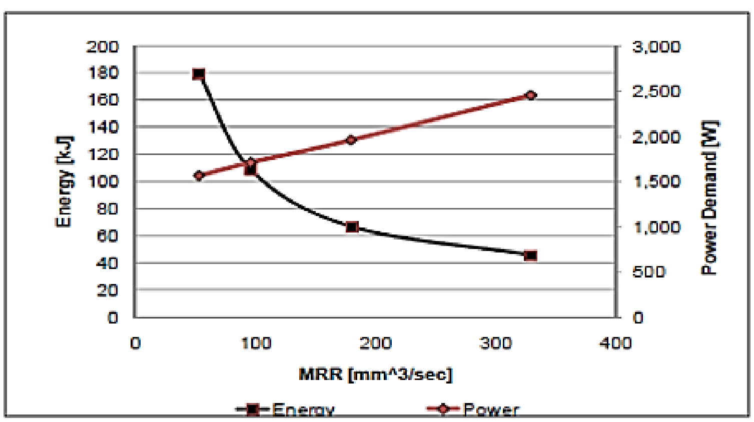

Figure 4.4: "Energy-Performance" - Case of a Single Machine [101]

4.4.2.2. Industrial Processes: Case of Multiple Machines

For industrial processes with multiple machines, the total energy usage is defined based on the number of machines, energy and performance profile of each machine, and non-value added times (such as machine starvation or blockage times). The non-value added quantities are dependent on the configuration of the industrial system, the control solutions put on machines and on the whole system as well as system's input and output. Consider a simple case of a machine (M_i) that is connected to its upstream machines via buffer storage b_i and to its downstream machines via buffer storage b_{i+1} as depicted in Figure 4.5 Machine M_i is starved if b_i the buffer is empty and blocked if b_{i+1} is full. The machine is "Idle" during starvation and blockage.

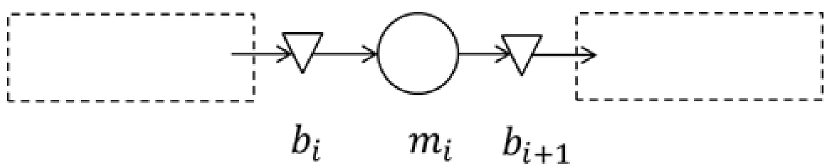

Figure 4.5: Serial Production Line

Each machine's energy consumption can be defined using Equation (4.12) similar to case of an isolated machine. However, in this case machines' production cycles and duration of visits to aforementioned states depend on the control solution in place to regulate the machines. Here, we introduce two rule-based control solutions, namely "High-Low" and "Linear" control in which a machine's process rate is regulated on the basis of upstream and downstream buffer levels. In "High-Low" control machines process rate (MRR) fluctuates between two values (MRR_L and MRR_H). Figure 4.6 shows the profile for "Processing" state of a single production cycle under the "High-Low" control. The fluctuation between process rates are controlled based on the upstream and downstream buffer levels according to the following algorithm:

- If b_i is near empty ($b_i \leq \alpha b_{max_i}$) or b_{i+1} is near its maximum capacity ($b_{i+1} \geq \alpha' b_{max_{i+1}}$), M_i works with $\mathrm{MRR_L}$.
- If $b_{i+1} \leq \alpha b_{max_{i+1}}$ or $b_i \geq \alpha' b_{max_i}$ $\mathrm{M_i}$ works with MRR_H.
- If b_i and b_{i+1} are in their "safe range" ($\alpha b_{max_i} \leq b_i \leq \alpha' b_{max_i}$ and $\alpha b_{max_{i+1}} \leq b_{i+1} \leq \alpha' b_{max_{i+1}}$ the possibility of starvation (for downstream) or blockage (for upstream) is low, therefore M_i continues processing with no change in the MRR. Note that $\alpha \,\&\, \alpha' > 0$ are constants measured in percentage of buffers' maximum capacity.

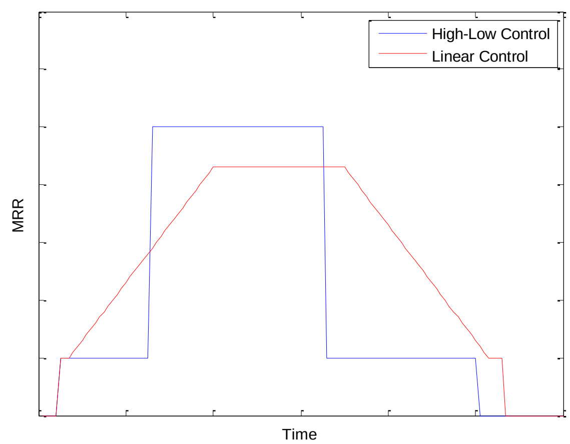

Figure 4.6: Single Production Cycle-"High-Low" vs. "Linear" Control

The energy usage rate of Low control mode is considerably lower than High control mode. Furthermore, changing from Low mode to High requires an acceleration step which consumes energy at a considerably higher rate. Using "Linear" control technique, the machine's process rate is regulated in a way to smooth out the impact of acceleration due to shift from “Low” to “High” mode. The process rate of M_i can change linearly with different slopes. According to this rule-based control, whenever b_i is near empty ($b_i \le \alpha b_{max_i}$) or b_{i+1} is near its maximum capacity ($b_{i+1} \ge \alpha' b_{max_{i+1}}$), M_i’s process rate is decreased with a slope s (units/second). Deceleration in process rate continues until buffers enter the safe range ($\alpha b_{max_i} \le b_i \le \alpha' b_{max_i}$ and $\alpha b_{max_{i+1}} \le b_{i+1} \le \alpha' b_{max_{i+1}}$). If $b_{i+1} \le \alpha b_{max_{i+1}}$ or $b_i \ge \alpha' b_{max_i}$, process rate is increased with slope s' and acceleration continues until buffer units reach safe range. Once the buffers are in a safe range, M_i’s process rate is kept constant, since the possibility of starvation or blockage is low. Notice, however, that switching from “High-Low” to a “Linear” control has a drawback of stretching the process time as is shown in Figure 4.6. Such phenomenon highlights the necessity of considering the “Energy-Performance” curve while making decisions on adopting the control policy to achieve energy reduction. In other words, the increase in processing time is accepted as long as the throughput stays above the demand requirement. Later in this chapter, this concept is further elaborated for the illustrative case.

4.4.2.3.Heating, Ventilation and Cooling (HVAC) System

Numerous calculation methods exist for estimating HVAC equipment energy consumption. In this thesis, energy consumption and performance of HVAC equipment is calculated using the EnergyPlus simulation package. EnergyPlus, developed by the Department of Energy is a simulation software that models heating, cooling, ventilation and other energy flows of a building structure. Given user inputs for building geometry, physical description and associated mechanical systems, EnergyPlus calculates heating and cooling loads necessary to maintain temperature set points, as well as HVAC equipment KPIs such as efficiency parameters. EnergyPlus computes thermal dynamics, such as hourly room air temperature and air/water flow rate, by differential equation systems. Weather profile and HVAC controls are also required inputs for EnergyPlus, to determine the building thermal behavior. Such controls for operating the HVAC equipment can be modelled on a separate platform (e.g., MATLAB). Note that temperature fluctuation in the facility as a result of imposing energy saving solutions, impacts the productivity of facility personnel. Such impacts can be accounted for by using temperature outputs from EnergyPlus simulation runs and quantitative relationships between thermal comfort and occupant task performance. ‘Performance’ dependency between the facility’s personnel and HVAC equipment is derived using ‘Productivity’, which is a measurable KPI in occupant performance evaluation studies. Task related performance of workers in a facility is significantly correlated with the human perception of thermal environment that in turn depends on temperatures. The definition of occupant’s ‘Thermal Comfort’ and Fanger’s ‘Predicted Mean Vote’ (PMV) is used here to derive a quantitative relationship between personnel ‘Productivity’ and thermal environment [53]. In this chapter, we have used methods introduced in chapter 3 and the polynomial function introduced by Kosonen et al. (2004) [51] , [101] and [103] to quantify a relationship between occupant productivity and temperature fluctuations as presented in Equation (4.14):

$$RP = 1.6PMV^5 - 1.55PMV^4 - 10.4PMV^3 + 19.23PMV^2 + 13.4PMV + 1.87 \tag{4.14}$$

In this work, EnergyPlus simulation is used to derive HVAC equipment’s energy consumption (π_j) as well as KPIs for HVAC equipment and facility’s personnel (PM_j).

4.5. Energy & Performance Dependency Parameters

Energy usage (π_j) and performance data (PM_j) are used to calculate the interdependencies between nodes (δ_{ij} and ρ_{ij}). Changes in node i's energy usage and performance upon energy saving in other nodes are derived as follows: (1) nodes' energy usage (π_j) and performance in terms of appropriate KPIs (PM_j) are recorded when no energy saving solution is in place. (2) Energy saving solutions introduced earlier, are implemented one at a time and nodes' energy usage and KPI are measured (π_i' and PM_i'), (3) Energy dependency is defined as:

$$\delta_{ij} = {\pi_i - \pi_i'}\Big/{\pi_j - \pi_j'} \tag{4. 15}$$

Nodes i and j are said to have a positive energy dependency denoted by $\delta_{ij} > 0$, if node i's energy consumption declines as a result of energy saving in node j. In other words the value $\delta_{ij} > 0$ represents an energy reduction in node i due to 1 kWh energy saving in node j.

(4) Performance dependency is defined as:

$$\rho_{ij} = {PM_i - PM_i'}\Big/{\pi_j - \pi_j'} \tag{4.16}$$

Positive "Performance" dependency between nodes i and j is denoted by $\rho_{ij} > 0$. Such relationship holds when "Performance" of node i, in terms of appropriate KPI, is improved as a result of energy saving in node j. It is worth mentioning that for interdependency calculations, energy saving solutions are imposed on nodes one at a time. For instance, while measuring π'_{M_1}, "Linear" control is set on M_1 while M_2 and M_3 operate with "High-Low" control.

4.6. Experiments and Discussion

EnergyPlus simulation package and Rockwell Automation's Arena Software are used to derive energy consumption (π_j) and KPIs (PMj) of the HVAC equipment and the industrial process respectively. The outputs of simulation models are then used to obtain the energy and performance dependency parameters for the industrial process and HVAC system as discussed in the previous section. These parameters are then used as inputs to solve the optimization problem introduced in section 4.3. The optimization model is then solved using LINGO 15.0. The energy saving solution for HVAC components (i.e. Set back control) has to be modeled on a separate platform. As mentioned in chapter 3, the communication between the two platforms is accomplished by a MATLAB script package, MLE+. The operating schedule for HVAC components is changed from a continuous to a schedule with equipment shut downs in off-peak hours. The building simulation is executed using "USA_OL_Chicago-Ohare.Intl.AP.725300_TMY3" weather file. Appropriate HVAC equipment's efficiency measures (i.e. Chiller's cooling efficiency (EIR-fPLR), boiler's heating efficiency (HIR-fPLR) and fan's specific power (SFP)) are used as appropriate KPIs to obtain "Performance" interdependencies. EnergyPlus includes several correlation curves that predict the energy use of HVAC systems. These correlation curves are intended to predict efficiency as a function of the part load ratio. In this study, we have used default curves given by EnergyPlus simulation package and coefficients provided by Henderson et al. (1999) [104]. Energy consumption and performance data from EnergyPlus simulation suggest clear interdependencies between energy usage and performance of HVAC components during cooling and heating seasons. More specifically set back control on chiller during cooling season creates efficiency degradation in fan and increases the amount of fan's energy consumption by as much as 3% ($\delta_{31} < 0$ and $\rho_{31} < 0$ where assuming $i, j = 1, \ldots, 3$ represent chiller, boiler and fan respectively). In the same fashion, boiler and fan also have negative energy and performance dependency ($\delta_{32} < 0$ and $\rho_{32} < 0$). Simulation results also show that daily productivity of industrial system's employees degrades by about 2% per unit electricity saving in chiller during cooling season (i.e. $\delta_{41} < 0$). Optimal productivity is achieved at neutral thermal conditions (PMV ≅0). In this case, setback control on chiller modifies room temperature and shifts PMV away from neutral conditions leading to productivity loss. Note however, that set back control on HVAC components does not impose high temperature fluctuations in the industrial facility during peak hours during heating season. Thus, the impact of the boiler's set back energy saving solution alternative is considered negligible. There is no requirement in terms of indoor air quality and temperature for the machines in the industrial process, therefore no interdependency exists between HVAC components and the process. However, imposing "Linear" control on any of the machines not only increases the energy usage of the other two, but also negatively impacts the machines' throughput ($\delta_{ij} < 0$ and $\rho_{ij} < 0 \; \forall \; i, j$= machine 1, machine 2, machine 3). As noted earlier, dynamic performance interdependencies between nodes need to be considered while making a decision on imposing energy reduction solutions so as to ensure demand requirements are successfully satisfied. Table 4.1 summarizes $\delta_{ij}$and ρ_{ij} parameters used in this illustrative case. Potential energy reduction (PER) for nodes is defined according to node-specific technological, physical and economic limitations. Moreover, each node has a minimum required performance. Such requirement is defined in terms of demanddriven system throughput for the three machines of industrial process. As for the HVAC components, η parameters are defined in terms of efficiencies so as to ensure facility temperature complies with set points defined by ASHRAE standards [52].

Table 4.1: "Energy" and "Performance" Dependency Parameters

"Energy" Dependency (KWh Per 1 KWh energy saving)			
δ_{ij}	Machine 1	Machine 2	Machine 3
Machine 1	1.0	-0.53	-0.05
Machine 2	-1.46	1.0	-1.09
Machine 3	-0.02	-0.75	1.0
Performance" Dependency (Machine throughout change per 1 KWh energy saving)			
ρ_{ij}	Machine 1	Machine 2	Machine 3
Machine 1	0.08	-8.54	-9.57
Machine 2	-0.317	-9.57	-10.46
Machine 3	-0.238	-9.23	-11.48

"Energy" Dependency (KWh Per 1 KWh energy saving)				
δ_{ij}	Chiller Cooling Season	Boiler Heating Season	Fan Cooling Season	Fan Heating Season
Chiller	1	0	1.20	0
Boiler	0	1	0	-8.25
Fan	-0.021	-0.016	1	1
Employee	0	0	0	0
Performance" Dependency (Machine throughout change per 1 KWh energy saving)				
ρ_{ij}	Chiller Cooling Season	Boiler Heating Season	Fan Cooling Season	Fan Heating Season
Chiller	0.08	0	0.002	0
Boiler	0	0	0	0.00002
Fan	-0.317	0	0.144	-0.0023
Employee	-0.238	0.0003	0	0.0003

In other words, energy saving through operational scheduling is acceptable as long as average temperature stays above the required temperature set points by ASHRAE standard. Assuming the facility owner has a 3% daily energy saving requirement,

Table 4.2 summarizes optimization outputs for the industrial facility in cooling and heating seasons respectively. Cost and penalty coefficients are defined based on average unit prices for electricity and gas in Chicago, IL. As illustrated in Figure 4.7(a), machine 1 takes the highest share of energy saving (up to 30%) on the process side when compared to the base scenario.

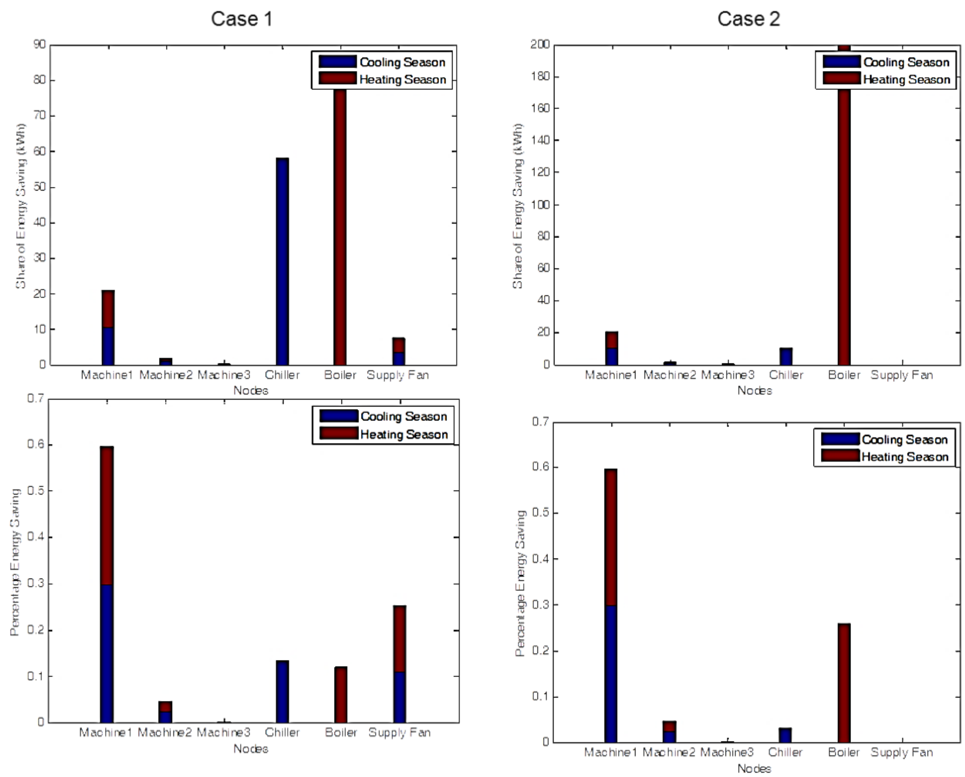

Figure 4.7: Amount and Percentage Share of Energy Savings in (a) case 1 (b) case 2

The chiller and boiler get approximately 13% and 12% daily energy saving in cooling and heating seasons using a setback control. Implementing a combination of the aforementioned energy saving solutions according to the output of optimization, can lead to a 7% reduction in industrial system's energy consumption. Let us consider another energy saving solution for the chiller and boiler in which cooling and heating set points are adjusted according to facility personnel's work schedule to avoid unnecessary cooling and heating loads on HVAC components. In other words, set points are adjusted to the lowest and highest temperatures allowed by ASHRAE standard to assure occupant thermal comfort. The results suggest a decrease in percentage savings in chiller (%3 energy saving with adjusted set points). However, decreasing the heating set point during heating season provide an appealing opportunity for savings in boiler's energy (up to %26 reduction compared to base case).

Table 4.2: Nodes' Optimal Share of Energy Saving

Nodes	Energy Saving (%)			
	Case 1		Case 2	
	Cooling Season	Heating Season	Cooling Season	Heating Season
Machine1	30	30	30	30
Machine2	2	2	2	2
Machine3	0.1	0.1	0.1	0.1
Chiller	13	0	3	0
Boiler	0	12	0	26
Fan	11	14	0	0

It can be argued that facility personnel productivity is not impacted drastically with lower indoor temperature during the heating season, but an elevation in cooling set point and resulting higher temperature in the facility degrade the productivity; which in turn decreases the share of energy saving for the chiller. These results are summarized in Table 4.2 and Figure 4.7(b). It is worth to note that developing energy simulations for buildings (using EnergyPlus or similar systems) are becoming common practice in the industry for new buildings. Such simulation models are normally calibrated with building's monthly utility bills and real time data received from Building Energy Management System (BEMS). Thus, depending on the model granularity and accuracy of weather input files, these simulations are able to provide reasonable energy forecasts for buildings. In this case, archived and validated simulation models are used, thus HVAC energy consumption simulation model is valid. Given actual data on an industrial process' energy and efficiency, the accuracy of simulation model used here, can be validated.

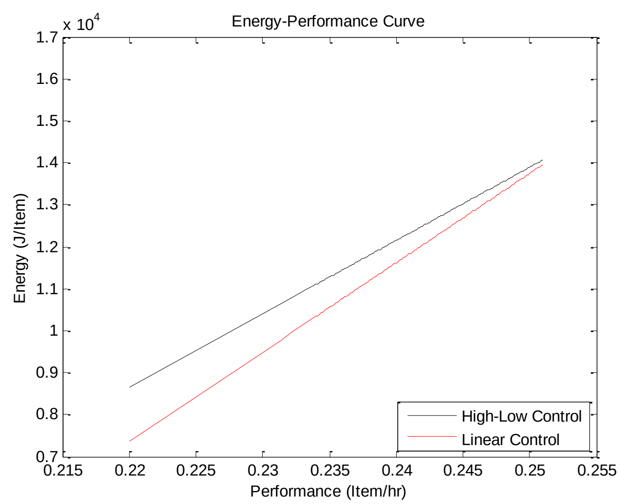

Figure 4.8: Energy-Performance – Serial Production Line : "High-Low" vs. "Linear" Control

Figure 4.8 compares the "Energy-Performance" profile for the above illustrative industrial process in two control scenarios: (1) All machines work with "High-Low" control and (2) Machine 2 works with "Linear" control and the other two machines keep the same control as in (1). Number of items produced per unit time are selected as appropriate KPI to reflect the performance requirement at industrial process. According to Figure 8, total process time in "Linear" control is longer than "High-Low" control. In the present case study average process times are approximately 9.5 and 10 for "High-

Low" and "Linear" control, which leads to 0.16 and 0.17 items per minute for the scenarios respectively. Assuming daily demand of 150 units, despite an opportunity to save energy by switching to "Linear" control, the network owner is at risk of unsatisfied demand. However, for lower demand rates, such as 100 units, switching to energy saving control seems a plausible choice for the facility owner.

4.7. Conclusion

In this chapter we presented models to optimize the energy efficiency in an industrial system using a network approach. The proposed model uniquely integrates energy usage of industrial processes with the usage attributed to the facility that houses the processes. These two perspectives were commonly treated separately in the literature. The optimization model takes into account the interdependencies between nodes of the network in terms of "Energy Consumption" and "Performance". We also introduced the concept of "Energy-Performance" curves which can assist the owner to achieve energy saving while maintaining the performance of nodes in desired levels. The integrated energy efficiency problem is formulated as a general network optimization problem and a solution methodology is presented using an illustrative case study. Nodes in the network represent machines in the production line and HVAC assets in the building. For the facility, we focused on HVAC energy usage and modelled the facility using EnergyPlus. In the illustrative example, we used ARENA simulation to compute KPIs for the production processes. Other simulation packages can also be used or one can adopt more analytical techniques for such calculations – this is outside of the scope of this work. Data derived from these simulations is used to compute nodes' interdependencies. The energy efficiency optimization considers worker productivity and comfort issues. It is assumed that a set of feasible alternatives is given for energy efficiency at each node of the network. The generalization of the approach based on a larger set of feasible alternatives will be an extension to this work. Incorporating the “Energy-Performance” curve in investment, compliance and process risk analysis is also investigated as a future work for this study.

Chapter 5

5. Data and Metering Infrastructure for Sustainable Consumption and Production

5.1. Preliminaries

The work in this chapter is motivated by the fact that sustainable industrial practices require coordinated measures and integrated practices on production and consumption. Consumer products are the common denominator for this integration. The necessity of such integrated metrics has been addressed in the literature. One of the key research issues is development of applied tools for use by designers and decision-makers, validation of life cycle assessments, and validation of metrics for comparing different types of environmental impacts [105]. Data integrity and availability will be major requirements to run sustainable businesses and will ultimately guarantee the success of Sustainable Consumption-Production (hereafter denoted as SCP) across industries. Sustainable production and consumption is the use of goods and services that respond to basic needs, while minimizing the use of natural resources, toxic materials and emissions of waste and pollutants over the life cycle, so as not to jeopardize the needs of future generations. Against this background, this chapter presents a framework to construct a distributed information and computation system to calculate the energy footprint of consumer products. Footprints are excellent tools to assess the overall intensity (e.g. Energy intensity, resource intensity and material intensity) of a defined activity, product or organization. Any type of footprint is fundamentally an audit that provides a quantitative assessment of substances such as greenhouse gases (carbon equivalents), water and even energy consumption for a specific time frame. In this chapter, the time frame under which the energy content calculation is performed is a consumer product's whole life cycle. In order to calculate the energy footprint of a product, one needs to first define the energy consuming stages and processes within the product's life cycle. In this chapter we propose a "Top-Down" mapping of energy flow over the two dimensions of "Life Cycle" and "Supply Chain". The "Top-Down" approach (i.e. Decomposition) is essentially the breaking down of a system to gain insight into its compositional sub-systems. In a "Top-Down" approach an overview of the system is formulated, specifying but not detailing any first-level sub-systems. Each sub-system is then refined in yet greater detail, sometimes in many additional sub-system levels, until the entire specification is reduced to base elements. In other words, considering a treelike structure, mapping is performed by moving from the roots to leaf nodes. In our context, the system under study is a product over the two dimensions; thus, first-level subsystems (denoted as nodes of the network) are stages of the life cycle. System's base elements, denoted as "Atomic" nodes hereafter, are the leaf nodes of the network where no further decomposition is possible. Note that this hierarchal mapping of energy flow across the two aforementioned dimensions allows for defining appropriate node ownerships along the stages of "Life Cycle" and "Supply Chain". At the network atomic level (representing industrial or business processes), energy consuming activities as well as data requirements at process or activity level are defined. One of the critical and key components of the energy content calculation is data metering infrastructure. This chapter focuses on the information infrastructure that is needed to support SCP. In particular, it attempts to address all the three aspects of "what data to collect", "where to get the data from”, and “how to get the data”. While we will not present any specific data values for our illustrative case study, we will map out all the necessary details to build a systematic infrastructure, to perform a collaborative and concurrent analysis of energy flow across supply chains. The hierarchical “Top-down” approach (The network construction process) eventually leads to solutions on the first two of the above questions. The third question above is handled on the basis of constructing a metering and sensing infrastructure within the same information platform. We classify energy metering into “Physical”, “Virtual” and “Simulated”. The framework introduced in this chapter, including the metering infrastructure supports the data and “Energy-Performance” calculations in the preceding chapters.

The major differentiating factors between the work in this chapter and earlier works are described next. The previous related research and commercially available software products are mainly database tools covering aggregate and semi-aggregate data on many industries and common business/industrial processes. An example of such methods is Economic Input-Output models for Environmental Life Cycle Analysis (EIO-LCA) [106-107]. EIO-LCA calculates the impacts of different types of products, materials, services, and industries regarding their resource use and emissions throughout the product’s supply chain. The model uses publicly available information about industry transactions and also environmental emissions of industries. This method suffers from such limitations as high degree of aggregations and only a limited number of factors for which public data are available. In order to reduce the level of aggregation in EIO-LCA based models Process Analysis has been introduced. In this method inputs such as raw materials and energy resources, and also outputs, namely emissions and wastes to the environment, are defined for a specific product or process under study. This task should be done across products or process' entire life cycle; therefore, this method can be overwhelming in terms of number of inputs and outputs needed to be defined, not to mention being costly and time consuming. Some existing Life Cycle Assessment (LCA) software tools based on the process model are: the Ecobilan's group TEAM™ [108], SimaPro from Pre' Consultants [109], GaBi4.0 from PE international [110]. These systems can be used by individual companies to calculate the energy footprint of their processes at any level of aggregation. They come far short of offering any systematic tool for collaboration and concurrent analysis/optimization of energy flow across supply chains. Furthermore, our approach builds on existing collaborative principles and covers all stages of the product life cycle. All interdependencies between different stages and activities that contribute to the making of the product are captured and utilized for the betterment of the product quality and functionality. This includes material, information and energy flow between stages. In our paradigm, similar to the case of an industrial system, nodes' energy and performance across this network are interdependent, and lowering energy over one node could impact the energy and/or performance over some downstream or upstream node. Node's Performance can be quantified in terms of production output, a total time span of a machine, etc. Using top-down schemes we are able to interpolate and extrapolate as necessary and quantify impacts and dependencies at sub-network or network levels.

This chapter outlines as follows. Next section introduces a top-down hierarchal approach to build networks representing a product's "life cycle" and "supply chains". This network defines ownerships and dependencies between nodes over the two dimensions. Defining such ownership, will determine "what data to use" as the first step towards the construction of an information infrastructure needed to support SCP. Network demonstration is followed by introducing a computation engine to capture and measure the aforementioned energy, material and information flow along the network. This computation engine addresses the question of “where to get the data from”. Data and metering infrastructure supporting the computation engine (“how to gather the data”) is discussed, followed by illustrative case studies to elaborate suggested methods of data metering.

5.2. Network Decomposition and Ownership Allocation

In order to map out a consumer product across two dimensions of “Life Cycle” and “Supply Chain”, we propose a “Top-Down” hierarchal approach to construct a Consumption Production – Entity relationship (CP-Er). The outcome of such hierarchical mapping is a network which includes ownership relationships between stakeholders. This model assumes there is a master owner (e.g. Major retailer) who starts the decomposition and the mapping process. This hierarchal structure leads to “Atomic” nodes with no further decomposition where energy calculation is performed at process level. In CP-Er network ownership is defined on the basis of material flow between stages of life cycle as well as supply chain stakeholders. This type of breakdown is particularly similar to breakdown structure of conventional supply chains. The hierarchical model includes relationship between owners/stakeholders and different nodes in the two dimensional space. CP-Er construction process briefly follows. Figure 5.1 illustrates a preliminary view of a CP-Er network for a typical fruit juice such as an orange juice. The first layer of hierarchy breakdown includes sub-systems (nodes) representing stages of life cycle of the orange juice product. Common stages of an orange juice supply chain over the life cycle are: juice production, transportation or distribution, retailer, customer usage and recycle or final disposal. These nodes are laid out horizontally within the CP-Er network as shown in Figure 5.1 below.

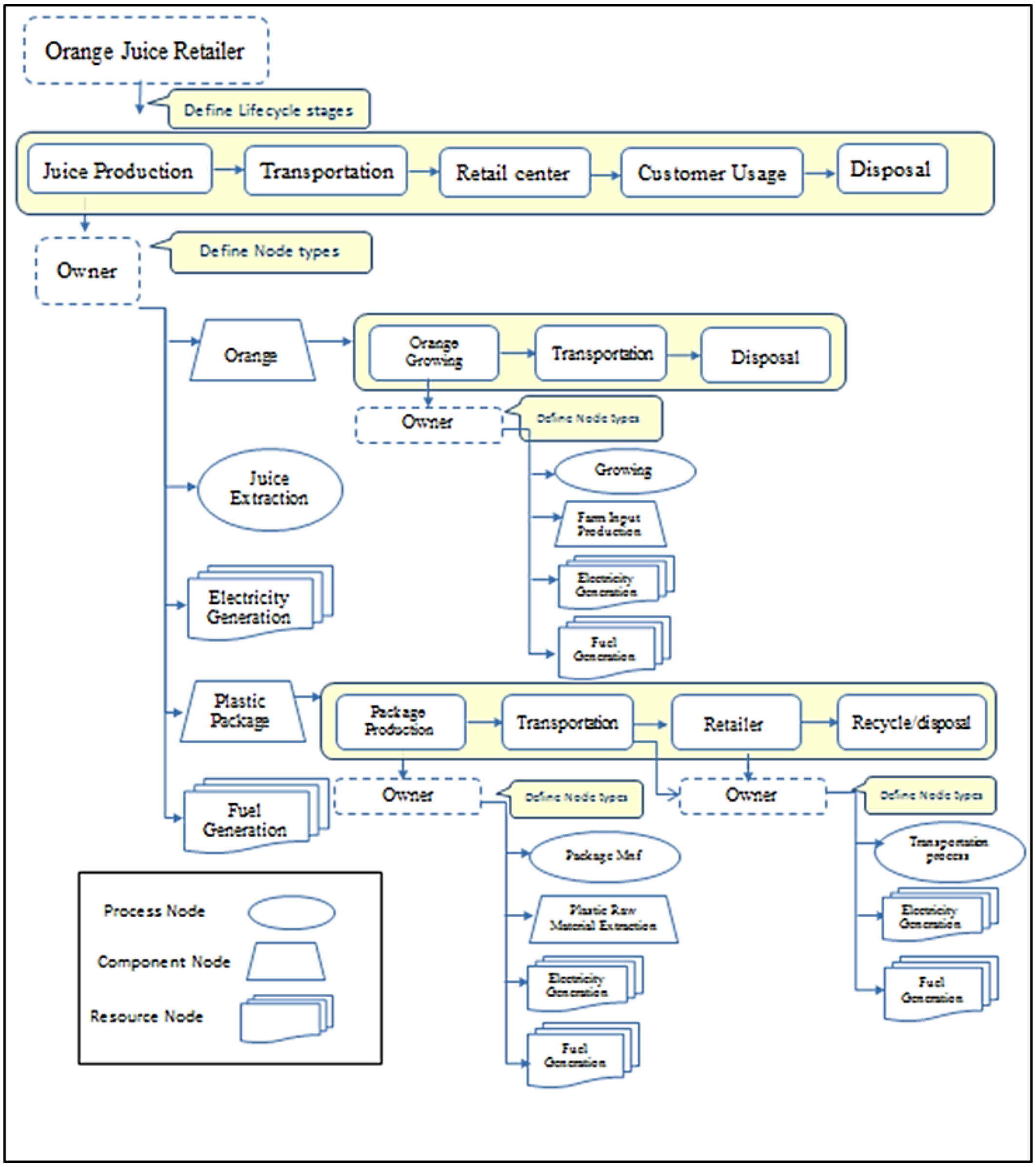

Figure 5.1: CP-Er for Orange Juice

Each such node will point to one or more owners vertically, who will be required to follow the decomposition further down. The vertical breakdown of the hierarchy will take into account the ownership relationship, with a "parent" owner relating to one or more "child" owners. We will assume that every "parent" owner will have access and will be able to communicate to its "child" owners. Each node is characterized by a node "type" namely:

- Component or ingredient nodes
- Process / atomic nodes
- External resource nodes

"External Resource" nodes do not need further breakdowns. The data for these nodes come from external sources such as publicly available data websites [111-114]. In our orange juice example resource nodes are electricity and fuel generation. Electricity generation resource node represents the energy used to generate total on-site electricity required for a manufacturing facility. These nodes have a great contribution to overall energy consumption of products. According to the EPA, of the total energy consumed in America, about 39% is used to generate electricity. "Component" nodes may have their own corresponding life cycle with its separate owners. These nodes usually represent production of raw material and packaging material input. Component or ingredient nodes designated here are fruit input and packaging (plastic containers or cardboard cartons). Each of these components has its own lifestyle, which is laid horizontally on a component level of the CP-Er hierarchal structure as shown in Figure 5.1. The breakdown continues horizontally for each stage of component life cycle. Hierarchal breakdown is continued until atomic nodes (i.e. Nodes with no further decomposition) are reached. Atomic nodes may correspond to machines, processes or any other business entity. Each atomic node is tagged with an owner, embedded energy, and performance index as well as energy and performance dependency with all other nodes within the CP-Er network. Once network decomposition is finished and all atomic nodes are identified, energy and performance can be calculated using a computation engine.

5.3. Energy Computation Engine

Our proposed computation engine quantifies energy consumption of an atomic node and measure performance of the node in terms of the defined performance index. It is assumed that the energy consumption of each node changes upon any modification in energy (i.e. Energy conservation) of other nodes within the CP-Er network. Such interdependency is also valid for performance of each node in terms of the defined performance index. Tools such as continuous and discrete simulation or spreadsheet based approaches may be used to quantify the energy flow of each node. Micro level calculation of energy at each atomic node requires process and activity level analysis of energy usage. All physical and logical processes or activities use energy to transform inputs to outputs. Each resource (e.g., machinery, equipment, and personnel resources) used by an activity has its own energy consumption, which has to be brought to our calculations with some degree of accuracy. This approach employs spreadsheets (hereafter denoted as "Activity Vector") which categorize related data at each stage of the product lifecycle in forms of vectors. These "Activity Vectors" are generic and may be used as a guide for energy calculation of any class of product. For instance, in manufacturing Activity Vector energy consuming systems are classified into:

- Combustion/Thermal systems
- Motor Systems
- Lighting

- Air conditioning (heating and cooling)
- On-site fuel/energy generation
- On-site fuel consumption (propane, etc.)

In manufacturing “Activity Vector” energy consumption (in kWh) of motor systems can be approximated with Equation (5.1):

$$\frac{(N) \times (P) \times (T) \times 0.7457}{\eta \times 1000} \tag{5.1}$$

Where N, P, T and η represent the total number of motors, the horse power of motors (the rate at which work is done), the total operating hours and the efficiency of the motors respectively.

In Equation (5.1) P and T can be approximated with mean values in this paradigm. Note that the constant (0.7457) is used to convert horsepower of the motors to kilowatts. The performance of each node is also quantified in similar fashion in terms of appropriate performance indices defined (i.e. Number of items processed per unit time in production line of manufacturing plant). A generic energy consumption calculation approach at atomic nodes of a fruit juice product is included in the appendix E.1-E.4. Although such generic spreadsheet-based methods require considerably less time and effort in comparison with simulation approaches, they come far short of offering realistic results for energy and performance interdependencies between nodes of a CP-Er network. Simulation approaches can be used to model the dynamics of CP-Er’s atomic nodes taking into account strong interdependencies between activities at micro level. Two sets of factors are introduced here that classify the type of energy reduction technologies at a process level of an atomic node. These factors can then be used to formulate energy and performance dependency between nodes as well as node's energy content.

5.3.1. Profile Factors

These factors are mostly inherent to the specifications of a process, activity or device at the atomic level. In other words, these factors can be considered as energy efficiency in an activity or device which refers to using less energy for a constant service. Energy efficiency differs from energy conservation, which refers to reducing energy through using less of an energy service. For example, driving less is an example of energy conservation. Driving the same amount with a higher mileage vehicle is an example of energy efficiency. Consider an HVAC (heating, ventilation, and air conditioning) system of a manufacturing facility as a part of building services. HVAC is the technology which creates conditioned air, heating and cooling for the production line's personnel resource. This system may be directly or indirectly involved in actual value adding activities of the facility. An example of energy reduction methodology in the manufacturing plant or distribution centers of a CP-ER network is energy reduction in the HVAC system supporting personnel and processes in such environments. Energy reduction in HVAC systems may be achieved via frequent and on-time maintenance of the components of the system (e.g. Supply and return fan, chiller water system). Another example of energy reduction techniques for an HVAC system which falls into profile factors category is the replacement of old components with new and more efficient ones.

5.3.2. Schedule Factors:

As can be expected from the title, schedule factors, mostly depend on the way an activity, process or device is scheduled within the system. Most energy conservation methods for energy reduction fall into this category. Going back to example of HVAC system optimized and efficient process control (e.g. Avoiding unnecessary high or chilled temperatures in buildings and shut down in non-peak hours) is a method for energy saving in HVAC systems. Such energy conservation methods fall into schedule factors. Energy consumption of most processes in a production line of a manufacturing facility can be reduced using schedule factors. Examples are energy reduction of machines (tool handling and actual processing) and material handling by minimizing waste of energy through stand-by loss and machine idle time reduction (planning of production program), or dynamically regulating and controlling production speeds of machines [115]. Another instance of schedule factors for energy reduction at a CP-Er network is minimizing waste of energy in transportation stage, through use of cruise control in distribution vehicles, and appropriate lot sizing in vehicles. In atomic level energy reduction is obtained through energy saving policies on single or a combination of the aforementioned two types of factors. Energy consumption at each of the systems defined above can be approximated using simple equations. For instance, let us assume energy consumption of atomic node N is denoted as E_N:

$$E_N = \sum_{j \in F_P} \Theta[\sum_i \pi_i(\theta_i)]_j + \sum_{k \in F_S} \Phi[\sum_m \pi_m(\gamma_m)]_k \tag{5.2}$$

F_P Set of systems with profile factors

F_S Set of systems with schedule factors

θ_i Profile factor i

$\pi_i(.)$ Energy consumption function due to profile factor i

$\Theta(.)_j$ Energy consumption of system j

γ_m Schedule factor m

$\pi_m(.)$ Energy consumption function due to schedule factor m

$\Phi(.)_k$ Energy consumption of system k

A holistic simulation approach can be used which couples, different simulation tools and methods. Coupling of simulation tools and techniques has been practiced for planning and managing production facilities. Hesselbach et al. (2008) [92], describe an approach to energy efficient design and management of a production facility. They propose coupling of simulation tools HKSim and TRNSYS for modeling technical building services and building itself, SIMFLEX/3D for machines and material flow simulation as well as AnyLogic software for simulation of production management system in the production facility [96] and [116]. In the previous chapters, we presented applications of simulation methods for dynamic quantification of interdependency (energy and performance dependency vectors) between nodes of a simple CP-Er (An industrial facility). Simulation tools employed are Arena simulation software and EnergyPlus simulation. These simulation tools are established solutions within the specific fields of application. Coupling these tools allows a more realistic simulation result for energy and performance calculations in atomic nodes of the CP-Er network. The energy content calculations will be carried out in British Thermal Units (Btu) or kilowatt-hours (kWh). These energy units can ultimately be converted to units of Greenhouse Warming Potential (GWP) to assess the mass of carbon dioxide gas emitted per time or amount of energy consumed.

5.4. Data Sourcing and Metering Infrastructure

The distributed nature of data and data ownership by different businesses are major technical challenges in using simulation-centered computation engine. This problem is far more complex than current practices on data sharing, e.g., product or process quality data, between companies within a supply chain. Some of the challenges that need to be addressed are:

- The lack of standards – The businesses within the CP-Er network use different processes and accounting systems, and follow different practices for data collection, process monitoring, etc.
- Data ownership, privacy, transparency, contractual agreements between different companies within the supply chain business and technical challenges that must be tackled. These all contribute to the complexity of constructing CP-Er network.
- Data availability and integrity – Some elements of energy content at process level can be extracted from the process related data, usually saved and archived in the process database. Examples are energy consumption rate of a process in different modes (warm-up, runtime, actual process and idle). Other elements can be obtained from the company's accounting and inventory systems. Publicly available web sites and reports from government organizations can be a source of aggregate statistics. Identification of these sources per process and overall processes for the product is a major challenge. Moreover, the integration of these data elements into a data repository system and maintenance of data integrity are technical challenges that must be addressed

Figure 5.2 depicts the energy profile on a production machine (e.g. Grinding process). Other elements can be obtained from the company's accounting and inventory systems. Publicly available web sites and reports from government organizations can be a source of aggregate statistics. Identification of these sources per process and overall processes for the product is a major challenge. Moreover, the integration of these data elements into a data repository system and maintenance of data integrity are technical challenges that must be addressed. Given the CP-Er network, this step includes data sourcing analysis, and the development of data sourcing models that take into account common business models and best practices. Until recently energy calculation per process has not been a usual practice by companies. However, due to the rising price of energy as well as increased rules and regulations for environmentally sound and energy efficient practices, energy consumption monitoring is getting into focus for many business owners and companies.

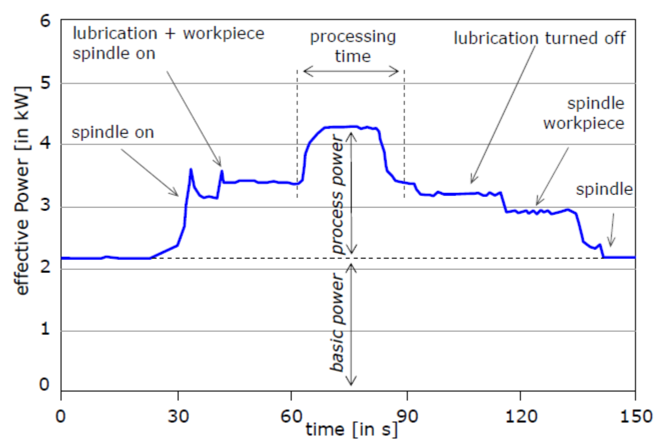

Figure 5.2: Energy profile on a production machine (e.g. grinding process)

In a manufacturing process, the energy content of a process depends on the operating conditions and production schedule. In transportation, energy consumption depends on miles traveled, fuel type, size and load of transport vehicles, among other things. In office related activities (e.g., design process) the energy requirement depends on the size and location of the facility, number of occupants, building materials, etc. There are several sources where data values can be obtained from, such as, metering devices for equipment and facilities, "name tags or labels" of the equipment used in the process, accounting or billing databases currently used by companies and external databases or web sites for aggregate data. Gathering of data is subject to technological and economic constraints. An information infrastructure must be built within each business to support data collection and energy calculations. We recognize three different types of metering devices:

- Physical Metering (PM)
- Virtual Metering (VM)
- Simulated Metering (SM)

5.4.1. Physical Metering

Physical metering corresponds to cases where the elemental data can be directly obtained from sensor or smart meters. An example is a power metering of industrial equipment by sensory instrumentation of the power flow through the equipment. Physical metering also is possible using plug in devices within the power network of a facility. Smart metering technology now is commonly used for buildings and facilities, and is regarded as class of PM devices here.

5.4.2. Virtual Metering

Virtual metering refers to cases where no physical metering is available, but the energy content can be calculated through indirect means, such as from accounting or billing databases. For instance, VM for lighting in a facility can be computed from the number of lighting sources, their wattage, and number of usage hours (estimated from facility schedule). VM for HVAC can be computed by the capacity of HVAC systems known from company documentation or device name tags, number of operating hours (estimated from facility schedule), SEER (Seasonal Energy Efficiency Ratio) or AFUE (Annual Fuel Utilization efficiency) numbers from the websites, In many instances, VM formulations are not readily available, but can be constructed using the laws of physics, accounting principles, inventory and scheduling rules. In other words, there is a computational model behind every virtual meter. VM calculations are assumed to be deterministic in nature. Appendix E.1-E.4 provides a virtual metering approach for energy content calculation in various stages of a product lifecycle. The results of such virtual metering are mostly aggregated with a high level of abstraction.

5.4.3. Simulated Metering

In cases where calculations are not deterministic, the governing rules are not readily available, and/or statistical estimations are required, we propose SM devices. With a typical SM device, there will be simulation and statistical inputs. For instance SM for motor systems in a manufacturing facility is performed using discrete event simulation of the machinery equipment such as milling, grinding, etc. For illustration, consider a three-station serial flow line as part of a typical automotive manufacturing plant. This includes a reaming, hardening (in a curing oven) and final grinding process. Arena simulation software is used here as a SM with the objective of measuring energy consumption and performance (i.e. Parts per hour) for each of the three stations. Two invariants are considered in the analysis, namely T and P, where T indicates the time interval during which P units must be completed and released from the flow line. Several scenarios were simulated incorporating profile factors such as a machine process controller to measure the energy content as well as performance of stations in an 8-hour shift. Another example for application of SM as a metering device for energy and performance calculation in CP-Er network employs EnergyPlus simulation software. EnergyPlus is used to measure the dependency between personnel performance (in terms of relative productivity, i.e. relative performance when compared to maximum performance) and energy saving in air conditioning (cooling) system. Scenarios simulated include schedule factors such as peak hour energy saving strategies for HVAC system. Temperature fluctuations from optimal set points, in which personnel have maximum productivity, is monitored and measured for various schedule factors for HVAC energy saving. The models presented in section 3.3 can then be used to define the change in personnel performance as a function of temperature fluctuations using P.O. Fanger's predicted mean vote (PMV) index.

5.5. Conclusion

In this chapter tools were presented to construct a distributed information and computation system to calculate the energy content of consumer products at a micro level. An ownership network (CP-Er) was introduced which breaks down the production stages and business entities on the basis of material flows over the aforementioned two dimensions. Data sources and data metering structure to model such a CP network has been issued. Data metering types introduced in this chapter help process and activity owners of a Consumption-Production network, identify opportunities to gather data taking into account data availability and possibly make investments for data collection projects. Such metering infrastructure also supports the "Energy-Performance" calculations presented in the previous chapters. We conjecture that it should be possible to use the simulation based computation engine and methods of metering presented in this study for a wide variety of consumer products and services.

Chapter 6

6. Concluding Remarks and Future Researches

6.1. Introduction

In this chapter, we point out some concluding remarks and briefly review relevant potential future extensions. In this research, we aim at developing models that facilitate cost effective and optimal energy efficiency practices for owners of manufacturing companies. The following main problems have been addressed: (1) Manufacturing enterprises have strict requirements in terms of productivity and throughput which makes it particularly challenging for owners of such businesses to invest in energy efficiency solutions. Moreover, most owners of such systems are reluctant to make changes in their existing optimal process performance; thus, the question arises on how to simultaneously account for energy reduction goals and performance requirements in an industrial facility? How to incorporate existing infrastructure and practices in an industrial facility, to reduce the energy consumption and expenditure without sacrificing productivity? (2) Industrial facilities are often complex systems consisting of different components and equipment; therefore one needs to make sure to account for possible conflicting outcomes of practicing energy saving solutions in such complicated system. In other words, owners of a manufacturing company need to know how to incorporate the dynamic interdependencies inherent in the components of a manufacturing environment to achieve optimal energy efficiency solutions. (3) The fact that most aforementioned energy and performance optimization and analysis are highly data-intensive highlights the necessity of a data infrastructure to support such studies. The question arises on how to use existing data bases to acquire necessary data and information to carry out such studies.

Operating at the intersection of multiple sensing and control systems designed for profitability, performability, operational efficiency and occupant productivity, modern manufacturing enterprises represent a prototypical Cyber-Physical System (CPS) that is increasingly becoming part of smart manufacturing or "*Industry 4.0*". We conjecture that as energy efficiency and optimization is rapidly becoming a crucial requirement in "*Industry 4.0*" and smart manufacturing, a potential valuable extension to the work delivered in this research is to integrate the presented network optimizations to achieve energy efficient cyber-physical systems.

In the remainder of this chapter, we provide brief conclusions for each chapter and discuss how we have addressed the above research questions. We further provide potential researches to expand and improve the work presented in each chapter.

6.2. Energy-Performance as the Driver for Energy Optimization in an Industrial System

In Chapter 2, we have provided an optimal production planning based on a two-dimensional "Energy-Performance" measure. By incorporating this measure, the production planning will explicitly include manufacturing machine-level requirements as well as process control strategies and demand patterns. The "Energy-Performance" measure is introduced based on the definition of "Specific Energy" at machine level, and is expanded to define "Energy-Performance" profile at industrial process level. We then formulate the production planning problem as a stochastic MILP with risk-averse constraints to account for manufacturer's risk averesness. The objective is to define the production plan so as to minimize the total loss distribution subject to system throughput, probabilistic risk constraints as well as constraints imposed by the "Energy-Performance" pattern. The stochastic variables are electricity price and demand per unit time. Conditional Value at Risk (CVaR) of loss distributions, which is the expected value of the %5 of worst losses, is used as the manufacturer's risk measure. We have evaluated the applicability of the presented optimization for production planning of a single machining operation as well as a serial operation consisting of multiple machines, under various electricity pricing schemes.

Electric Demand Side Management (DSM) focuses on changing the electricity consumption patterns of end use customers through improving energy efficiency and optimizing allocation of power. In the recent years there have been a mounting interest in manufacturing enterprises to participate in Demand Response (DR) programs offered by utility companies. DR is a DSM solution and an integral part of the Smart Grid paradigm, which targets industrial customers, and is developed for demand reduction or demand shifting at a specific time for a specific duration. The optimization model introduced in chapter 2 can be extended to implement such DR programs and load shifting in industrial processes given production and inventory constraints.

In chapter 3, energy reduction strategies at facility building level was discussed. We have presented asset management as a viable solution to achieve energy saving and improve performance and reliability of building components. We formulate the asset management problem as a multi-objective stochastic optimization problem (MOSOP) with a trade-off between capital expenditures and energy savings. In order to ensure "Performance" requirements are accounted for, we developed a Business Value model to quantify the economic consequence of degradation of assets; Such business values are then integrated into the optimization to define the optimal maintenance schedule. We further integrated the physics-based building energy simulation technology into the maintenance modeling and optimization to allow for multiple scenario testings and through several case studies, illustrated that substantial energy savings can be realized through optimal asset maintenance policies.

We envision a number of extensions to the maintenance optimization presented in chapter 3. The Building Value Model can be extended so as to include the impact of asset failure/degradation on changes in relative humidity and other parameters that in turn modify the Predicted Mean Vote (PMV) and thermal comfort measures. Moreover, the relationship used to define the productivity loss as a result of fluctuations in the thermal comfort, can potentially be extended to include a wider variety of tasks performed by the occupants. On the other hand, a future potential research would be to integrate some load forecasting models, and to include optimization of HVAC asset operational strategies to develop schedules that allow the building owner to respond to DR signals and effective load-shedding strategies.

6.3. Network Energy Efficiency Optimization in an Industrial System

In chapter 4, we presented models to optimize energy efficiency in an industrial system using a network approach. The proposed model uniquely integrates energy usage of industrial processes with the usage attributed to the facility that houses the processes. The industrial system is considered as a network where nodes are interdependent in terms of their energy consumption and performance as measured by appropriate Key Performance Indicators (KPI). We formulated the integrated energy efficiency problem as a general network optimization problem and further provided a framework to effectively quantify the nodes' interdependencies. Finally a solution methodology is presented using an illustrative case study in which the network represents machines in a production line and HVAC assets in the industrial facility's building. For the facility, we targeted the HVAC energy usage and modelled the facility using the EnergyPlus simulation package, while ARENA simulation was used to compute the energy consumption and KPIs for the production process. Data derived from these simulations was used to compute nodes' interdependencies and define the optimal share of energy reduction for each node of the network studied. In the presented illustrative case, it is assumed that a set of feasible alternatives is given for energy efficiency at each node of the network. Generalization of the approach based on a larger set of feasible energy reduction alternatives will be a potential extension to this work. Incorporating the introduced "Energy-Performance" measure in investment, compliance and risk analysis can also be investigated as a future work for this research.

6.4. Data Metering Infrastructure

In chapter 5 we provided tools to construct a distributed information and computation system to calculate the energy content of consumer products at a micro level. An ownership network (CP-Er) was introduced which breaks down the production stages and business entities on the basis of material flows over the two dimensions of supply chain and life cycle. We further presented a data metering structure to support the energy consumption and performance measurements to support the modelling approaches presented in the preceding chapters. The data sources and metering structures to model the introduced CP-Er network, include physical, virtual and simulated metering approaches.

In cyber-physical systems, a large number of sensor and control systems continually generate measurements that should be received by other nodes. Cyber-Physical System (CPS) are deeply coupled with this sensing and networked information processing. A potential future research to extend the work presented in this chapter is to examine the potential to incorporate the presented metering structure to create an embedded sensing network to support the Cyber-Physical Systems (CPS) as part of “Industry 4.0” advancements.

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Appendices

Appendix A - Production planning optimization outputs for a risk-taker manufacturer ($\beta = 0.3$)

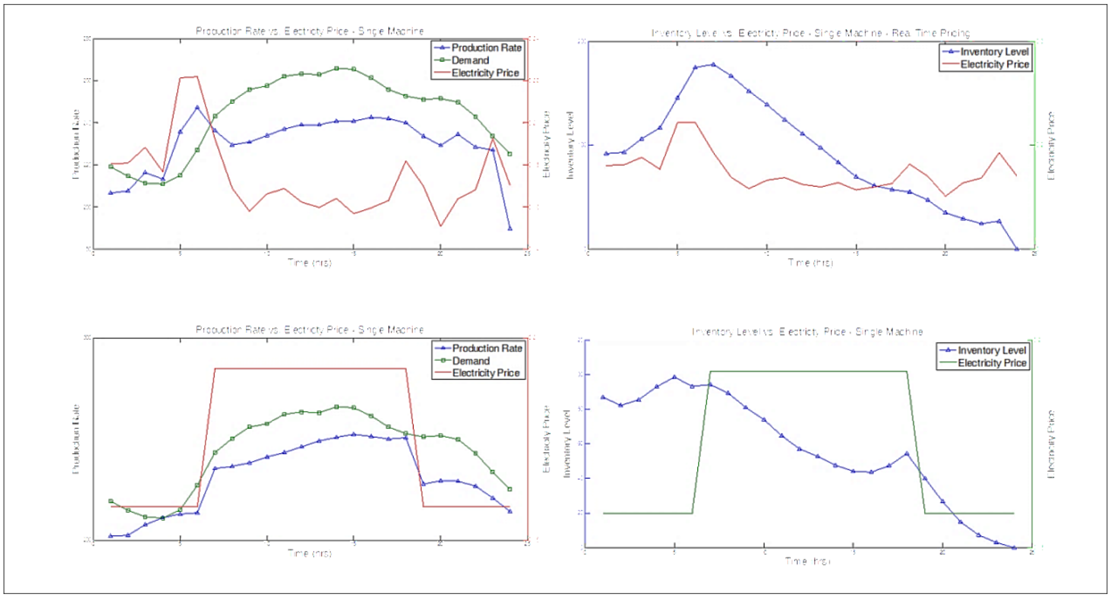


Figure A.1: Production Rate and Inventory Level vs. Electricity Price Case of a Single Machine - (top) Real Time Electricity Pricing (bottom) Time of Use Electricity Pricing

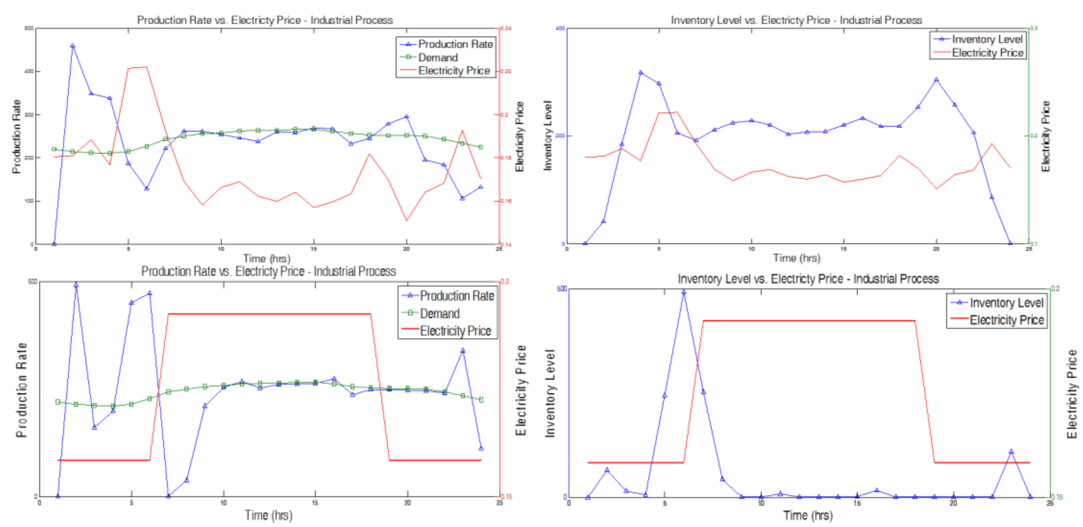
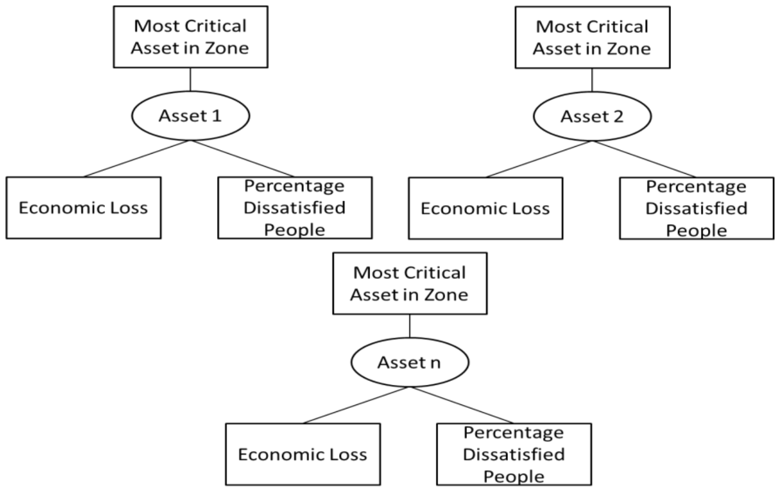


Figure A. 2: Production Rate and Inventory Level vs. Electricity Price Case of a Multiple Machines - (top) Real Time Electricity Pricing (bottom) Time of Use Electricity Pricing

Appendix B – Inverse of AHP Method

The figure below shows the modification in the hierarchal structure of the traditional AHP, which is used in BVM.



Let

A_i= The matrix of pairwise comparison of criteria at levels measured for asset i

a_{ikl}= The relative importance of criterion k to criterion l at the levels that are exhibited by asset i

ω_{ik}= The importance of criterion k at the level exhibited by asset i

$TEC_i^{z_j}$ = the economic consequence of failure of the asset in zone z_j.

ϑ_{ik}= Value of criterion k upon loss of asset i

EC_{ik}= Economic consequence of criterion k upon loss of asset i

Table 3 summarized ϑ_{ik} values for the 3 assets studied in our case study. The pairwise comparison process is carried out with questions posed in the following form: "With respect to the most critical Asset in the zone, specify how important is having % ϑ_{12} dissatisfied people in the zone versus suffering \$ ϑ_{11} of economic loss?". Using the survey and judgmental evaluation, a matrix of pairwise comparison of criteria is constructed as follows:

$$A_i = \begin{bmatrix} a_{i11} & a_{i12} \\ a_{i21} & a_{i22} \end{bmatrix} \quad (1)$$

Where

$$a_{ikl} = {}^{1}/_{a_{ilk}}$$
$$a_{ikl} = {}^{\omega_{ik}}/_{\omega_{il}} \quad (2)$$

Tables B.1 and B.2 show matrices of pairwise comparison (A_i) for the assets serving ballroom and auditorium, obtained from surveys.

Table B.1: Matrices of pairwise comparison of criteria at levels measured for assets serving Ballroom ($\boldsymbol{A_i}$)

Asset **Season**	**Cooling peak**		**Cooling off-peak**		**Heating peak**		**Heating-off peak**	
Chiller	1	1/3	1	1/5	1	1/9	1	1/9
	3	1	5	1	9	1	9	1
Boiler	1	1/9	1	1/9	1	1/2	1	1/4
	9	1	9	1	2	1	4	1
Supply Fan	1	1/2	1	1/4	1	1/3	1	1/5
	2	1/2	4	1	3	1	5	1

The eigenvector of each A_i matrix reveals the relative importance of criterion to the overall objective. The eigenvector can be found by dividing the elements of each column in A_i matrix by the sum of the column (normalizing the column) and then adding the elements in each resulting row and dividing the sum by the number of elements in the row.

Table B.2: Matrices of pairwise comparison of criteria at levels measured for assets serving Auditorium ($\boldsymbol{A_i}$)

Asset **Season**	**Cooling peak**		**Cooling off-peak**		**Heating peak**		**Heating-off peak**	
Chiller	1 3	1/3 1	1 5	1/5 1	1 9	1/9 1	1 9	1/9 1
Boiler	1 9	1/9 1	1 9	1/9 1	1 2	1/2 1	1 4	1/4 1
Supply Fan	1 2	1/2 1/2	1 4	1/4 1	1 3	1/3 1	1 5	1/5 1

Eigenvectors of $A_i$matrices are presented in Table B.3 and B.4.

Table B.3: Eigenvector of Matrices of pairwise comparison ($\mathbf{A_i}$) for assets serving Ballroom

Asset **Season**	**Cooling peak**	**Cooling off-peak**	**Heating peak**	**Heating-off peak**
Chiller	0.25 0.75	0.16 0.83	0.1 0.9	0.1 0.9
Boiler	0.1 0.9	0.1 0.9	0.33 0.66	0.2 0.8
Supply Fan	0.33 0.66	0.2 0.8	0.25 0.75	0.16 0.83

Table B. 4: Eigenvector of Matrices of pairwise comparison ($\mathbf{A_i}$) for assets serving Auditorium

Asset **Season**	**Cooling peak**	**Cooling off-peak**	**Heating peak**	**Heating-off peak**
Chiller	0.25 0.75	0.16 0.83	0.1 0.9	0.1 0.9
Boiler	0.1 0.9	0.1 0.9	0.33 0.66	0.2 0.8
Supply Fan	0.33 0.66	0.2 0.8	0.25 0.75	0.16 0.83

In particular, the first element of each eigenvector, ω_{i1}, gives the contribution of "business value loss" criterion, to the total economic consequence of asset failure. Thus, the real measurable economic consequence of failure of asset i, which serves zone z_j, is simply obtained by Equation (3),

$$TEC_i^{z_j} = {}^{\vartheta_{i1}}\!/_{\omega_{i1}} \tag{3}$$

Table B. 5: A.5 Real Measured Economic Consequence of Failure of Asset Serving Ballroom ($\boldsymbol{TEC_i^{z_1}}$)

Asset **Season**	**Cooling peak**	**Cooling off-peak**	**Heating peak**	**Heating-off peak**
Chiller	40000	18000	0	0
Boiler	0	0	42000	20000
Supply Fan	30000	15000	56000	24000

Results for $TEC_i^{z_j}$ for both ballroom (z_1) and auditorium (z_2) zones are presented in Table B.5 and B.6.

The contribution of the having “Dissatisfied People” in a zone to the economic consequence of asset loss can be found by:

$$EC_{i2} = TEC_i^{z_j} \times \omega_{i2} \tag{4}$$

Table B. 6: Real Measured Economic Consequence of Failure of Asset Serving Auditorium($\boldsymbol{TEC_i^{z_2}}$)

Asset Season	**Cooling peak**	**Cooling off-peak**	**Heating peak**	**Heating-off peak**
Chiller	28000	12000	0	0
Boiler	0	0	24000	10000
Supply Fan	21000	10000	32000	12000

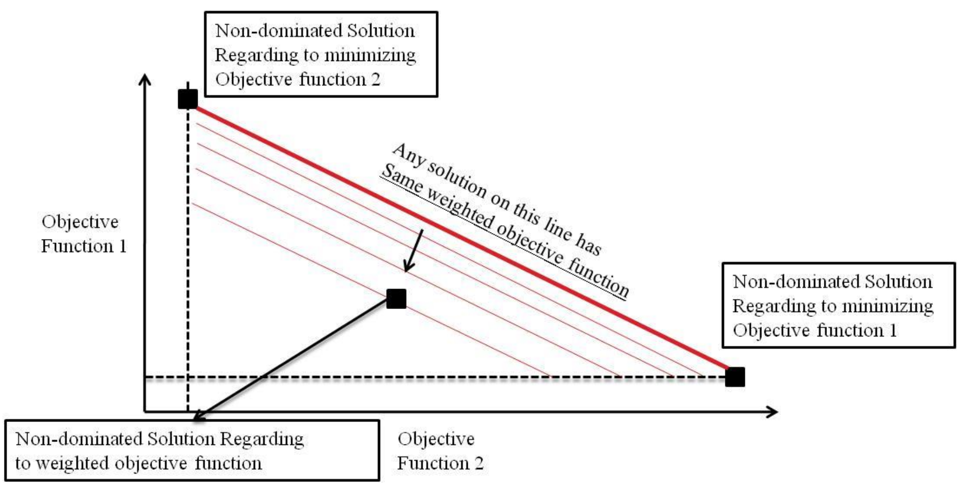
For an asset serving multiple zones, using Equation (5), total “Business Value” is:

$$TEC_i = \sum_{z_j} TEC_i^{z_j} \tag{5}$$

Appendix C – Weighted Sum Approach

Weighted Sum Approach is common technique to find the non-dominated solutions for multi objective optimization problem. Solution A dominates solution B if solution A does as well as solution B in terms of each of the objectives and strictly better than solution B

in terms of one or more objectives. We begin by finding the best non-dominated solution with respect to each of the two objectives. Next step is to find a weight (w) for the two objectives such that any solution on the line connecting these two solutions will have the same value. Once we find the correct value of w, we minimize w times the first objective plus $(1 - w)$ times the second objective and find a new solution. Geometrically, this is equivalent to trying to push the line connecting the two solutions down and to the left in a direction that is perpendicular to the line connecting the two solutions (See figure below). We now repeat the process for each of the original and the new solutions. This process will be repeated until the optimization problem with the updated weighted objective function no longer has any feasible solution.



Appendix D: "What-If" scenarios used for validation

Scenario number	**"What-if" scenario**	
	Asset	**Maintenance Option**
1	Chiller	Reactive Maintenance
	Boiler	Reactive Maintenance
	Supply fan	Reactive Maintenance
2	Chiller	PM clock, type 3, fr=3
	Boiler	PM clock, type 3, fr=6
	Supply fan	Reactive Maintenance
3	Chiller	PM clock type 3, fr=6
	Boiler	PM clock type 3, fr=3
	Supply fan	Reactive Maintenance
4	Chiller	Reactive Maintenance
	Boiler	PM clock, type 3, fr=3
	Supply fan	PM clock, type 3, fr=3
5	Chiller	PM clock, type 3, fr=6
	Boiler	PM clock, type 3, fr=6
	Supply fan	Reactive Maintenance
6	Chiller	PM clock, type 3, fr=3
	Boiler	PM clock, type 3, fr=3
	Supply fan	PM clock, type 3, fr=3
7	Chiller	PM clock, type 3, fr=6
	Boiler	PM clock, type 3, fr=6
	Supply fan	PM clock, type 3, fr=6
8	Chiller	PM clock, type 3, fr=3
	Boiler	PM clock, type 3, fr=3
	Supply fan	PM clock, type 3, fr=6
9	Chiller	PM clock, type 3, fr=6
	Boiler	PM clock, type 3, fr=6
	Supply fan	PM clock, type 3, fr=3
10	Chiller	PM clock, type 3, fr=6
	Boiler	Reactive Maintenance
	Supply fan	Reactive Maintenance

Appendix E.1 - Orange Juice Production Activity Vector

A	B	C	D	E	F	G
1	Manufacturing AV		Needed Data	Data Source	Method of Energy Metering	energy Consumption
2	component 1 Plastic Package)	Decomposable				
3	component 2 (Orange)	Decomposable				
4	Resources (electricity generation/fuel generation)			web	aggregate	
5	Combustion/Thermal Systems	Furnace/Oven	Capacity of the furnace (Btu/hr)	Metering (nametag)	PM-VM-SM	Capacity of the furnace × Operating hours / (3413(Btu/kWh) × Efficiency)
6			Efficiency (eff)	Metering (nametag)		
7			Operating hours (hr)	Inventory		
8		Boilers	Capacity of the boiler (Btu)	Metering (nametag)	PM-VM-SM	Capacity of the boiler × Operating hours / (3413(Btu/kWh) × Efficiency)
9			Efficiency (eff)	Metering (nametag)		
10			Operating hours (hr)	Inventory		
11		Cooling Systems		Metering (nametag)	PM-VM-SM	
12		Drying Systems		Metering (nametag)	PM-VM-SM	
13	Motor Systems	Motors	No. of motors	Inventory	PM-VM-SM	No. of motors × hp of motors × Operating hours × 0.7457(kW/hp) / (Efficiency × 1000)
14			hp of motors	Metering (nametag)		
15			Efficiency (eff)	Metering (nametag)		
16			Operating hours (hr)	Inventory		
17		Air Compressors	No. of compressors	Inventory	PM-VM-SM	No. of compressors × hp of compressors × Operating hours × 0.7457(kW/hp) / (Efficiency × 1000)
18			hp of compressors	Metering (nametag)		
19			Efficiency (eff)	Metering (nametag)		
20			Operating hours (hr)	Inventory		
21	Lighting	Lighting	No. of fixtures (N)	Inventory	PM-VM-SM	No. of fixtures × No. of operating hours × Wattage of the fixture /1000
22			No. of operating hours (hr)	Inventory		
23			Wattage of the fixture (W)	Inventory		
24	Air Conditioning (heating)		No. of the units (N)	Inventory	PM-VM-SM	(No. of the units × Heating capacity of the system × Load factor × Efficiency × Operating hours / AFUE number) / 3413(Btu/kWh)
25			Heating capacity of the system (Btu/tonnage)	Metering (nametag)		
26			Load factor (LF)	Metering		
27			Efficiency (eff)	Metering (nametag)		
28			AFUE number	web		
29			Operating hours (hr)	Inventory		
30	Air Conditioning (cooling)		No. of the units (N)	Inventory	PM-VM-SM	(No. of the units × Cooling capacity of the system × Load factor × Efficiency × Operating hours × 12000(Btu/cooling ton)/ SEER number)/1000
31			Cooling capacity of the system (tonnage)	Metering (nametag)		
32			Load factor (LF)	Metering		
33			Efficiency (eff)	Metering (nametag)		
34			SEER number	web		
35			Operating hours (hr)	Inventory		
36	On-site Energy/Fuel Generation	PV	Power required (kWac) - 75 kWac or 100 kWac	Inventory	PM-VM-SM	Desired System Performance Capacity in DC power/(0.95 × 0.95 × 0.9)
37			Desired System Performance Capacity in DC power, Inverter Eff, Wiring Eff, Other Eff's (0.95, 0.95, 0.9)	Inventory		
38	Fuel Consumption, in-plant (propane, electricity, …)		Fuel Consumption (gal)	Bills/Metering	PM-VM-SM	Fuel Consumption *Energy per gallon/3413(Btu/kWh)
39			Energy per gallon (Btu/gal)	web		
40	**Total**					0

Append ix E.2 -

Transportation Activity Vector

A	B	C	D	E	F	G
1	Transportation and Warehouse AV		Needed Data	Data Source	Method of Energy	Energy Consumption
2	Vehicle Manufacturing	Decomposable				
3	Resources (electricity generation/fuel generation)			Web	aggregate	
4	Fuel Consumption, off-plant (gas, …)	plane	Fuel Consumption (gal)	Bills/Metering	PM-VM-SM	(D4 × D5) / 3413
5			Energy per gallon (Btu/gal)	Web		
6		Ship	Fuel Consumption (gal)	Bills/Metering		(D6 × D7) / 3413
7			Energy per gallon (Btu/gal)	Web		
8		Train	Fuel Consumption (gal)	Bills/Metering		(D8 × D9) / 3413
9			Energy per gallon (Btu/gal)	Web		
10		Ground	Fuel Consumption (gal)	Bills/Metering		(D10 × D11) / 3413
11			Energy per gallon (Btu/gal)	Web		
12	uel Consumption, in-plant (propane, electricity, …		Fuel Consumption (gal)	Bills/Metering	PM-VM-SM	(D12 × D13) / 3413
13			Energy per gallon (Btu/gal)	Web		
14	Lighting (in warehouse)		No. of fixtures (N)	Inventory	PM-VM-SM	D14 × D15 × D16 / 1000
15			No. of operating hours (hr)	Inventory		
16			Wattage of the fixture (W)	Inventory		
17	Air Conditioning (heating)		No. of the units (N)	Inventory	PM-VM-SM	[(D17 × D18 × D19 × D20 × D22) /D21] / 3412.14
18			Heating capacity of the system (Btu/tonnage)	Metering (name tag)		
19			Load factor (LF)	Metering		
20			Efficiency (eff)	Metering (name tag)		
21			AFUE number	Web		
22			Operating hours (hr)	Inventory		
23	Air Conditioning (cooling)		No. of the units (N)	Inventory	PM-VM-SM	D23 × D24 × D25× D26 × D28 × 12000) / D27] / 10
24			Cooling capacity of the system (tonnage)	Metering (name tag)		
25			Load factor (LF)	Metering		
26			Efficiency (eff)	Metering (name tag)		
27			SEER number	Web		
28			Operating hours (hr)	Inventory		
29	**Total**					**0**

Appendix E.3 - Retailer Activity Vector

A	B	C	D	E	F
1	Point of Sale AV	Needed Data	Data Source	Method of Energy Metering	Energy Consumption
2	Resources (electricity generation/fuel generation)		Web	aggregate	
3	Lighting (in warehouse)	No. of fixtures (N)	Inventory	PM-VM-SM	(C3 × C4 × C5)/ 1000
4		No. of operating hours (hr)	Inventory		
5		Wattage of the fixture (W)	Inventory		
6	Air Conditioning (heating)	No. of the units (N)	Inventory	PM-VM-SM	(C6*C7*C8*C9*C11/C10)/3412.14
7		Heating capacity of the system (Btu/tonnage)	Metering (name tag)		
8		Load factor (LF)	Metering		
9		Efficiency (eff)	Metering (name tag)		
10		AFUE number	Web		
11		Operating hours (hr)	Inventory	PM-VM-SM	
12	Air Conditioning (cooling)	No. of the units (N)	Inventory		[(C12 × C13 × C14 × C15 × C17 × 12000) / E16]/ 1000
13		Cooling capacity of the system (tonnage)	Metering (name tag)		
14		Load factor (LF)	Metering		
15		Efficiency (eff)	Metering (name tag)		
16		SEER number	Web		
17		Operating hours (hr)	Inventory		
18	**Total**				**0**

Appendix E.4 - Recycle and Disposal Activity Vector

A	B	C	D	E	G
1	Disposal/ Recycle AV	Needed Data	Data Source	Method of Energy Metering	Energy Consumption
2	Resources (electricity generation/fuel generation)		Web	aggregate	
3	Pumps	No. of pumps	Inventory	PM-VM-SM	(C3 × C4 ×C6 × C7 × 0.745) / (C5 × 1000)
4		hp of pumps	Metering (name tag)		
5		Efficiency (eff)	Metering (name tag)		
6		Operating hours (hr)	Inventory		
7		load factor	Metering		
8	Motors (aeration, grinding,..)	No. of motors	Inventory	PM-VM-SM	(C8 × C9 × C11 × 0.7457) / (C10 × 1000)
9		hp of motors	Metering (name tag)		
10		Efficiency (eff)	Metering (name tag)		
11		Operating hours (hr)	Inventory		
12	Compressors (aeration, ..)	No. of compressors	Inventory	PM-VM-SM	(C12 × C13 × C15 × 0.7457) / (C14 × 1000)
13		hp of compressors	Metering (name tag)		
14		Efficiency (eff)	Metering (name tag)		
15		Operating hours (hr)	Inventory		
16	Ozone generation		Metering/Inventory	PM-VM-SM	
17	UV lamps		Metering/Inventory	PM-VM-SM	
18	Energy generation (landfills, biogas from anaerobic digestion, waste combustors, incineration)		Metering/Inventory	PM-VM-SM	
19	Lighting	No. of fixtures (N)	Inventory	PM-VM-SM	(C19 × C20 × C21)/1000
20		No. of operating hours (hr)	Inventory		
21		Wattage of the fixture (W)	invenory		
22	Air Conditioning (heating)	No. of the units (N)	Inventory	PM-VM-SM	[(C22 × C23 × C24 × C25 × C27) / C26] / 3412.14
23		Heating capacity of the system (Btu/tonnage)	Metering (name tag)		
24		Load factor (LF)	Metering		
25		Efficiency (eff)	Metering (name tag)		
26		AFUE number	Web		
27		Operating hours (hr)	inevntory		
28	Air Conditioning (cooling)	No. of the units (N)	Inventory	PM-VM-SM	[(C28 × C29 × C30 × C31 × C33 × 12000) / C32] /1000
29		Cooling capacity of the system (tonnage)	Metering (name tag)		
30		Load factor (LF)	Metering		
31		Efficiency (eff)	Metering (name tag)		
32		SEER number	Web		
33		Operating hours (hr)	Inventory		
34	**Total**				**0**