ENERGY OPTIMIZATION AND CONTROLLER PERFORMANCE ASSESSMENT IN A PULP MILL COGENERATION FACILITY

by

DEVIN JAMES MARSHMAN

B.A.Sc., The University of Waterloo, 2008

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

THE FACULTY OF GRADUATE STUDIES

(Chemical and Biological Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

August 2010

Abstract

Over the past few decades, the production and sale of "green" electricity from cogeneration has become a critical component of economic and environmental sustainability for the pulp and paper industry. As with almost every complex industrial process, the true value of a cogeneration facility is highly dependent on how efficiently and effectively it is utilized. This thesis develops and demonstrates two optimization-based process management tools that maximize the economic outputs from cogeneration: a high level unit economic performance assessment method, and an energy management strategy for optimal real time cogeneration facility management.

The economic performance assessment tool simultaneously optimizes the steady state operating setpoints and process variability loads according to an economic objective function. Setpoints are optimized based on a back-off approach to constraint handling, and variability loads are optimized based on the comparison of current control with LQG control strategies. The result is a realistic quantification of potential process performance. Additionally, the convex form of the optimization problem results in quick solution times. Results are presented in the form of two case studies.

The energy management system maximizes cogeneration profitability in real time by effectively coordinating key process parameters and various external influences according to an economic objective function. Potential process configurations are constrained using a cogeneration plant model. The optimization procedure is carried out using a flexible forecast horizon that predicts such time-dependant influences as electricity sale prices, limited fuel costs and supplies, and special cases of dynamic operational safety constraints. By constructing such a complete optimization problem based on the complex operation of a cogeneration facility, a sustainable and economically optimal plant management strategy is achieved. Additionally, the convex form of the optimization problem results in quick solution times, which is critical to effective online implementation. Results are presented in the form of three case studies.

Preface

This thesis was written in partial fulfillment of the requirements for the degree of Master of Applied Science in the Faculty of Graduate Studies in Chemical and Biological Engineering at the University of British Columbia. The content herein describes two proposed optimization-based algorithms for cogeneration plant management in the pulp and paper industry: an economic performance assessment algorithm, and an energy management algorithm.

Portions of this work have been accepted for publication. D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Energy optimization in a pulp and paper mill cogeneration facility. Applied Energy, 2010. [57].

Portions of this work also appear in conference proceedings. D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Economic performance assessment with optimized LQG benchmarking in MIMO systems. In DYCOPS-9, 2010. [55]. D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Energy management optimization in a pulp and paper mill cogeneration facility. In ACC 2010, 2010. [56].

I, Devin Marshman, was the main contributor with respect to both research and writing for the above articles and proceedings, along with all other content of this thesis. Check footnotes on the first pages of each chapter for more information.

Contents

Abstract . . . . **ii**

Preface . . . . **iv**

Contents . . . . **vii**

List of Tables . . . . **viii**

List of Figures . . . . **x**

Notation . . . . **xi**

Acknowledgements . . . . **xiv**

1 Introduction **1**

2 A Brief Overview of Industrial Optimization **6**

2.1 Branches of optimization 7

2.2 Industrial optimization and control 8

2.3 Linear-quadratic Gaussian control 11

3 Literature Review **15**

3.1 Cogeneration plant modeling 15

3.1.1 Steady state modeling 16

3.1.2 Dynamic modeling 19

3.2 Cogeneration unit performance assessment 21

3.3 Cogeneration energy management system 24
3.3.1 Heuristic optimization 26
3.3.2 Non-heuristic optimization 31

4 Problem Statement 34
4.1 Economic process performance assessment 35
4.2 Cogeneration energy management system 36

5 Cogeneration Plant Model 40
5.1 Cogeneration process description 40
5.2 Individual unit model development 43
5.3 Plant-wide energy management model development 45
5.4 Cooling reservoir temperature model 47

6 Economic Performance Assessment 51
6.1 Setpoint shift 52
6.2 LQG benchmark with setpoint shift 53

7 Energy Management System 60
7.1 Special cases of energy management 64
7.1.1 Reservoir temperature forecasting 66
7.1.2 Reservoir temperature limited production scheduling 66

8 Case Studies 71
8.1 Steady state performance assessment 71
8.1.1 Multi-stage evaporator 72
8.1.2 Industrial Case Study: Three-stage condenser 76
8.2 Mill energy management 77
8.2.1 Case I: Daily Production Scheduler 78
8.2.2 Case II: Weekly Production and Purchasing Scheduler 83

8.3 Mill energy management: thermal reservoir-limited case 85

9 Conclusions and Future Work 89

9.1 Summary of contributions 90

9.2 Future research 91

Bibliography 92

List of Tables

5.1 Evaporator first order process models 45

5.2 Cogeneration process models 48

8.1 Evaporator steady state property values 74

8.2 Case II: hog fuel suppliers 84

8.3 Case II: economic results 84

8.4 Thermal reservoir-limited case: results summary 87

List of Figures

1.1 Hierarchy of industrial process control strategies 3

2.1 2-D examples of linearity and convexity 9

2.2 Mean shift towards constraint due to reduced variance 11

2.3 Example of tradeoff between servo and regulatory control 12

5.1 Pulp and paper mill cogeneration system schematic 41

5.2 Model output versus actual output for several cogeneration unit operations . 49

6.1 Typical LQG input-output standard deviation tradeoff curve over a range of λ 54

6.2 Summary flow chart of the proposed EPA strategy 58

7.1 Summary of EMS optimization algorithm 64

7.2 Modified EMS algorithm flow chart 69

8.1 Multi-stage, counter-current evaporator schematic 73

8.2 Evaporator hourly profit based on current operation, setpoint shift, and LQG benchmarking methods with setpoint shift 74

8.3 Product density operation distribution curves for various stages of economic performance analysis 75

8.4 Black liquor condensing system schematic 77

8.5 Condenser estimated profitability relative to current operating conditions . . 78

8.6 Electricity production schedule for limited hog fuel supplies over a 24 hour period with hourly market-based sale prices 80

8.7 Optimized unit inlet valve positions over 24 hours for a 100 tonne hog fuel supply . . . 80
8.8 Comparison of electricity production schedules for 40 tonne hog fuel supply over a 24 hour period with hourly market-based sale prices . . . 82
8.9 Comparison of profitability for 40 tonne hog fuel supply over a 24 hour period with hourly market-based sale prices . . . 82
8.10 Comparison of electricity production schedules over a seven day period under a two tier electricity sale price contract . . . 84
8.11 Thermal reservoir temperature profile over a 24 hour period for the original EMS and the temperature constraint modified version of the EMS . . . 87
8.12 Power generation profile over a 24 hour period for the original EMS and the temperature constraint modified version of the EMS . . . 88

Notation

C_t	cost of operation during period t
$c_{e,t}$	cost of electricity during period t
c^j_{hog}	cost of hog fuel from supplier number j
c_{ng}	cost of natural gas
c_u	economic performance coefficient vector of process inputs
c_w	cost of fresh water treatment
c_y	economic performance coefficient vector of process outputs
E_t	cooling reservoir thermal energy at time t
g^i_t	natural gas consumption by boiler number i during period t
H^{X_i,Y_j}_{in}	inlet steam enthalpy to ith unit of type X and jth subunit of type Y. If no subunits exist then the corresponding inlet enthalpy is denoted by $H^{X_i}_{in}$
H^{X_i,Y_j}_{out}	outlet steam enthalpy to ith unit of type X and jth subunit of type Y. If no subunits exist then the corresponding outlet enthalpy is denoted by $H^{X_i}_{out}$
$h^{i,j}_t$	hog fuel consumption from jth supplier to boiler number i during period t
f_o	total energy content of original fuel consumed
f_t	energy content of fuel used during time period t
K	steady state gain matrix
k_f	fuel scaling factor
m^{X_i,Y_j}_t	average steam mass flow rate into jth subunit of type Y in ith unit of type X during period t. If no subunits exist then the corresponding mass flow rate is denoted simply by $m^{X_i}_t$

$\Delta m_t^{PRV_i}$	steam mass flow rate increase through pressure relief valve i during period t due to contact with water supply during depressurization
m_t^w	mass flow rate of boiler feed water requiring treatment during period t
$m_{MAX}^{X_i,Y_j}$	max steam mass flow rate into ith unit of type X and jth subunit of type Y. If no subunits exist then the corresponding maximum mass flow rate is denoted simply by $m_{MAX}^{X_i}$
$\delta m_{MAX}^{X_i,Y_j}$	rate of change limit for steam mass flow rate into ith unit of type X and jth subunit of type Y over one period. If no subunits exist then the corresponding rate of change limit for mass flow rate is denoted by $\delta m_{MAX}^{X_i}$
n	total number of units
n^X	number of units of type X
$n^{X_i,Y}$	number of subunits of type Y in ith unit of type X
n^{sup}	number of hog fuel suppliers
P	profitability of operation
P_o	original profitability of operation
P_t	power generation during period t
Q_t	heat demand during period t
q_t^i	plant heat demand at ith steam pressure header during period t. There are usually three pressure headers: one each for high, medium, and low pressure steam
$q_t^{r,Z}$	rate of cooling reservoir heat transfer from source Z at time t where Z denotes either radiation (rad) or inlet flow (inf) or vaporization (vap) or sensible heating ($sens$) or outlet flow ($outf$)
s_j	available hog fuel from supplier j
t	index of a period within the optimization horizon
Δt	duration of an optimization period
$tmax$	total number of periods within the optimization horizon
$\bar{u}$	mean process input vector
$\bar{u}_o$	original mean process input vector

u_{min}	process input lower limits
u_{max}	process input upper limits
$w_{f,t}$	fuel weighting vector during time period t
X	major cogeneration units - biolers (denoted boi), turbines (tur), steam headers (sh), pressure relief valves (PRV), vents (ven)
Y	cogeneration subunits - stages in turbines (denoted sta)
$\bar{y}$	mean process output vector
$\bar{y}_o$	original mean process output vector
y_{min}	process output lower limits
y_{max}	process output upper limits
z_{α_u}	z-coefficient corresponding to input constraint violation probability $1-\alpha$
z_{α_y}	z-coefficient corresponding to output constraint violation probability $1-\alpha$
α_u	probability of an acceptable input
α_y	probability of an acceptable output
β	hog fuel combustion efficiency
γ^j	hog fuel energy content coefficient from supplier i
ϵ^{X_i,Y_j}	efficiency of jth subunit of type Y in ith unit of type X. If no subunit exists then the corresponding efficiency is denoted simply by ϵ^{X_i}
θ	natural gas energy content coefficient
λ	LQG weighting vector $[\lambda_u\ \lambda_y]$
λ_{min}	minimum LQG weight
λ_{max}	maximum LQG weight
λ_u	LQG input weighting vectors
λ_y	LQG output weighting vectors
$\Delta\lambda$	incremental testing resolution of λ
σ_u	input standard deviations
σ_y	output standard deviations
ϕ	natural gas combustion efficiency

Acknowledgements

This thesis would not have been possible without the encouragement, guidance, and dedication of my academic supervisors Bhushan Gopaluni and Guy Dumont, or my industrial supervisors and colleagues Terry Chmelyk, Manny Sidhu, and Carl Sheehan.

I would also like to thank NSERC, MITACS, NORPAC Controls Ltd. and Emerson Process Management, whose financial support made this work possible.

Finally, I am deeply indebted to my fiancee Veronica Kahgee-Cutbush and the rest of my family for their love, support, and for putting up with me throughout this work.

Chapter 1

Introduction

The formation of wood chips for paper production can yield up to 50% waste material, also known as "hog", depending on the type of wood and pulping process used. Rather than dispose of this excess material, the pulp and paper industry often exploits it by burning the waste in multi-fuel power boilers to produce steam. In addition to being a much cheaper source of fuel, the scrap product is considered to be a "green" fuel with significant environmental benefits when compared to conventional fuels such as natural gas or coal, as described by Sampson and Wright [73]. Once the hog fuel is combusted in the boilers, the resulting steam can be used as a source of heat for various unit operations within the pulp and paper mill, or alternatively passed through a series of turbines to generate electrical power. Systems used to carry out this process are referred to as combined heat and power, powerhouse, or cogeneration systems since they generate both steam and electricity; two commodities required by many industrial applications including pulp & paper production.

The generation of power and steam by a single system is economically advantageous compared to generation by two separate systems. Combining the two processes leads to savings in the range of 10% to 40% through reduced fuel costs due to higher overall efficiencies [52]. Increased efficiency results in an equivalent reduction in harmful emissions, making cogeneration beneficial from an environmental standpoint regardless of the fuel used. Many cogeneration facilities in pulp & paper mills are capable of producing power well in excess of plant demands. By selling that excess power to regional electricity providers, they effectively generate an additional source of income for the mill.

Cogeneration system configurations tend to be highly interconnected with complex networks of boilers, turbines, condensers, relief valves, vents and pressure headers. Utilizing the cogeneration system to its maximum potential requires an intimate knowledge of the process; stable, accurate and quick control over each of the individual units; and an effective strategy that coordinates all units towards a common objective such as maximum profitability. No single control strategy offers such a wide range of functionality. Instead, the proper management of such systems requires multiple interconnected levels of control.

A general hierarchy of control strategies for industrial processes described by Seborg, Edgar and Mellichamp [76] is depicted in Fig. 1.1. The bottom of the hierarchy contains essential control elements with high frequencies of execution that are tailored to a specific process. The highest (or supervisory) levels of control located at the top of the hierarchy are optional control elements with lower frequencies of execution and more generic designs [76]. Truly effective management of complex industrial processes, such as cogeneration, requires elements from every level.

This thesis will focus on the development of advanced process control strategies for cogeneration facilities within the top four tiers of Fig. 1.1, which range from *regulatory control* to *forecasting, planning and scheduling*. The top two tiers, *forecasting, planning and scheduling* and *real-time optimization*, are combined in an energy management system (EMS). The next two tiers, *multivariable control and constraint handling* and *regulatory control*, will be investigated using an economic performance assessment (EPA) algorithm. The lowest levels of control, *failsafe equipment and alarms* and *measurement and action*, are beyond the scope of this thesis and will therefore not be investigated.

An energy management system (EMS) is an optimization-based approach to high level plant control. By coordinating various unit operations within a facility, an EMS drives the operation of a plant, and the individual unit operations within that plant, towards a common goal through the use of mathematical models and optimization strategies. A typical EMS

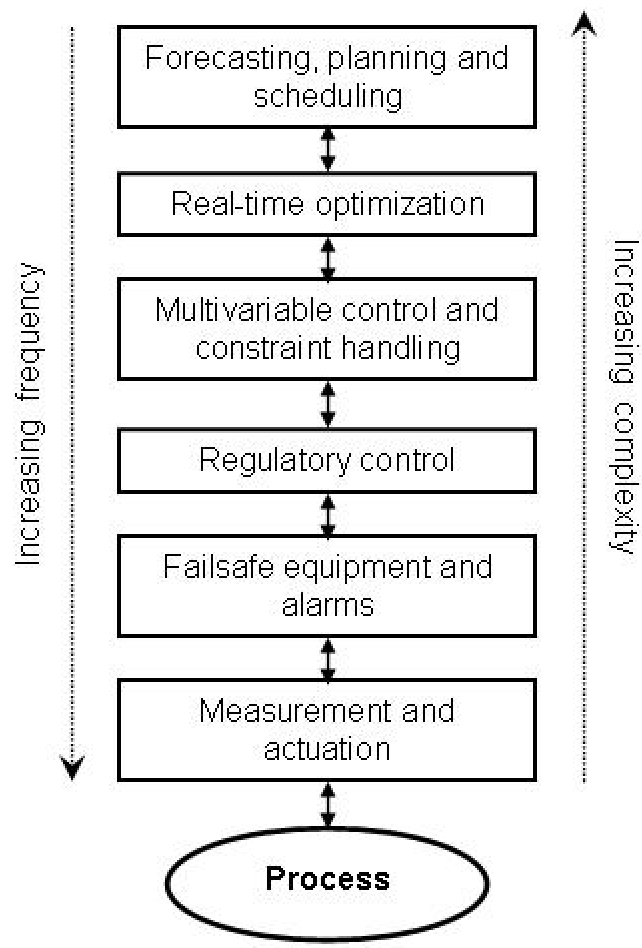

Figure 1.1: Hierarchy of industrial process control strategies

consists of two essential components; a unit coordination strategy and a forecasting scheduler. In a cogeneration facility, the forecasting scheduler uses real time energy pricing, fuel supply availability, and other time dependent variables and constraints to determine the most cost effective method of producing power over a given period of time. The unit coordination strategy manipulates handles of individual unit operations within the system in order to most efficiently meet the forecasted schedule. It is important to note that the EMS works with or on top of lower level control within the plant control hierarchy. The individual unit control systems (i.e. *multivariable control and constraint handling* and *regulatory control*) use conventional control strategies to achieve and maintain setpoints as dictated by the EMS.

The quality of the mid-level individual unit control strategies also contribute significantly to the performance of an overall system such as cogeneration. Poorly tuned/designed controllers may be incapable of achieving or maintaining the setpoints dictated by supervisory controls, such as an EMS. Additionally, processes with high levels of uncertainty necessitate less aggressive operation in order to ensure safety and stability. Less aggressive operation on key processes implies that operation is not at full potential, meaning that high uncertainty correlates highly with reduced overall performance. It follows that improved process control, which begets lower uncertainty in key process variables, will allow for more aggressive operation and therefore higher overall process performance.

The topic of controller performance assessment deals with the quantification of control system effectiveness. Typically, a baseline for process performance is derived based on a reference control strategy. The room for potential improvement through process control can then be analyzed by comparing current operating conditions to theoretical or simulated conditions under the reference control strategy. Economic performance assessment (EPA) is simply a form of controller performance assessment that is evaluated based on the economics of the unit operation in question.

The operation of a cogeneration facility can benefit greatly from the use of both an EMS (energy management system) and EPA (economic performance assessment). A knowledgable plant engineer can use EPA to analyze cogeneration unit controller performance and recommend improvements to increase the overall safe and stable range of operation for each process. An EMS can then effectively coordinate those individual processes and their corresponding controllers within process constraints in order to use a cogeneration facility to its full potential. The end result is aggressive but safe/stable unit operations coordinated in order to maximize economic output.

The remainder of this thesis is organized as follows: chapter two contains a brief overview of industrial optimization; chapter three covers a review of pertinent literature; development of the principle issues and problem statement for this work are discussed in chapter four; chapters five describes the cogeneration process and process model in detail; chapter six describes the development of an economic performance assessment method; chapter seven describes the development of an energy management system for a cogeneration facility; several case studies of EPA and EMS are presented in chapter eight; and conclusions and future work are presented in chapter nine.

Chapter 2

A Brief Overview of Industrial Optimization

A mathematical optimization procedure is one that strategically seeks out an extreme value from a given set using a variety of available tools or methods. Every optimization problem consists of either two or three distinct parts: an objective function, optimization variables, and in most cases constraint functions. The objective function quantitatively describes a value to be either maximized or minimized, which is a direct function of optimization variables. The optimization variables represent parameters that can be adjusted in order to obtain the extremum value of the objective function. Finally, the constraints represent limitations to variables or functions of variables. Constraints can take the form of equality constraints, where a function of variables must be exactly equal to a defined value; or inequality constraints, where a function of variables must be less, greater, not less, or not greater than a defined value. Optimization problems may consist of one or more variables, zero or more constraints, and a single objective function.

The application of optimization can be extremely valuable to process management. For any industrial process, outputs can be influenced by making changes to one or more process inputs. Optimization, if used correctly, can determine the set of inputs required to obtain the most desirable output, where "most desirable" is quantified by a pre-determined quality metric: the objective. The ability to carry out such assessments, both mathematically and in practice, is more or less difficult depending on several factors pertaining to the process at hand. Such factors include, but are not limited to:

- the complexity of relationships between inputs and outputs
- the complexity of constraints on inputs and outputs
- the nature of the objective function

The following sections will review several basic types of optimization problems and discuss the relevance of optimization to industrial control systems. For more information on optimization, see [5] and the literature reviewed in Chapter 3.

2.1 Branches of optimization

From a purely mathematical standpoint, linearity and convexity are two significant properties that greatly reduce optimization difficulty. Linearity of an optimization problem refers to the relationship between variables in the objective and constraint functions. If a change to one variable results in a consistently proportional change to the other regardless of the initial state, the relationship between the two variables is linear. If not, the relationship between the variables is creatively referred to as non-linear. Mathematically, linearity of a function is defined by (2.1). The definition of a convex function is slightly more complicated, as defined by (2.2). In Euclidean space, a set is convex if and only if for every two points in the set, a straight line connecting them also lies entirely within the set. If a variable set is not convex it is referred to as "non-convex".

$$f(\alpha x + \beta y) = \alpha f(x) + \beta f(y) \tag{2.1}$$

$$f(\alpha x + \beta y) \leq \alpha f(x) + \beta f(y) \tag{2.2}$$

From (2.1) and (2.2) we see that linearity is a special case of convexity. Accordingly, if a system is continuously linear, it is inherently convex. However, non-linearity does not imply non-convexity. Note also that it is possible to have a set defined by piecewise linear functions that is non-convex. Fig 2.1 depicts examples of all four combinations of linearity and convexity in two dimensions.

As previously mentioned, the linearity and convexity of an optimization problem determine the required computational effort required to solve it. Problems described by linear equalities and inequalities are generally less computationally expensive to solve than their non-linear counterparts, and convex problems are generally less computationally expensive to solve than non-convex problems. However, non-linear equations are usually capable of capturing significantly more detail, and may be much more appropriate when trying to describe the behaviour of a real process. Therefore, a tradeoff exists in optimization between solution accuracy and solution time, and depending on the process under investigation this tradeoff may be more or less severe. The oversimplification of process behaviour with linear equations may lead to faster solution times, but may do so at the cost of a reliable solution.

2.2 Industrial optimization and control

The use of optimization methods during the design and tuning of industrial control strategies is a common approach to maximizing the potential of any process. Unfortunately, defining the proper objective function based on control objectives is not a straightforward procedure.

Real processes never behave exactly as expected. Measurement errors, the impact of unmeasured disturbances, and unaccounted-for variations to internal or external process parameters all contributed to the uncertainty or stochasticity of a real process. The *back-off* approach to controller optimization has proven to be an effective way of dealing with the inherently stochastic nature of industrial processes [21][63][91][48]. Back-off refers to the size of the offset between the variable setpoint and upper or lower operating limit. This offset allows for the customization of failure probability by specifying back-off according to the

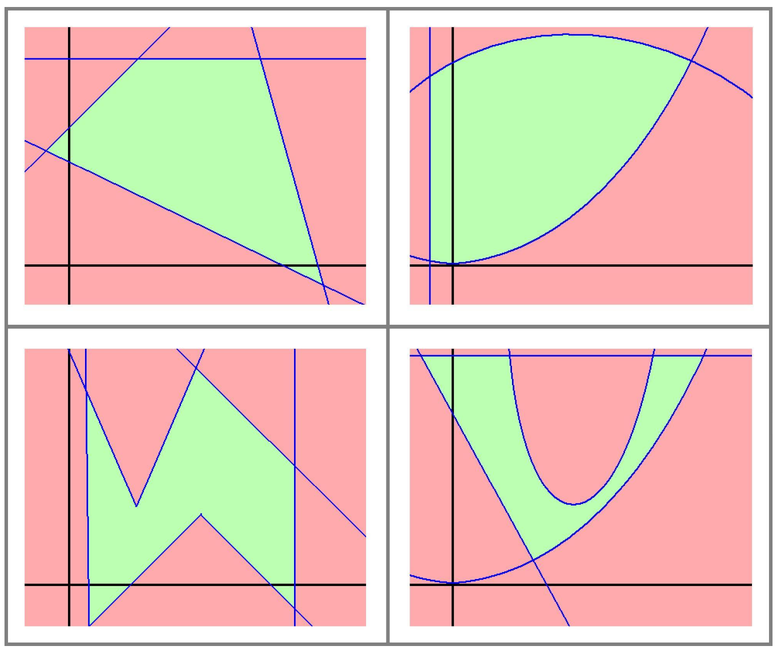

Figure 2.1: Two dimensional samples of linear convex (top left), non-linear convex (top right), piecewise linear non-convex (bottom left), and non-linear non-convex (bottom right) regions

known variability distribution according to (2.3). In this case the magnitude of back-off is set to two standard deviations of y, so the setpoint of y is restricted to values less than two standard deviations below its true upper limit and to values more than two standard deviations above its true lower limit.

$$ymin + 2\sigma \leq y_{sp} \leq y_{max} - 2\sigma \tag{2.3}$$

In most cases it is desirable to keep a process setpoint as close as possible to a constraint while maintaining an acceptably-low level of constraint violation [22]. For this reason, management of the stochastic nature of a process is a critical component of a successful control strategy. By reducing variance through improved process control, the setpoint can be moved closer to the limit while maintaining the same probability of failure, as illustrated in Fig. 2.2. Referring back to (2.3) it can be seen that by decreasing the value of σ through improved control, the valid range of setpoints for y is expanded. This setpoint shift may result in an improved product, which can easily be related to profitability through an economic performance function.

Stochastic economic performance optimization generally involves the development of a control strategy that allows for the highest economic output under conditions of inherent uncertainty [94]. This optimization procedure varies in difficulty depending on the size of the problem, starting from a relatively simple procedure for single input, single output (SISO) systems and becoming increasingly difficult for increasingly complex multiple input, multiple output (MIMO) systems, especially in the absence of obvious input-output controller pairings.

The back-off approach to industrial controller optimization is not the only approach available. The back-off method does, theoretically, achieve optimal performance when designing a controller configuration for stochastic steady state conditions. However, when the steady state assumption is removed to address common issues such as setpoint tracking, process drifts, and large input disturbances, the speed of process response/recovery must be considered. This distinction, illustrated in Fig 2.3, highlights the difference between two

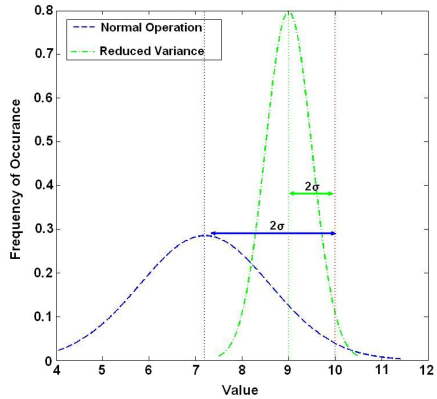

Figure 2.2: Mean shift towards constraint due to reduced variance

major types of control objectives; servo and regulatory. Regulatory control emphasizes the elimination of minor process disturbances at steady state, whereas servo control emphasizes setpoint tracking and the rejection of large, sustained disturbances.

Proper optimization of controller tuning parameters for industrial processes requires an assessment of benefits from servo versus regulatory control. For example, a process with frequently changing setpoints and an unreliable/uncontrolled input stream may benefit from sacrificing noise rejection for improved setpoint tracking. When optimizing controller tuning parameters for such a process, the objective function should contain elements of servo control. On the other hand, a process with relatively constant inputs and operating conditions would likely benefit more from an emphasis on regulatory control.

2.3 Linear-quadratic Gaussian control

The fields of advanced process control and optimization are so directly connected that some form of optimization is often used (directly or indirectly) in controller design. This connection is especially obvious in model predictive control, where the control objective is defined by the minimization of some objective function, which is usually in the form of a norm.

The linear-quadratic Gaussian (LQG) controller is one model based approach to control

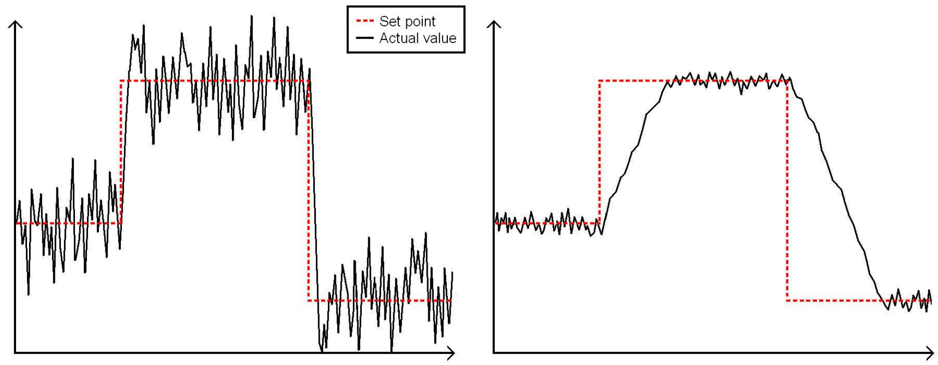

Figure 2.3: Example of tradeoff between servo (left) and regulatory control (right)

that combines a linear-quadratic regulator (LQR) with a Kalman filter. In this thesis, the LQG controller is used as a basis for the economic performance assessment algorithm. Although a detailed working knowledge of the LQG controller is not required for application of the EPA algorithm, an overview is provided in this section. A number of additional references on LQG controller formulation are readily available for further study, including the original publications by Kalman [42] [43] that eventually led to what is now known as LQG control, as well as additional works by Bernstein & Haddad [3] and Skogstad & Postlethwaite [77].

For the state-space system given by (2.4-2.5) the continuous version of the LQR minimizes the objective J given by (2.6). In these equations x, u & y are vectors of states, manipulated variables and control variables, respectively; A, B, G & H are state space parameter matrices; w & v are process and measurement noise, respectively; Q & R are state, and input weight matrices, respectively; and λ is a controller tuning parameter.

$$\dot{x} = Ax + Bu + w \tag{2.4}$$

$$y = Gx + Hu + v \tag{2.5}$$

$$J = \int_0^{\text{inf}} \left(x(t)^T Q x(t) + \lambda u(t)^T R u(t) \right) dt \tag{2.6}$$

The optimal feedback control based on this system is represented by a gain matrix K in the form of equation (2.7). The solution of K_c is calculated through either matrix factorization or iterative solution of the algebraic Riccati equations (2.8) where P is the unique solution to (2.9).

$$u = -K_c x \tag{2.7}$$

$$K = (H^T QH + \lambda R)^{-1}(B^T P + H^T QG) \tag{2.8}$$

$$A^T P + PA + G^T QG - (PB + G^T QH)(H^T QH + \lambda R)^{-1}(B^T P + H^T QG) = 0 \tag{2.9}$$

The continuous version of the LQG controller is almost identical to that of the LQR with one additional step: the application of a Kalman filter on the control input. The new state input is therefore calculated using (2.10), and the new control law is defined by (2.11) where $\hat{x}$ is the state estimate obtained using the Kalman filter.

$$\dot{\hat{x}} = A\hat{x} + Bu + K_f(y - G\hat{x} - Hu) \tag{2.10}$$

$$u = -K_c\hat{x} \tag{2.11}$$

In the original LQR problem, the state estimation error e is given by (2.12), and its derivative $\dot{e}$ is therefore given by (2.13). Therefore e converges to zero for an asymptotically stable A, but grows with an unstable A.

$$e = x - \hat{x} \tag{2.12}$$

$$\dot{e} = Ax - A\hat{x} = Ae \tag{2.13}$$

The Kalman filter is therefore incorporated into the LQG controller formulation in an attempt to drive the error e to zero regardless of the stability of A. By calculating $\dot{\hat{x}}$ according to (2.10), the derivative of the error is given by (2.14), which converges to zero as long as K_f is chosen to asymptotically stabilize the term $A - K_f G$.

$$\dot{e} = Ax - A\hat{x} - K_f(Gx - G\hat{x}) = (A - K_f G)e \tag{2.14}$$

The original papers by Kalman [42] [43] that formed the basis for LQG control were also fundamental to modern model-based control as a whole [66]. But despite LQG's academic notoriety, it never received significant attention from industry for several reasons cited by

Richalet *et. al.* [69] and Garcìa, Prett & Morari [27] including a lack of constraint handling, linear time-invariant (LTI) model parameters, inability to deal with unique performance criteria such as time-dependent or piecewise weights, and perhaps most importantly an industrial community focused on conventional control tools.

Despite these practical implementation obstacles, LQG provides an excellent basis for offline assessment of controller performance. Historical data sets may be pre-filtered or trimmed to negate the need for time variant models, and process constraints may be handled externally from the controller formulation in the performance assessment optimization problem itself. Additionally, the ability to obtain a controller gain matrix based on solution of the algebraic Riccati equation allows for relatively quick model-based formulation; the infinite horizon combined with the Kalman filter provides an inherent level of stability; and LQG does account for actions to manipulated variables along with constraint variables, which provides several advantages over certain other performance assessment methods. This last point will be discussed further in the following chapter. Still, the case of unique performance criteria does remain as an obstacle, so for these special cases an alternative to LQG-based performance assessment may be more appropriate.

Chapter 3

Literature Review

The topics for literature review in this chapter will be divided into three sections; cogeneration process and plant modeling, performance assessment, and energy management. All three topics have a rich history spanning several decades. Emphasis will be placed on contributions that are significant to the field and especially relevant to this work.

3.1 Cogeneration plant modeling

Accurate cogeneration plant modeling is an essential step in the development of an EMS optimization algorithm for two major reasons; a model is required in order to define constraints and relate them within the system to the objective function, and to evaluate the resulting optimization algorithm as testing the algorithm on the true system requires costly disturbances to normal operation. The classification of models is attributed to three major properties of the models; linear versus nonlinear, deterministic versus stochastic, and static versus dynamic.

The distinction between linear and nonlinear models lies in the structure of the model itself. Linear models are generally simpler, and can be distinguished by their additive properties. Nonlinear models are not additive, and vary greatly in complexity. Both linear and nonlinear models are useful, depending on the application.

The difference between deterministic and stochastic models lies in the model accuracy. Deterministic models assume that every state can be expressed solely as a function of other states, without any level of uncertainty. Stochastic models, on the other hand, do account for randomness and variability. Needless to say, deterministic models are often easier to use but are not as representative of practical applications, as all real systems have some level of uncertainty.

The time dependency of models classifies them as either static (time-invariant) or dynamic (time-variant) models. To put it simply, dynamic models account for some level of time dependency in model parameters, whereas static models do not. For the most part, modeling for optimization of cogeneration systems has been carried out under the assumption of steady state using time-invariant parameters, although there are a few cases where some time dependencies have been added to low frequency areas of the models. This subsection will review literature describing various modeling techniques applicable to the work at hand, using the dynamic versus static properties of the models as the major distinguishing factor.

3.1.1 Steady state modeling

Steady state or static models are generally less complex than dynamic models due to the lack of time dependence, and therefore require less complicated calculations. Each state in a static model is a function of other states and parameters, and is completely independent of any past values. Storing past state values is therefore unnecessary, although in most industrial settings such data is usually stored for monitoring, evaluation and future work. The majority of cogeneration plant modeling has been done using static models, as most of the work on these systems has required simpler models to ease computational commitments. The following paragraphs will review a small sample of the published work that uses steady state models for cogeneration facilities.

Sarimveis et al. [74], and Thorin, Brand and Weber [81] both model a cogeneration system based on linear mass and/or energy balances for each unit. The authors use adjustable efficiency parameters to fit data to the linearized equations, and make piecewise approximations where unit behaviour is nonlinear. Binary variables are used to identify the region of the piecewise approximation where operation is taking place, as well as to describe the on/off status of several units. These variables can either take the value of 1 or 0 depending on whether or not the unit is in operation, or depending on the active region in a linear piecewise unit model. Although the system is complex, especially in the case of [74], no mention is made of any coordination strategy between the units. It is only stated that the individual unit models will be used as constraints on the overall optimization problem. It should also be noted that both authors use non-heuristic optimization methods with these models.

Immonen [40] explores several linear modeling strategies in the form of both statistically based and theoretically based models. The first approach explored involves fitting linear input-output models using sampled data and regression techniques. The author notes that this approach is simple (when the data is available), but not flexible to changes in the system. The next approach taken involves the linearization of physical models. These models are derived from physical models, linearized, and then fitted with adjustable performance parameters. This strategy is still relatively simple, but provides more versatility than the straightforward linear fitting approach, as adjustments to the parameters can be made to account for changes in the system. A brief expansion of these models to piecewise versions is also included to account for cases where behaviour is not linear, but can be approximated as such in certain operating regions. Finally, the author combines the models into a neural network, which is a network of simple mathematical operations connecting individual unit models. By doing this, an overall, highly nonlinear system can be captured by a system of much simpler linear models. Several optimization algorithms exist, some of which are explored in the previous section in this chapter, which can then be performed on this new complicated network without the development of a complex underlying mathematical function.

Chen and Hong [7] provide a simple black box approach to modeling units in a cogeneration system. A black box approach is simply one with no theoretical basis, but instead consists of fitting data to a predefined form. The authors use a third order polynomial with four fitting parameters to relate boiler fuel enthalpy to steam generation, and a similar third order polynomial relating turbine enthalpy consumption to power generation. The authors then combine the two unit models to describe a single boiler-single turbine system, which they go on to use in their optimization objective function.

Lucas [50] presents a steady state modeling strategy for a cogeneration facility for the purpose of determining efficiency gains achieved through conversion from separate steam and power generation systems to a cogeneration system. Rather than create the model by beginning with individual unit operations, Lucas starts with a very simple equation relating total fuel consumed to power and heat produced in a cogeneration facility with an efficiency term. The author continues by breaking down the model into general terms for the major components (boiler and turbine) to get an overall nonlinear model that includes nonlinear state dependent parameters. The final model is developed through a series of steps based heavily on thermodynamic theory, making use of concepts such as Carnot efficiency and exergy. The direct connection between fuel used and power/heat output along with the calculation of harmful emission rates are particularly intriguing aspects of this approach. However, the system under investigation in this case is relatively simple in structure, and the application of this modeling strategy to a more complex system may prove to be more difficult.

Rodrguez-Toral, Morton and Mitchell [70] take a slightly different approach to modeling a cogeneration facility. Their approach is highly nonlinear, and involves two distinct steady state model types; process stream models and unit operations models. The authors model each process stream (water/steam or air) by using eight thermodynamic correlations based on the work by Morton [61]. Using this set of equations, the authors were able to obtain 11 different stream properties for a given pressure, enthalpy and flow rate. The correlations are nonlinear and contain a set of binary variables, which the authors go on to approximate using a smooth polynomial function. Ultimately, the authors present a method of accurately defining a number of stream properties at any point in the cogeneration system. The unit operations model sets are based entirely on mass, energy and momentum balances coupled with unit performance parameters to fit the given set of data. Although the resulting models are nonlinear, they are not overly complicated. A degree of freedom analysis is also provided in the appendices. Such an accurate but complex approach to nonlinear steady state modeling may be overcomplicated for several optimization approaches, but not for the strategy employed by these authors.

3.1.2 Dynamic modeling

Dynamic models, unlike their static counterparts, are usually described by a set of difference or differential equations that account for the development or evolution of a state over time. Although dynamic models are generally not as straightforward as static models, they can account for some very important behaviour depending on the system in question. As mentioned above, the majority of existing cogeneration plant models are static in nature, but dynamic models do exist and are growing in number. The following paragraphs will summarize a select portion of the literature addressing the use of dynamic models in a cogeneration facility.

Changliang, Jizhen, Yuguang and Weiping [6] present a detailed nonlinear dynamic model of a boiler unit connect to a turbine in the form of a set of differential equations. The derivation of the model is based entirely on mass and energy balances, and parameter values are based on physical characteristics of the boiler unit. The model is extremely detailed, with sub-models for the unit vapour pressure and water level. A detailed description of parameter calculations based on unit dimensions is also given. The final model relates fuel flow to the boiler to steam flow through a turbine, which again is connected in series with the boiler. Although the model is very detailed, the required number of inputs is limited to feedwater flow, fuel flow and turbine inlet valve position, which greatly increases the applicability of the model.

Ferrari-Trecate et al [20] also make use of a dynamic model in order to describe their system. More specifically, the authors use a linear time-invariant discrete-time dynamic model to describe the evolution of the processes within their system. As mentioned briefly in the previous section, these models are composed of binary variables that define a true or false state within the model, and auxiliary variables that define the linear relationship between input and output states within defined limits. The model itself uses four inputs. The gas turbine load and mill steam flow rate are continuous inputs, and the gas and steam turbine on/off states are binary inputs. All inputs are independent, with the notable exception that the steam turbine can only be on if the gas turbine is also on. The output variables for the model include the gas turbine fuel consumption and electrical power generation from both the gas and steam turbines. Input/output variables are paired appropriately, and either affine or piecewise affine function parameters are interpolated from data. Additional dynamic features such as turbine start up delays are also included, and counter variables to track downtime are introduced for this reason. Overall, the dynamics used in this method are relatively simple, but have a profound impact on the optimization algorithm used in the case study, which frequently switches between the on/off states of the units.

Chen, Lee, Hsu and Chen [8] consider the dynamic modeling of a cogeneration system from a control perspective without any discussion of optimization. The extensive modeling of the boiler-turbine pairing is significantly more detailed than any of the previously discussed works in this section and has been included as a reference for shortcomings of other models. Additionally Chen et. al. have assumed the existence of an underlying control system. The authors begin exclusively with a model of the boiler system comprised of numerous non-linear components, state dependant time constants, and several pure time delays. The turbine model is also nonlinear with time constants, but no pure delays are included for this unit. Some rules of thumb are also included, such as one that states that time delays from the fuel dynamics are generally greater than the time constant of the boiler itself.

The above subsections have covered a variety of methods used for modeling cogeneration units and facilities within the past decade, with an emphasis on modeling for optimization, each of which has its benefits and drawbacks. The properties (time dependence, complexity, linearity, etc.) of a model for a given application should be selected based entirely on the application itself. For instance, some systems are relatively simple and do not require complex, nonlinear, theory based models; but alternatively some systems do have such requirements. It is extremely important to keep this in mind when selecting a model, as it will lead to significant savings of time, effort and resources.

3.2 Cogeneration unit performance assessment

Large industrial facilities such as refineries, production plants, and pulp mills may be comprised of thousands of unit operations. Generating detailed models for each unit operation would be incredibly time consuming and an inefficient utilization of resources. Nonetheless, the ability to quantify controller effectiveness is critical to the successful management of operations since there is generally a clear relationship between reduced process variability, product quality, and therefore overall profitability [32][37][17]. Economic performance assessment (EPA) is a model-based tool that quantitatively measures this relationship by providing an assessment of controller performance in an economic framework.

Unlike an energy management system, however, EPA generally focuses on a single unit at steady state, with few exceptions. EPA methods are generally used as first-level tools when analyzing controller performance, considering potential capital investment, or discerning multiple control strategies [94]. In other words, EPA is a quick and easy tool used to determine whether or not further resources should be devoted to a problem, and has been an area of interest common to both industry and academia, especially over the past two decades [54].

Since a detailed analysis of individual unit operations is generally viewed (from an industrial standpoint) as an unnecessary expenditure of resources, EPA strategies tend to focus on rapid but effective analysis of raw data, which is typically readily available for such applications. The intention is to provide a reliable estimate of performance that may be used for financial proposals or to justify further investigation using more rigorous methods [94]. Initial work in the field of performance assessment implied the existence of a financial benefit to improved performance, but did not attempt to quantify it directly. Instead, a controller performance metric was usually a quantitative comparison of current operating conditions against a benchmark control strategy.

Astrom [2], Harris [32], Zhou and Forbes [95], and Marlin, Stanfelj and MacGregor [79] propose reference to a minimum variance (MV) controller performance as a benchmark for controller assessment. Many other algorithms based on slight modifications to MV benchmarking emerged in the early 1990s, either for ease of applicability or to address specific cases. Shah, Huang and Kwok [38] propose a filtering and correlation algorithm. Desborough and Harris [16] use a normalized performance index, while Kozub and Garcia [45] propose a similar measurement called closed loop potential. Tyler and Morari [84] develop a MV based algorithm to deal specifically with non-minimum phase processes and unstable poles, and Tsiligiannis and Svoronos [83] address the issue of unstable zeros. Xu, Huang and Akande [90] introduce a constrained MV approach by using a forecasting horizon to assess potential performance from model predictive control (MPC) strategies. Other notable works from the 90's based on MV benchmarking include work by Eriksson and Isaksson [18], Rinehart [68], and Miao and Seborg [60], among others. Lynch and Dumont [51], Martin, Turpin and Cline [58], and Latour [46] provide a few examples of work focusing on industrial application of such strategies.

However, the use of MV benchmarking has several downfalls. The most notable of these is the impracticality of implementation due to a lack of constraints on control action, which is assumed to be potentially infinite. MV control also provides the best possible feedback regulatory control, but does not provide a good benchmark for servo control applications [18]. Finally, MV is not realizable (infinite control impracticalities aside) for non-square systems where the number of control variables exceed the number of manipulated variables [38].

The disconnect between MV benchmarking and achievable performance has led to the development of alternative approaches to performance assessment. Patwardhan [64] proposes a comparison of the current MPC controller against the MPC objective. By using the MPC objective as a benchmark, the current state is compared to a more realistic measurement of attainable performance (as opposed to the unrealistic, idealized case of MV benchmarking). However, this approach necessitates that the current control strategy is MPC, and is not able to distinguish between errors caused by plant model mismatch versus disturbance model mismatch. Furthermore, although the performance index does provide an assessment of the controller, it does not provide a reliable estimate of potential improvement through controller redesign or tuning.

Performance assessment referencing linear-quadratic Gaussian (LQG) control is a strategy that has received significant attention over the past decade. Several notable publications based on LQG based performance assessment include, but are not limited to, work by Huang and Shah [35][36], Huang [34], Loeblein and Perkins [49], Zhao and Su [93], Zhao, Zhao, Su and Huang [94], and Gu, Zhao, Su and Chu [31]. The work of Zhao, Zhao, Su and Huang [94] is of particular interest due to its formulation of the performance assessment problem based on the economics of operation. Unlike MV control, LQG provides a realistic benchmark for control performance by including a penalty term on controller action in its objective function. At the same time, the infinite horizon form of LQG also provides an inherent level of stability. Unlike direct comparison to an MPC objective function, LQG provides a realistic measurement of improved control through tuning (or controller redesign, depending on the current control configuration). This is due to the fact that the LQG control law can be quickly obtained from an objective function by solving the matrix Ricatti equation (see chapter 2 for more detail), so simulation under the improved control law is possible with a set of operational data.

One may note that LQG is not extensively used in practice [66], however it is very applicable as a referenced strategy. One reason that LQG is not widely used has to do with the linear time-invariant nature of process model parameters. Online updates to the process model require a complete re-calculation of the controller, which can be difficult to implement continuously online. However, performance assessment is usually based on operation from a set of historical data. Therefore, since the model parameters (based on the historical data set) will not change during the course of the performance assessment calculation, no model update is required, thus eliminating a major downfall of LQG implementation. Another major deterrent of LQG application is the lack of its ability to handle constraints. However, the referenced control strategy for performance assessment can be an unconstrained control strategy such as LQG if the assessment is to be based on steady state operation. By approximating variability using the unconstrained LQG control strategy and then choosing setpoints through constrained optimization, a realistic assessment of potential performance through infinite horizon model-based control is achieved. That assessment of potential performance can then be used as a good approximation of expected performance from industrial model-based advanced process control tools such as dynamic matrix control (DMC) from Aspen Tech, robust model predictive control technology (RMPCT) by Honeywell, or DeltaV Predict Pro from Emerson. A more complete survey of commercially available model-based control products is provided by Qin and Badgwell [66].

Economic performance assessment is an excellent tool for quick and easy application in an industrial setting. It can put a dollar value on current and potential controller performance with relatively minimal effort, making it extremely valuable for project planning. However, the limitations of EPA lies in the scope of the optimization. Every unit within a system may be perfectly tuned as individual units, but overall plant profitability is the ultimate goal, not just that of a single unit. Therefore, the coordinated control and optimization of multiple units is often much more desirable from a plant management perspective, which is where the capabilities of EPA end and energy management begins.

3.3 Cogeneration energy management system

Energy management, like EPA, is a tool with roots primarily in industry rather than academia. With the emergence and successive growth of computational automation in the 1970s, software packages were being developed to allow for more elaborate control of systems. Beyond basic control, these packages were able to monitor overall costs, and identify "optimal" conditions depending on the system at hand [89]. In 1977, a patent by Leyde [47] was issued named 'Digital load control circuit and method for power monitoring', which claimed to provide a rule based circuit control method for activating and deactivating multiple electrical loads in order to increase or decrease power consumption as dictated by predefined operation limits. Publication of the Leyde patent was followed by several subsequent patents by Helwig [33] and Schmitz et. al. [75] that coined the term Energy Management System (or EMS). These patents, like that of Leyde, described methods for switching between electrical loads based on desired power consumption.

Shortly thereafter, EMSs began to appear in a wide variety of applications in conjunction with the introduction of personal computers to replace conventional automation. Applications of EMSs were prominent in electronic and power generation industries, but the systems also saw applications ranging from large scale pumps [14] to industrial facility resource management [12]. By the late 1980s, the EMS structure had evolved into a few well defined models, the most popular of which was the distributed model, which consisted of four major parts: network analysis, generation scheduling (and control), supervisory control and data acquisition, and a centralized database [19]. The network analysis section took care of functions such as state estimation based on input data, optimal conditions, and the selection of contingency modes of operation. Generation scheduling and control calculated economic conditions and managed scheduling requirements between modes of operation. Supervisory control and data acquisition retrieved data from the process, managed alarms, and provided an interface between the process and the operator. The centralized database was the key component linking the other three parts by storing and retrieving data from each of them.

Although there has been substantial work on EMSs since the 1980s, significant changes to the general structure of the system have not been deemed necessary. Rather, work in the field has focused on the development of each section within the EMS to improve overall performance. The ability of the data acquisition and centralized database components have grown considerably with the available computational technology, and have allowed for the realization of more advanced network analysis and generation scheduling strategies. Forsyth and Ahmad [24] provide an excellent summary of available technology in a real system. Due to the high dependency of the data acquisition and centralized database components on computational technology as well as limits to the scope of this project, the work in the following sections will focus exclusively on the network analysis and generation scheduling aspects of the EMS, as stated in the introduction of this chapter.

Network analysis and generation scheduling are by no means straightforward tasks due to the highly complex process structure, time dependant variables such as steam demand and electricity prices, and numerous manipulated variables and constraints. Such highly integrated problems would be impractical for operators to handle without the aid of sophisticated optimization tools [78]. Early EMS optimization strategy development for practical applications favoured heuristic methods, which guided plant operation towards a more profitable state of operation. A survey of these early approaches can be found in [30]. Early non-heuristic approaches were proposed, but computational limitations at the time led to impractical run times for reasonably accurate solutions [13]. Significant research, therefore, went into development of more effective heuristic methods for this purpose. Gradual progress in the fields of mathematical programming and computational power, however, has recently made the use of advanced, non-heuristic optimization methods possible as well. The following subsections will review literature based on the application of a variety of available optimization tools for EMS applications.

3.3.1 Heuristic optimization

The definition of a "heuristic" method can be traced back to the origin of the word itself, which comes from the Greek word "heuriskein" meaning "to discover" [92]. A heuristic algorithm is essentially one that operates with a trial-and-error methodology, and adjusts itself based on its surroundings and past experiences. Most of these methods have actually been developed by attempting to mimic naturally occurring phenomena.

Mathematically speaking, heuristic algorithms require the calculation of states under various conditions, but the derivatives of the states are not needed. These algorithms generally perform well in real applications, but have two major downfalls: the solution is not guaranteed to be the globally optimal solution, and the run time is not bounded [28]. Most heuristic solutions are not subject to both of these pitfalls, as one can be sacrificed to prevent the other. For example, an algorithm can limit the run time, but such a limitation will in turn reduce the probability of obtaining the optimal solution.

These drawbacks appear to seriously impair the reliability of heuristic algorithms, but in practice the consequences are usually much less severe. Although heuristic methods are not guaranteed to find a globally optimal point, the solution obtained is usually a good approximation. Perhaps more importantly, the major benefits of heuristic methods lie in their robust nature. They are typically more resilient to complex systems, coming up with solutions where non-heuristic methods cannot, and are generally applicable to multiple problems without the need for significant changes to the algorithms [28]. Winker and Maringer [88] developed the following four general properties common to heuristic optimization problems:

> First, a heuristic should be able to provide high quality (stochastic) approximations to the global optimum at least when the amount of computational resources spent on a single run of the algorithm or on repeated runs is increased. Second, a well behaved heuristic should be robust to changes in problem characteristics, i.e. should not fit only a single problem instance, but the whole class. Also, it should not be too sensitive with regard to tuning the parameters of the algorithm or changing some constraints on the search space. In fact, these requirements lead to the third one, namely that a heuristic should be easily implemented to many problem instances, including new ones. Finally, despite of its name, a heuristic might be stochastic, but should not contain subjective elements.

The following paragraphs will review several recently published works based on heuristic optimization strategies, with an emphasis on energy management system applications.

Childress [11] presents a relatively straightforward algorithm to achieve optimal performance in a cogeneration facility. He emphasizes that a steady state optimization method is not applicable to a process that never truly achieves steady state. His solution, therefore, is based on calculating the effect of making incremental changes to steam production from the boilers. For each of these incremental changes, a cost function of the overall system is evaluated, and the most profitable move (or lack thereof) is made. This method has the advantage of being simple in nature and provides an industrial insight to issues such as real time pricing, electricity contracts, and operator preferences.

Chen, Tsay and Gow [9] propose a scheduling algorithm for a cogeneration facility called an enhanced immune algorithm. The algorithm works by considering all potential combinations of boiler steam production rates and fuel compositions, then performs random 'crossover' and 'mutation' steps until an optimal solution is reached according to stopping criteria. This method is analogous to natural selection and genetics, hence the name. The investigated system in the paper is relatively complex, considering the often ignored cost of emissions. The authors are also unique in taking into account the possibility of electricity "wheeling", which is an accumulation of power trading effects on the bidding price of power under a deregulated market environment. Simulations resulted in a reduced solution time compared to the conventional immune algorithm.

Rajan and Mohan [67] combine the simulated annealing optimization and evolutionary programming methods to generate an algorithm for use in a cogeneration facility. The annealing optimization algorithm involves taking a feasible solution, applying random alterations to manipulated variables, and then settling on a new, neighbouring feasible solution. If the cost function has decreased as a result of this step, the new solution is taken as the base case. This optimization is based on the process of annealing metals. The evolutionary algorithm is somewhat similar, and involves taking a parent or base case, and applying an alteration according to a predefined distribution, then repeating. The case with the lowest cost function is kept as the solution. The advantage of the simulated annealing algorithm is its ability to escape local optimal points, but its downfall is its slow convergence. The evolutionary algorithm excels at quickly finding locally optimal solutions, but is not as effective at escaping local optima. This proposed solution uses simulated annealing at first, then evolutionary optimization for the last step(s). Results showed an improvement in both robustness and speed compared to five different heuristic algorithms.

Williams, Huff and Francino [87] describe an optimization method combining the Nelder-Mead simplex method and evolutionary optimization known as the simplex self-directing evolutionary operation technique. This algorithm starts with a base case, which is usually a set of operating conditions known to be stable. The algorithm then applies a sequence of perturbations to the manipulated variables in the system, and evaluates a cost function at each of those points. Once each cost function is evaluated, the algorithm discards the worst variable set and strategically selects a new one. This procedure is repeated until either a satisfactory solution is obtained, or a constraint placed on the calculation time is violated. The algorithm is relatively simple overall, and several existing expansions on the Nelder-Mead simplex method such as those presented by McKinnon [59] may improve overall performance. Time of convergence, however, may become an issue with a large number of manipulated variables depending on the shape of the cost function.

Vasebi, Fesanghary and Bathaee [86] introduce a recently developed optimization method named the "harmony search algorithm" that was developed based on the method used by musicians to tune their instruments. This algorithm is slightly different from most heuristic algorithms in that it contains a solution memory component, which allows for comparisons with past solutions. The algorithm begins by filling the memory with random solutions, then methodically generates new solution vectors based on a probability of choosing values from the historical set or randomly from the valid range. Every time a new solution is obtained, the worst solution in the memory is discarded. Two simulations were presented, and the quality of the optimal solution was used as a comparison between five heuristic algorithms. Only the genetic algorithm, also known as the immune algorithm, achieved a better optimal solution. However, the test cases were relatively simple and the speed of convergence was not analyzed.

Sudhakaran and Slochanal [80] combine the genetic (or immune) algorithm with the tabu search algorithm to produce a heuristic search method for a cogeneration system. The genetic algorithm takes an existing solution and performs crossover and mutation steps to the manipulated variables. The tabu method is basically a random search method with a built in memory component to forbid the repetition of states (hence certain moves become 'tabu'). The proposed algorithm utilizes the search method of the genetic algorithm and prevents repeated states with the memory component of the tabu method. Simulation results showed that the proposed algorithm provided a reasonable solution, although not the best, in a significantly reduced amount of time as compared to three other heuristic methods.

Rong, Lahdelma and Grunow [72] present an "improved unit decommitment" algorithm as designed for cogeneration applications in a deregulated power market. This is a multi-step approach based on a large, non-convex system or set of systems. The algorithm begins by assigning an economic rank to individual units within a given system by solving a "state-relaxed" problem. Next, at the core of the algorithm is a heuristic procedure to generate an "improved initial solution" from the state-relaxed solution whereby several on/off handles are set in order to establish a good initial approximation to the overall optimization problem. The problem is subsequently approximated as convex and a "unit decommitment" algorithm [82] is used to obtain a final operating point. Trial results showed sustained improvements over the "unit decommitment" method alone. This approach, although designed for a larger system or set of systems, may provide a reasonable heuristic approach of obtaining a starting point or exiting a local minimum for an optimization algorithm.

Makkonen and Lahdelma [53] use decomposition techniques to optimize a cogeneration system without reducing the system model to a linear approximation. The authors do cover the case where the plant model is linear and convex, but do not make that requirement. For the linear cases, the authors make use of an algorithm known as the Extended Power Simplex algorithm. For the more general non-convex case, a method is proposed whereby the non-convex system is divided up into convex sub-regions, which can be identified based on the unique setup of the system under investigation. Each sub-region is defined by the characteristic model, but with additional binary variables that essentially eliminate the non-convex components from each sub-region. The overall non-convex problem is then solved using the

Branch-and-Bound algorithm, which is essentially an algorithm that loops through each of the sub-regions and solves a linear programming (LP) problem. The LP solution can lead to 3 conclusions: infeasible solution, optimal solution with violated nonlinear constraints, or optimal solution with satisfied nonlinear constraints. Based on the conclusion reached, a restarting, branching, or trimming step is taken until all remaining potential solutions have been explored. A case study uses the algorithm on three nonlinear cogeneration plants, wherein reasonable convergence times are achieved even when using a non-convex model in a very complicated system.

3.3.2 Non-heuristic optimization

Optimization strategies in the non-heuristic category rely heavily on the system models that are already in place to work with, so the accuracy of those models is a major determining factor of an optimization method's success. Several energy management systems in the early 1990s did attempt to make use of non-heuristic methods in the form of linear programming [62], [65], [39], but most of the models were oversimplified with excessively long computation times for successful application in a cogeneration system [13].

Recent advances in mathematical tools and computational technology have made complex online calculations feasible for real applications with cogeneration systems. Work on cogeneration energy management systems within the last decade has taken advantage of this, leading to the publication of works based on non-heuristic methods using reformulated model predictive control (MPC) [20], linear, quadratic and mixed integer programming [10] approaches, and combinations thereof. It should be noted that work on heuristic approaches has by no means ceased as a result of this progress, which is evident from the numerous recent works presented in the subsection above.

The following paragraphs will review several recently published works based on non-heuristic optimization strategies, with an emphasis on energy management applications.

Thorin, Brand and Weber [81] approach the problem of cogeneration system optimization using mixed integer linear-programming and a Lagrangian relaxation iteration step. The authors provide a detailed description of the model and optimization problem formulation, with special emphasis on constraint modeling and the Lagrangian iteration procedure. The strategy is particularly flexible with respect to the time period over which optimization is performed, and allows for accurate long-term planning of cogeneration plants. Results show that the inclusion of the Lagrangian step does not have a negative effect on the optimality of the solution, but does provide a more robust approach, converging in cases where methods without the Lagrangian step fail to converge.

Arroyo and Conejo [1] propose a mixed integer linear programming (MILP) approach to the cogeneration optimization problem. The optimization strategy is based on an objective function that takes into account revenues, production costs, start-up costs and shut-down costs. A notable distinction of this paper is the consideration of spinning reserve, which is extra power generation capacity available for output from the generator(s), as revenue. They state that additional terms can be added to the objective function in order to account for competitor actions and their effect on market energy prices and demand, but do not proceed to use these terms. The authors also impose a wide variety of constraints based on unit and ramp rate limitations. The authors then detail the methods used to rid the objective function of nonlinearities, and present a final linear version thereof. A case study is presented to confirm the efficiency and performance of the method. The effect of incorporating spinning reserve is shown to provide 10% additional cost savings.

Ferrari-Trecate et al [20] use hybrid system methodologies to address the modeling and optimization of a cogeneration process. To build the model, they use discrete-time hybrid systems in mixed logical dynamical form. This involves the use of binary and auxiliary variables to model the evolution of the linear time-invariant discrete dynamic system. The binary variable takes the value of 1 or 0, representing the on or off state of a unit. The auxiliary variable is a linear multiplier, which dictates the unit operation over a feasible range, given that the value of the binary variable is 1. The authors note that this modeling technique can be used with heuristic approaches, but propose an MPC based optimization based on reference trajectories instead. More details on the specific modeling strategy used by the authors will be provided in the next section of in this chapter. The optimization of the plant operation is achieved through the use of MPC based optimization, which uses the model to predict future evolution of the system over a fixed period of time and determine a sequence of control actions to achieve the best possible performance based on these predictions. The 'best possible performance' is determined by a cost function based on individual unit operation costs and revenues, which is optimized subject to various constraints. At each time step, the first control action in the planned trajectory is carried out, and then the optimization procedure is repeated. Finally, the authors present a method of recasting nonlinear terms of the problem as linear terms, which allows for the use of mixed integer linear programming (MILP) techniques and solvers. A test case shows that computational time increases with the prediction horizon used in the optimization procedure, but that reasonable computational times are still achieved.

Rodriguez-Toral, Morton and Mitchell [70] present a quadratic programming approach to the cogeneration optimization problem called Sequential Quadratic Programming (SQP). The SQP algorithm essentially involves, as implied by the name, the sequential solution of quadratic programming problems based on the system model. One fundamental benefit of the algorithm is that each point in the sequence of solutions does not necessarily satisfy the constraints of the optimization problem. Instead, there are separate repeating steps that involve approaching the optimal point through a path that doesn't necessarily obey given constraints, and then returning to the feasible region as defined by the constraints. The authors do note, however, that the cost of optimization may become quite large as the size of the system increases.

The work reviewed in this subsection provides a variety of non-heuristic approaches to the optimization of a cogeneration system. Unlike the heuristic approaches, the methods have the advantage of achieving a truly optimal solution under the assumption of an accurate model. This assumption, however, cannot be readily made as the optimality of these solutions relies heavily on model complexity. In order for a non-heuristic approach such as these to be considered for the purposes of this study, the plant model must be chosen appropriately.

Chapter 4

Problem Statement

The objective of this work may be divided into two distinct sections:

- a high level assessment of industrial unit controller performance on an economic basis, which is referred to as economic performance assessment
- a generic strategy for energy management in a cogeneration facility, which is referred to as an energy management system

Economic performance assessment provides a high-level quantitative evaluation of the effectiveness of unit operation and control strategy through comparison to an economically optimized baseline. In doing so EPA can be used to distinguish between poor operating practices and poor controller performance, justify funding for process control upgrades, or rank multiple processes and their respective control strategies in terms of need for improvement.

Energy management systems transform the operation of an entire plant into an optimization problem. When combined with an objective that relates key plant inputs and outputs with overall economic performance, an EMS can co-ordinate a very complex system of individual unit operations in a way that exploits the full potential of the plant.

These tools, when applied properly, may be extremely useful for industrial engineers seeking advanced methods of connecting the mid-upper tiers of an advanced process control network with business objectives through the use of optimization. The following sections will elaborate on these two objectives of this thesis.

4.1 Economic process performance assessment

Many industrial facilities contain thousands of process control loops that are responsible for achieving and maintaining set operating conditions for various processes throughout that facility. But how effective are those controllers, and is normal operation even targeting the "right" conditions? An economic performance assessment will be developed in this thesis to address these two questions.

This approach to economic performance assessment transforms the operation of an individual unit into an optimization problem. When combined with an objective that effectively relates unit input and output values to overall plant economics, unit setpoints and control strategies will be assessed in an economic framework. The results from such an optimization procedure will provide valuable insight into controller performance and the effectiveness of current operating conditions, which may then be used to justify process and/or control improvements.

In order to be truly useful, such an optimization tool must be effective and efficient. Industrial engineers cannot afford to devote significant amounts of time to diagnosing controller performance, especially in the large facilities commonly seen in fields such as pulp & paper, oil & gas, etc. The EPA method developed here will therefore satisfy these criteria by making use of existing data sets and efficient optimization strategies.

A significant number of performance assessment approaches referencing minimum variance performance have been discussed in Chapter 3, however such strategies do not provide a reliable baseline of performance. In most practical cases, especially when dealing with MIMO systems, minimum variance performance is impossible to attain [38]. Direct reference to the MPC objective function provides a more realistic benchmark than MV control, but lacks a true assessment of attainable improvement from better tuning. Perhaps more importantly, it is only implementable if the current control strategy is MPC.

The approach by Zhao et al. [94] provides an excellent basis for this work. By referencing LQG controller performance Zhao et al. establish a reliable, practical and attainable baseline. However, the authors limit the baseline controller performance by using a single controller weighting parameter in the base performance analysis. This work will therefore attempt to modify the method proposed by Zhao et al. in order to obtain a more aggressive, but still practical performance assessment method. In a competitive industrial setting, additional performance achieved by exploring a wider range of control tuning parameters may be the determining factor between the approval or rejection of a control upgrade project. However, it is important that solution time is not significantly increased as the intended use is, again, a high level approach to controller performance assessment.

The development of steady state models for effective performance assessment is described in further detail in Chapter 5. Chapter 6 details the approach to setpoint optimization, the concept of variability distribution as related to LQG control, and the overall optimization procedure on an economic basis. Case studies are provided in Chapter 8.

4.2 Cogeneration energy management system

The effective management of complex industrial facilities is an incredibly daunting task that requires intimate knowledge of all unit operations, interactions between unit operations, and the financial objectives of the facility as they relate to key process variables. This task can be even more complicated when dealing with dynamic system influences including constantly changing prices for raw materials and finished products, variable unit efficiencies, and complex contractual agreements. The expectation that an individual can continuously, manually optimize large scale industrial facility operation is optimistically naïve.

The goal of this work is to develop a generic energy management strategy for application in a pulp and paper mill cogeneration facility. The EMS should be readily applicable to a variety of situations including, but not limited to:

- steady-state operation subject to negligible external, dynamic influence

- dynamic operation subject to external, time-dependent trends and contracts
- special cases involving external, dynamic factors with no direct financial impact

The "special cases" refer to unique features of individual mills that impact normal operation. One example of such a feature is a mill reservoir climate dependency, where extreme weather may impose practical limitations on day to day operation.

In each of the above scenarios, the energy management system should have the following objectives:

- maximize profitability by effectively coordinating unit operations over a flexible horizon
- incorporate a variety of external, time dependent factors through accurate forecasting
- satisfy a wide variety of operational constraints that include physical, safety, environmental, and financial limitations

The proposed industrial application in a pulp & paper mill presents a rather unique energy management problem. Unlike most cases, the individual unit models are (almost surprisingly) linear under normal operation conditions, and therefore do not require highly sophisticated and computationally expensive non-linear solvers. The difficulty in this application, however, lies in the nature of the economic objective. Complex power contracts, dynamic electricity prices, variable fuel costs, and limited fuel supplies make forecasting a critical component of the EMS design. EMSs such as that proposed by Childress [11], which operate based solely on instantaneous economic conditions (see Chapter 3 for more detail), are therefore not extremely useful in this application.

The majority of other heuristic approaches to energy management focus significantly on dealing with nonlinearities rather than dynamic economic conditions. The required computational efforts to deal with both of these challenges may provide excessively long run times for practical industrial application.

Non-heuristic approaches provide more reasonable starting points for this work, although in several instances the emphasis on dealing with nonlinearities may again prove to be not worth the effort. The approach by Arroyo and Conejo [1] using MILP is especially of interest as the focus is on constantly changing costs of operation. However, their solution is tailored to specifically address the issue of wheeling, which has a significant direct impact on the economics of operation and is therefore not of concern in this application. On the other hand, unique operating constraints with indirect economic influence over system management, such the cooling reservoir temperature constraint, have not been addressed in any other works and must therefore be developed here.

The proposed approach involves the formulation of a MILP problem that is representative of plant operation. The objective of the optimization problem is a linear function closely related to plant profitability with a flexible parameter vector and optimization horizon. Optimization variables include a variety of handles within the system at distinct points over the aforementioned horizon. Constraints enforce relationships captured by an complex system model, as well as relatively simpler safety and/or environmental constraints on specific units. The model is developed semi-heuristically, and is sufficiently complex such that the disabling of select units within the model allows for quick and easy representation of a wide variety of pulp and paper cogeneration facilities.

The original energy optimization problem, as described in detail in Chapter 7, focuses exclusively on operation within the plant and ignores the cooling reservoir constraints. For many facilities, the cooling reservoir is not a production or profit limiting stage. However, one mill in particular raised concerns around the pond temperature, stating that power generation had to be stopped if and when the temperature exceeded an environmentally-motivated upper limit. The scope of the optimization problem was therefore expanded to include instances of energy management with an additional system feature that has the following properties:

- has no direct impact on the economic performance of the system, but may occasionally constrain production/performance
- is dependent on one or more dynamic variables independent of normal process operation (such as external temperatures)

- is dependant on one or more process variables within the system (such as required cooling duty)
- can be readily modeled based on both the external and process variables above

The incorporation of such constraints into the EMS are developed based on potential cooling reservoir temperature limitations, which is described in Section 7.1 of this paper. Case studies are provided in Chapter 8.

Chapter 5

Cogeneration Plant Model[1]

The optimization-based tools for performance assessment and energy management developed in this thesis require not only general knowledge of the cogeneration facility at hand, but also mathematical models of the unit operations within that cogeneration facility. This chapter provides a description of the particular cogeneration process studied in this work as well as the modeling strategies used for the purposes of unit performance assessment and facility energy management. An additional section based on model generation for the plant-specific, production limiting unit operation (thermal reservoir) is also provided.

5.1 Cogeneration process description

This work is motivated by several industrial applications of cogeneration in pulp and paper mills across British Columbia, Canada, and has therefore been designed with a specific system configuration in mind. The configuration schematic, as shown in Fig. 5.1, contains aspects from several facilities that have been combined in order to create a single, generic system applicable in a number of mills. The relative complexity of this process and the corresponding

[1]Portions of sections 5.1, 5.3 and 5.4 from this chapter have been accepted for publication. Marshman, D.J., Chmelyk, T., Sidhu, M.S., Gopaluni, R.B., and Dumont, G.A. (2010) Energy optimization in a pulp and paper mill cogeneration facility. Applied Energy. doi:10.1016/j.apenergy.2010.04.023

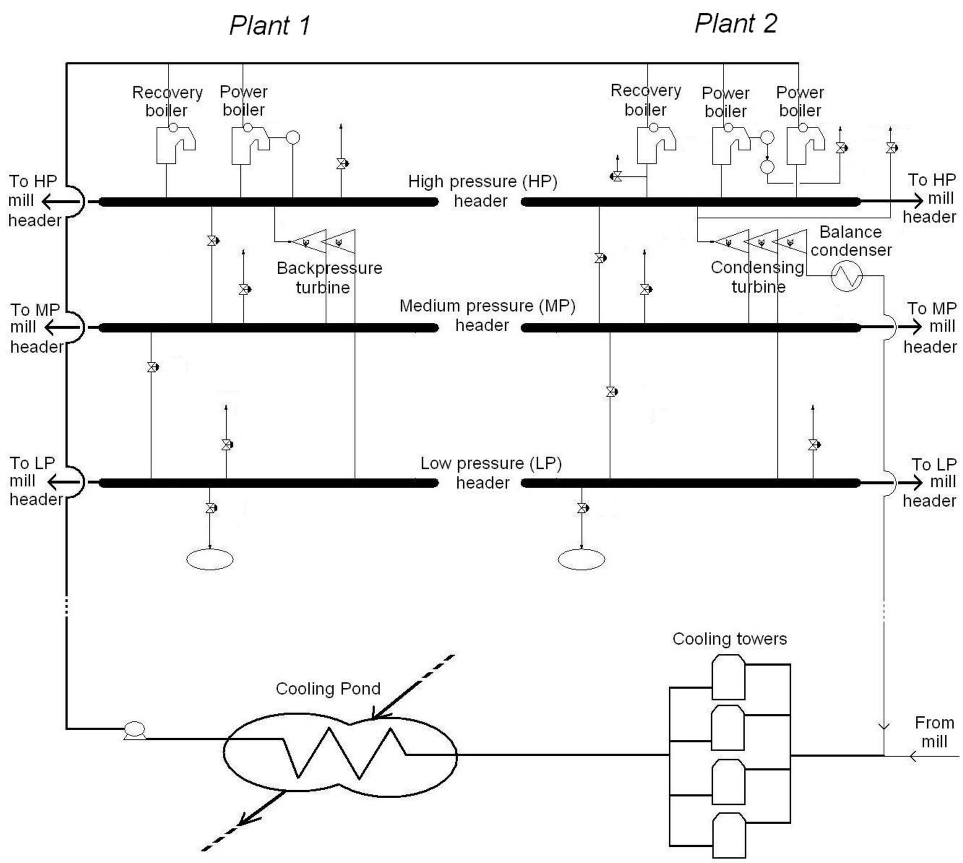

Figure 5.1: Pulp and paper mill cogeneration system schematic

model allows for representation of smaller (but similar) facilities in the industry simply through binary coefficient unit de-activation. The energy optimization method presented here is therefore widely applicable with minimal changes.

The facility is essentially split into two distinct plants separated through the middle of Fig. 5.1, which share supplies of water and fuel. The plant on the left (containing the backpressure turbine) that makes up half of the system will be referred to as Plant 1. The plant on the right (containing the condensing turbine) that makes up half of the system will be referred to as Plant 2. The system features a total of two recovery boilers and three power boilers, which burn the fuel supplies in order to generate high pressure steam. The recovery boilers use a fuel byproduct from the pulping process known as black liquor, which is a rich slurry containing combustible wood components such as lignin and hemicellulose, to heat the water source at a constant rate. The combustion to steam heating efficiency in a black liquor fueled recovery boiler is approximately 75% [25]. Alternatively, power boilers produce steam at variable rates using either hog fuel or natural gas. The combustion to steam heating efficiency in a hog or natural gas fueled power boiler is approximately 70% [25]. Hog fuel is also a combustible byproduct from the pulp mill with a mulch-like consistency. Natural gas can also be used to provide heat to the boilers, but is significantly more expensive than the mill byproduct fuels; hog and black liquor. For this reason, fuel management is critical to economically efficient cogeneration plant operation.

High pressure steam from the power boilers passes through a high pressure header on its way to the mill, where it is used as a heat source for various pulping processes including washing, drying and refining; to a turbine unit, where it expands, rotating the turbine, which in turn powers a generator producing electricity; or to a pressure relief valve (PRV), where it descends to a lower pressure and picks up additional water during de-superheating. Like any real process, an efficiency is associated with each of these steps to account for heat losses.

After passing through either the first stage of the turbine or pressure relief valve, the steam is at medium pressure. From there the steam is again used to heat mill processes, power the turbine, pick up additional steam through a PRV, or exits through a vent. The vent may be opened either to force additional steam through the first stage of the turbine (although this is rarely economically feasible at medium pressure), or for safety purposes.

Upon exiting the second stage of turbines or pressure relief valves, the steam is at low pressure (which is still well above atmospheric pressure). From there, the steam can again enter the mill, the final condensing stage of a turbine, or exit the system through a vent. The low pressure vent is used more frequently than its medium pressure counterpart as it allows for more steam to be passed through two stages of the turbine rather than just one. If fuel costs are low enough to warrant this measure, it can be exploited to produce additional power in the turbine, increasing plant profitability.

Upon exiting the low pressure header application the steam has usually condensed back to liquid form, although it is too hot to be treated and pumped back to the boilers. To reduce the water temperature, it is passed through a series of cooling towers, then through a heat exchanger unit. The heat exchanger is cooled by a natural water reservoir or pond. The effluent stream from the heat exchanger is pumped back to the boilers, completing the cogeneration side of the plant water cycle. At this stage additional freshly-treated water is added to the system to compensate for lost steam due to evaporation, venting, etc.

The rate of heat and electricity cogeneration within a typical kraft pulp mill depends on the size, or more importantly the pulp production capacity, of the mill itself. Francis, Towers, and Browne [25] approximate that for every air dried tonne (ADt) of pulp produced in a typical kraft mill, an average of 15.8 GJ of heat from steam and 655 kWh of electricity are produced. However, a typical kraft mill consumes approximately 15.8 GJ/ADt of heat, 638kWh/ADt of electricity, and 1.2 GJ/ADt of natural gas according to Francis, Towers, and Browne [25], leaving an excess of 17 kWh/ADt of electricity for sale and a deficit of 1.2 GJ/ADt of natural gas that must be purchased. These values, of course, vary from mill to mill. Further details behind technical and economic pulp mill operation, including cogeneration, can be found in the works of Francis, Towers, and Browne [25].

5.2 Individual unit model development

Strong motivation from industry necessitates quick and easy implementation of economic performance assessment methods. It is therefore desirable to make use of existing operational data while analyzing performance for two main reasons: the experimental collection of data can be time consuming and/or disruptive to a process, and operational data is almost always readily available in an industrial setting.

Model generation based on a set of operational data can be relatively straightforward, especially when the objective is to provide an estimate of controller performance. It is important to note that any assumptions in model generation for controller re-design will be reflected in the accuracy of the assessment. The intended use of results from EPA must therefore be considered before hand. The strategy presented in this work, as detailed in Chapter 4, is intended to provide a quick, first-level assessment of controller performance. Therefore only a very basic level of process knowledge is required, such as the ability to distinguish disturbance variables from manipulated and control variables.

The quality of a model generated from industrial operational data is dependent on the nature of the data itself. For example, model identification is much more difficult when dealing with a set of closed loop (as opposed to open loop) data. Forssell and Ljung [23] provide an excellent survey of identification methods based on closed loop data. Processes with recycling streams present similar difficulties [29].

Outliers and regular sampling disturbances may also deteriorate the quality of a data set. Such errors can be dealt with manually, or through the application of an appropriate filter. Although not entirely necessary, data can be normalized around operating setpoints in order to simplify the modeling and subsequent assessment procedures.

First order transfer function process models will likely suffice for quick analysis, although more thorough models should be investigated for implementation of controller redesign. The magnitude of deviation from steady state operation relative to the potential unit operating range is often between 5% and 15%. Over such a small range, the assumption of linear behaviour is reasonable for most processes. The use of simple, first order models makes the extraction of the steady state gain matrix fairly straightforward. For this work, the MATLAB System Identification Toolbox was used to generate first order transfer function matrices capturing system behaviour based on sets of operational data. Once such transfer function matrix for a multi-stage evaporator is presented in Table 5.1. The corresponding process gain matrix is given by (5.1).

For the purposes of economic performance assessment, the modeling of process stochasticity is also of concern. Data recorded over periods where process inputs are controlled manually can used to quickly determine variability distributions associated with each process variable. When manual-mode data is not available for analysis, low frequency trend removal methods may be used to estimate true process noise. For more information on such

Table 5.1: Evaporator first order process models

	Steam flow rate [kg/h]	Inlet steam pres. [bar]	Inlet flow rate [kg/h]	Inlet enth. [kJ/kg]	Inlet conc. [kg/kg]
Product conc. [kg/kg]	$\frac{0.0322}{0.067s+1}e^{-0.64s}$	$\frac{0.0151}{1.180s+1}e^{-0.87s}$	$\frac{-0.0155}{28.866s+1}e^{-29.09s}$	$\frac{-0.8834}{0.169s+1}e^{-15.0s}$	$\frac{0.0935}{0.0033s+1}e^{-16.0s}$
Product flow [kg/h]	$\frac{-0.3981}{30s+1}e^{-0.52s}$	$\frac{-0.0160}{30s+1}e^{-30s}$	$\frac{0.3898}{1.014s+1}e^{-16.8s}$	$\frac{-0.1998}{4.043s+1}e^{-15.7s}$	$\frac{0.0064}{0.01s+1}e^{-30s}$

methods, see the work of Denholm-Price and Rees [15]. For the purposes of this work, all noise was assumed to be Gaussian in nature.

$$K = \begin{bmatrix} 0.0322 & 0.0151 & -0.0155 & -0.8834 & 0.0935 \\ -0.3981 & -0.0160 & 0.3898 & -0.1998 & 0.006 \end{bmatrix} \tag{5.1}$$

5.3 Plant-wide energy management model development

A network of single-input single-output (SISO) models has been developed to represent a cogeneration system that is relatively complex for a pulp and paper mill. It is based on a facility in British Columbia, Canada, as described earlier in this chapter and shown in Fig. 5.1. The models track steam and water enthalpy throughout the system, making state changes and fuel combustion easy to represent.

This model set is complex enough to represent the inherent relationships between operating costs, power generation and heat generation, which can be described by sets of differential and algebraic equations of varying levels of complexity [71]. Several model simplifying assumptions, such as linearization and model order reduction have been made to allow for the development of a convex energy optimization problem. For example, by considering only turbine inlet and extraction pressures that lie in a normal operating range where operation takes place 99% of the time, a linear turbine model fit is sufficiently accurate (as opposed to the full range of potential operating conditions, which may account for that additional 1%

but require a high order model). This assumption is validated and enforced by the presence of turbine and steam header valve controllers, which operate independently of the energy management system and restrict header pressures to the normal operating range. Likewise, boiler and PRV unit models can be assumed to be linear, due to the consistency of header pressures. Ideally, deviation into regions where linearity does not reasonably hold will be limited by underlying control mechanisms independent of the EMS.

Validation of the linearization assumptions was carried out using the identification toolbox in MATLAB. Six months of industrial operation data were obtained from a facility very similar to the one represented in Fig. 5.1. This data included a number of monitored variables throughout the system such as flow rates, pressures, and temperatures. The primary, unobserved modeling state of steam and water enthalpy was calculated based on this data using the methods presented in [41]. Enthalpy flow rate of unit operation input and output streams were imported into the MATLAB system identification toolbox, and subsequently fit to linear transfer function models shown in Table 5.2. Validation of these process models was carried out via comparison to a separate set of industrial data from the same facility. Figure 5.2 contains plots comparing normalized process data to the normalized linear model outputs for four different processes; plant 2 HP-MP PRV (top left), plant 2 MP turbine stage flow rate (top right), plant 2 power boiler #1 (bottom left), and plant 2 condensing turbine stage power generation rate (bottom right).

It should be noted that process models were formulated by pairing a single process input and output. This was made possible by the nature of the processes under investigation, the decoupling of larger processes, and the existence of underlying control logic. An instance of decoupling can be illustrated using a turbine; power generated from a three stage turbine is a function of multiple flow rates (or, alternatively, valve positions), but after decoupling of the individual stages the turbine was successfully modeled using a network of three SISO linear models. An instance of underlying control assumptions can be illustrated by a boiler; the steam production rate of the boiler depends on numerous variables including feed water flow rate, furnace air intake, steam pressure, etc. During operation of the unit, an underlying control strategy balances feed rates of water, fuel and air to produce steam at a given rate, temperature and pressure. Therefore, by assuming that the underlying strategy is functioning as intended, boiler operation can be reduced to a SISO model with fuel feed rate as an input and steam production rate as an output.

It should be also noted that model quality could have potentially been improved by selecting large order model structures, but the practical applicability of the algorithm would have suffered. For example, nonlinear or gain-scheduling approaches may have compromised the convex nature of the resulting energy optimization problem, which would greatly increase solution time in most cases. Linear models were deemed to be both sufficiently accurate and efficient for practical application. The resulting transfer functions were used to establish certain equality constraints. Unit time constants and delays were used to generate constraints restricting the rate of setpoint changes.

5.4 Cooling reservoir temperature model

Pond thermal energy models developed by Van Buren, Watt, Marsalek, & Anderson [85], and Gao & Merrick [26] were employed to forecast future pond temperatures based on meteorological forecasts and the rate of heat exchange required by the level of cogeneration operation. Both of these pond models account for five contributing factors of heat exchange: short (solar) and long wave radiation, vaporization, sensible heating (convection and conduction), inlet flow, and outlet flow. Reservoir thermal energy influx/efflux was characterized by the difference equation in (5.2). For further pond model details see [85] and [26].

$$E_{t+1} = E_t + \Delta t \cdot (q_t^{r,rad} + q_t^{r,inf} - q_t^{r,vap} - q_t^{r,sens} - qr_t^{r,outf}) \tag{5.2}$$

The radiation, vaporization, and sensible heating terms are functions of, among other factors, environmental conditions including temperature, wind speed, humidity, pressure, and cloud cover. It is these three terms that raise the pond temperature above its feasible

Table 5.2: Cogeneration process models

Plant #	Unit operation	Inlet variable	Outlet variable	Transfer function
1	Power boiler	Hog feed rate	Steam flow rate	$\frac{0.3030}{3s+1}e^{-7s}$
1	Power boiler	Gas feed rate	Steam flow rate	$\frac{0.3160}{3s+1}e^{-2s}$
1	Recovery boiler	Black liquor feed rate	Steam flow rate	$\frac{0.3080}{42s+1}e^{-3s}$
1	HP turbine stage	Steam flow rate	Power generation rate	$\frac{0.8433}{s+1}e^{-s}$
1	MP turbine stage	Steam flow rate	Power generation rate	$\frac{0.7896}{s+1}e^{-s}$
1	HP-MP PRV	Steam flow rate in	Steam flow rate out	$0.9030e^{-s}$
1	MP-LP PRV	Steam flow rate in	Steam flow rate out	$0.7955e^{-s}$
2	Power boiler 1	Hog feed rate	Steam flow rate	$\frac{0.3042}{3s+1}e^{-7s}$
2	Power boiler 1	Gas feed rate	Steam flow rate	$\frac{0.3170}{3s+1}e^{-2s}$
2	Power boiler 2	Hog feed rate	Steam flow rate	$\frac{0.3074}{3s+1}e^{-7s}$
2	Power boiler 2	Gas feed rate	Steam flow rate	$\frac{0.3262}{3s+1}e^{-2s}$
2	Recovery boiler	Black liquor feed rate	Steam flow rate	$\frac{0.3052}{43s+1}e^{-3s}$
2	HP turbine stage	Steam flow rate	Power generation rate	$\frac{0.8486}{s+1}e^{-s}$
2	MP turbine stage	Steam flow rate	Power generation rate	$\frac{0.7876}{s+1}e^{-s}$
2	LP turbine stage	Steam flow rate	Power generation rate	$\frac{0.9919}{s+1}e^{-s}$
2	HP-MP PRV	Steam flow rate in	Steam flow rate out	$0.8965e^{-s}$
2	MP-LP PRV	Steam flow rate in	Steam flow rate out	$0.7962e^{-s}$

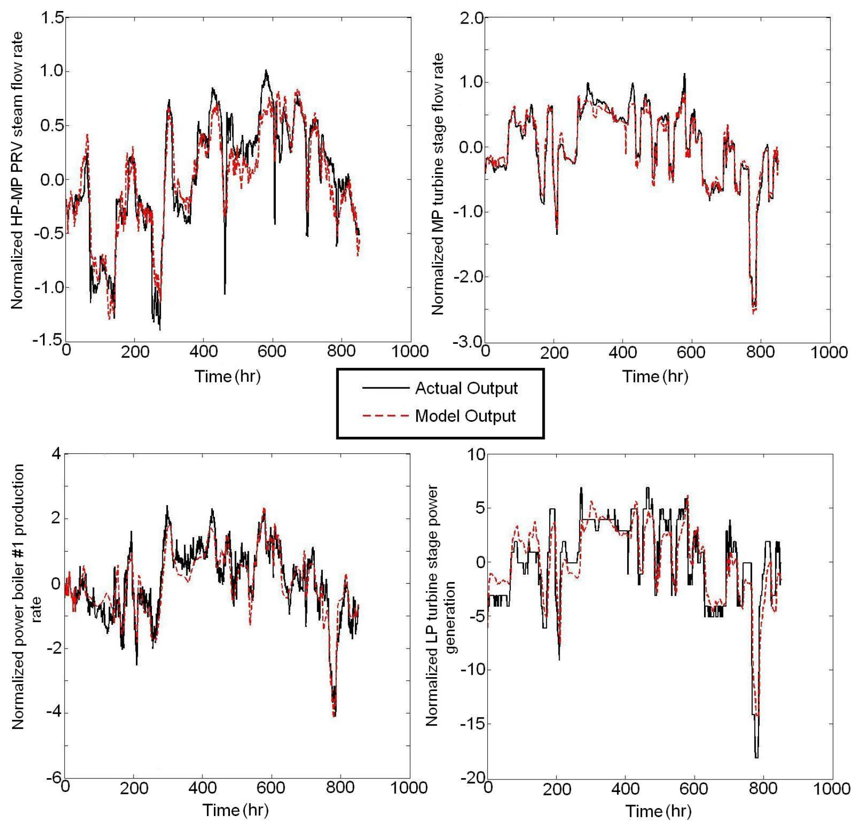

Figure 5.2: Model output versus actual output for several cogeneration unit operations

operating limit under conditions of extreme weather. In the event of precipitation the inlet energy flow terms are also significantly effected, which usually then negate the heating effects from all other sources. For optimization horizons of 24 hours or less, hourly meteorological forecasts are generally available online from local or national sources such as www.theweathernetwork.com. For longer horizons and areas where hourly forecasts are unavailable or insufficient, less detailed or daily forecasts can be supplemented using historical weather trends. An extensive database of hourly, historical meteorological data in Canada is available at www.climate.weatheroffice.ec.gc.ca.

Chapter 6

Economic Performance Assessment[1]

The first major objective of this thesis was to develop an economic performance assessment strategy, as stated in Chapter 4. This chapter will cover the establishment of an objective function, the optimization of process operating conditions, and the optimization of a feedback control strategy. All three of these aspects will then be combined to form an optimization-based economic performance assessment strategy.

A metric of performance is required for the meaningful assessment of a system control strategy, and basing that metric on economics is an intuitive choice for industrial applications. A cost function is one that can provide such a metric by quantifying system operation in an economic framework. The constituents of a cost function are variables representative of process inputs & outputs, and coefficients representative of relative costs or profits associated with each variable. Solution of the cost function yields the overall cost (or profit) of operation for the process in question. By comparing current cost of operation with an "ideal" case, a dollar value can be placed on the potential room for improvement.

A linear cost function in the form of (6.1) [94] allows for the economically-based weighting of variable priority using cost vectors c_u and c_y. The cost vector parameters in c_u and c_y can

[1]Portions of this chapter have been accepted for presentation at DYCOPS-9. Marshman, D.J., Chmelyk, T., Sidhu, M.S., Gopaluni, R.B., and Dumont, G.A. (2010) Economic performance assessment with optimized LQG benchmarking in MIMO systems.

be chosen to represent a monetary gain or loss associated with a one unit shift in the mean operating condition over a given period of time. A basic understanding of plant economics is required to properly select the cost vector parameter values. For most applications, several of these parameters will be equal to zero, implying no direct relationship of those respective variables with overall plant profitability. Current operating conditions, $\bar{y}_o$ & $\bar{u}_o$, may be used to establish a baseline for comparison in the form of (6.2).

$$P = c_y^T \bar{y} + c_u^T \bar{u} \tag{6.1}$$

$$P_o = c_y^T \bar{y}_o + c_u^T \bar{u}_o \tag{6.2}$$

The use of (6.1) as the objective function in a optimization procedure allows for quick and easy calculations, and establishes a convex basis for the problem. In this work, an objective function of this form is used for two economic optimization steps: setpoint shift, and LQG benchmarking with setpoint shift.

6.1 Setpoint shift

Before addressing issues of controller performance, there are generally steps that can be taken to improve the economics of operation based on the establishment of ideal steady state conditions under the current control strategy [94]. Process setpoints may be set further from constraint limits than is required according to back-off analysis. Financial benefits through improved product may be attainable simply by finding the minimum back-off, and moving then adjusting setpoints to that level. Implementation of this step is quick, easy, and requires no capital investment.

The steady state gain matrix (K) and variability vectors (σ_y, σ_u) can be readily extracted from process data. Constraint violation tolerance vectors ($1 - \alpha_y, 1 - \alpha_u$) and cost function parameters (c_y, c_u) can be obtained from process engineers. For more information on how to calculate z-coefficients $(z_{\alpha_y}, z_{\alpha_y})$ based on a given constraint violation probability, see [94]. Solution of the minimum back-off setpoints can then be calculated using the following optimization procedure, outlined by equations (6.1)-(6.5), as developed by Zhao *et. al.* [94].

Maximize: $\underset{\bar{u},\bar{y}}{}$ $$P = c_y^T \bar{y} + c_u^T \bar{u}$$

Subject to:

$$\bar{y} - \bar{y}_o = K(\bar{u} - \bar{u}_o) \tag{6.3}$$

$$y_{min} + z_{\alpha_y/2}\sigma_y \leq \bar{y} \leq y_{max} - z_{\alpha_y/2}\sigma_y \tag{6.4}$$

$$u_{min} + z_{\alpha_u/2}\sigma_u \leq \bar{u} \leq u_{max} - z_{\alpha_u/2}\sigma_u \tag{6.5}$$

Since (6.1), (6.3)-(6.5) are all linear with respect to the optimization variables $\bar{u}$ & $\bar{y}$, the above optimization problem is convex and can be solved using a variety of readily available methods. The improvement in operation profitability expected with application of these new setpoints $\bar{u}$ & $\bar{y}$ (without any change to the existing control strategy) is given by $P - P_o$.

6.2 LQG benchmark with setpoint shift

Once setpoints are optimized based on current controller performance, the EPA turns to controller assessment with the objective of reducing or redistributing variability through implementation of an optimized control strategy. By doing so, it may be possible to shift setpoints further towards constraints, as depicted in Fig. 2.2. LQG control is one benchmarking method that has grown in popularity since first proposed for this purpose by Huang and Shah [35].

An LQG controller works by formulating a set of control laws based on the minimization of the objection function (6.6), where $\lambda = [\lambda_u \ \lambda_y]$ is a tuning parameter vector used to balance control effort with output variance. When λ_u is empty, a MV controller is produced. When λ_y is empty, no control action is applied. By varying the values of λ over a feasible

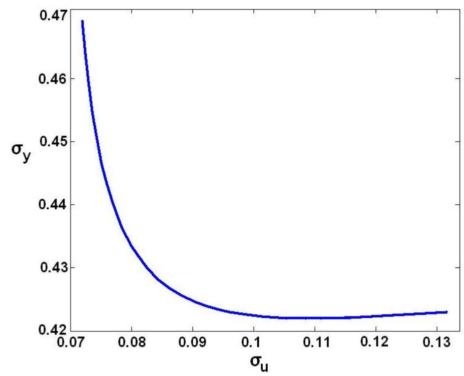

Figure 6.1: Typical LQG input-output standard deviation tradeoff curve over a range of λ

range, a tradeoff curve between σ_y and σ_u, such as that shown in Fig. 6.1, is produced [4] with asymptotes of $\sigma_y = \sigma_{y,MV}$ and $\sigma_u = \sigma_{u,min}$.

$$J(\lambda) = \sum_{i=1}^{n_y}(\lambda_{y,i}E(y_i^2)) + \sum_{j=1}^{n_u}(\lambda_{u,i}E(u_i^2)) \tag{6.6}$$

These input-output variance tradeoff curves represent a lower bound on attainable variability through feedback control, where each point along the curve corresponds to specific controller weights λ_u, λ_y. Therefore, these functions can be used to systematically choose values of λ_u, λ_y corresponding to ideal ratios of σ_y:σ_u. These ratios can be expressed in the form of (6.7). By transferring uncertainty from constraint-limited variables to variables not operating at minimum back-off levels, it is usually possible to shift steady state operating conditions to more economically advantageous points. Unlike the case of MV benchmarking, this method results in solutions that are feasible using feedback control.

$$\sigma_y = f(\sigma_u) \tag{6.7}$$

The relationship in (6.7) can be applied as an additional constraint on the optimization problem outlined in Section 4.1. The result is the following LQG tradeoff-based stochastic algorithm, as presented by Zhao *et. al.* [94].

Maximize: $$P = c_y^T\bar{y} + c_u^T\bar{u}$$

$$u,y,\sigma_u,\sigma_y$$

Subject to: (6.3), (6.4), (6.5), (6.7), and

$$\sigma_y \geq 0 \tag{6.8}$$

$$\sigma_u \geq 0 \tag{6.9}$$

Optimizing the variance tradeoff is relatively straightforward for the SISO case, but becomes increasingly difficult as the size of the system increases. In a SISO system $\lambda = [\lambda_y \; 1]$, where λ_y is a single constant value, and is optimally chosen based on a single tradeoff curve. However, λ can take several forms when dealing with MIMO system.

Optimal performance is not necessarily achieved simply through the minimization of variance for economically critical variables. Instead, all interactions between input and output variables must be explored. Ideal operation of a process almost always involves one or more variables operating at a process constraint, or at a minimum back-off from a constraint, but these are not necessarily the most (directly) economically significant variables. In order to further increase the economic output, the variability of these constrained parameters must be reduced, thus allowing the critical operating setpoints to be moved closer to the constraint.

For example; a filtration process may be described by a 2x2 system with two inputs: slurry and vapour stream inlet flow rates; and two outputs: a filtrate production rate, and an internal pressure. Even though the filtrate production rate is most likely the economically significant output with the highest cost function parameter, the production rate may be constrained due to a maximum pressure. Therefore, a reduction in pressure variability could allow operation at a higher pressure, which may increase the rate of filtration. This illustrates that even though pressure is an economically insignificant variable, it may be the focus of an improved control strategy in an economic framework.

For MIMO systems, Zhao *et. al.* [94] propose the use of a weighted summation of input and output variances to generate the LQG tradeoff curve with an objective function of the form (6.10), where λ is a constant. However, determining the appropriate weighting elements for summation may be difficult, as they will not necessarily be the same as the parameters of the cost function. As mentioned above, optimal cost benefit is not always achieved through reduction of the most economically significant variables. The method proposed by Zhao *et. al.* [94] allows for limited customization beyond the cost function, as λ is a single constant even for large MIMO systems.

$$J_{LQG}(\lambda) = \sum_{i=1}^{p} w_i \sigma_{yi}^2 + \lambda \sum_{j=1}^{m} r_j \sigma_{uj}^2 \tag{6.10}$$

Gu *et. al.* [31] proposes a similar solution by incorporating input and output cost-based weighting matrices directly into the LQG objective function for MIMO cases. Again, the economically optimal weighting of inputs and outputs LQG objective may not necessarily reflect the weighting of those variables according to the cost function. In order to improve performance in an economic framework, a control strategy must target constrained process variables, which may or may not be the most economically significant. The weighting function for controller design and cost function should be chosen separately. This work proposes a simple iterative optimization procedure where each iteration involves the selection of one value in the LQG weighting vectors λ_u and λ_y in (6.6) according to the stepwise procedure below. A more complete depiction of the performance assessment method in its entirety is shown in Fig. 6.2.

1. vary one element 'i' of λ over an appropriate range while testing the system in closed-loop to obtain a LQG tradeoff curve for every σ_u-σ_y pairing in the form of (6.7).

2. perform the optimization procedure described above using (6.1), (6.3)-(6.5), (6.7)-(6.9) to determine the ideal value of $\lambda(i)$

3. repeat until each element in λ has been optimally chosen

The nature or order of (6.7) will determine both the accuracy of solution and the difficulty of the optimization procedure. For the simplest optimization procedure the relationship between σ_u and σ_y can be approximated as linear, but this yields inaccuracies in the solution, as Fig. 6.1 is clearly seen to be nonlinear. Higher order approximations for (6.7) will result in more accurate control, but will also require more robust optimization techniques. Alternatively, the observed paired sets of σ_u and σ_y during step 1) may be used to iteratively solve for each optimal value of λ. In this case, the iterative procedure would be revised as follows:

1. select λ and perform a closed-loop test to determine σ_u and σ_y
2. perform the optimization procedure described in chapter 6.1 using (6.1), (6.3)-(6.5) and the observed values σ_u and σ_y to determine the optimal profitability
3. repeat 1) - 2) while varying one element 'i' of λ over an appropriate range
4. select the value of $\lambda(i)$ corresponding to the highest profitability observed in 2)
5. repeat until each element in λ has been optimally chosen

Every value of the weighting vector λ in these methods corresponds to a weighting of control effort on a single input or output parameter. The most influential elements of λ should be established first. An approximate order of significance can be determined through a preliminary screening procedure, where priority is given to variables with the lowest value of (6.11). Due to the iterative nature of these methods it should be noted that the computational expense is increased by a factor of $n_{inputs} + n_{outputs}$ in the first case, and $(n_{inputs} + n_{outputs})(\lambda_{max} - \lambda_{min})/(\Delta\lambda)$ in the second case. Alternatively, if it is available, the MATLAB MPC toolbox can be used to provide a sufficient approximation to the LQG problem, as recommended by Zhao *et. al.* [94].

$$min(|\bar{x} - x_{min} - z_{\alpha_x/2}\sigma_x|, |x_{max} - z_{\alpha_x/2}\sigma_x - \bar{x}|), \qquad (6.11)$$
$$x \,\epsilon\, u, y$$

Although values of the LQG weighting parameters λ_u & λ_y do not appear in the optimization problem, they implicitly determine the relationship between σ_u & σ_y. Since this

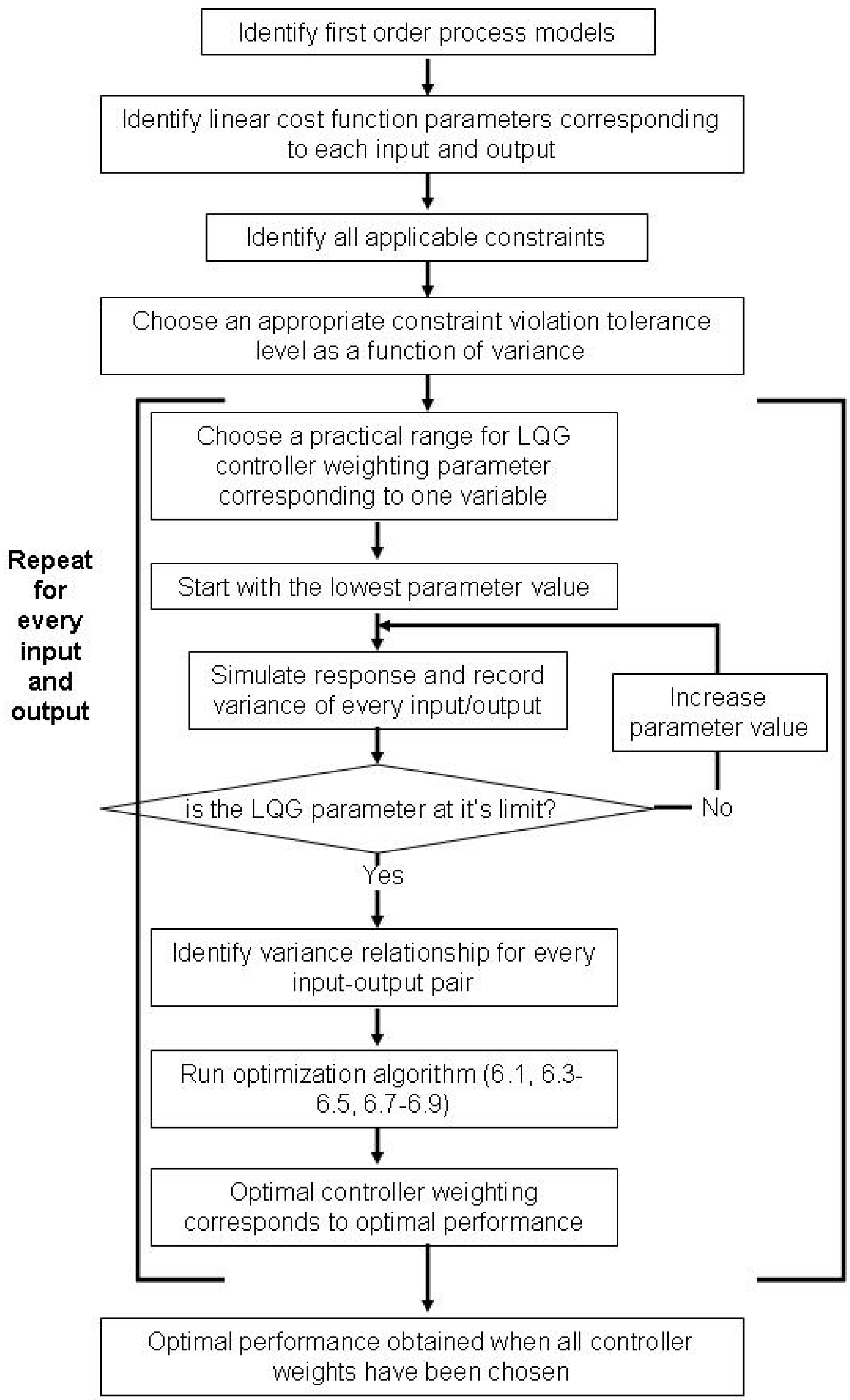

Figure 6.2: Summary flow chart of the proposed EPA strategy

procedure is intended as a method to assess economic performance rather than finalize a controller design, it may not be necessary to explicitly determine the optimal values of λ_u & λ_y. However, if these controller parameters are desired it should be relatively straightforward to determine them based on the optimized variables σ_u & σ_y.

The true value of the economic performance assessment strategy described in the above section is the quantification of current and potential process performance in an economic framework. The value of P_o from (6.2) gives the economics of performance under the current control strategy. The value of P obtained from solution of the optimization problem in chapter 6.1 gives the economics of performance under the same control strategy and tuning, but with optimized process setpoints. Finally, the value of P obtained from solution of the optimization problem in chapter 6.2 gives the economic performance under an ideally- tuned LQG controller at optimized process setpoints.

It should be noted that LQG control, and therefore LQG-based performance assessment strategies, focus on regulatory control as opposed to servo control. Since pulp and paper mill processes are generally continuous in nature, and are not usually subject to frequent setpoint changes, special emphasis in this work was placed on noise reduction control strategies, thus making LQG control an excellent frame of reference.

Chapter 7

Energy Management System[1]

The second major objective of this thesis was to develop an energy management system, as stated in Chapter 4. This chapter will cover the fundamental components of an energy management optimization algorithm for normal cogeneration and for cogeneration with an abnormal production limiting constraint as defined in Chapter 4.

The overall objective of the EMS is to maximize profitability over a given time horizon through the coordination of individual unit operating conditions within the facility. The time horizon is divided into a number of equi-spaced time periods and each unit is given a distinct setpoint for every period over the course of the horizon, all of which are subject to operational constraints such as feasible operation limits, rate of change limits, and unit co-dependencies as captured by process models. The operational costs are expressed as linear functions of fuel flow rate to each boiler and fresh water treatment rate, as shown in (7.1). The fuel cost coefficients in (7.1) represent the various costs of available fuels, which must be determined on a case by case basis. The price of natural gas is commonly set at a relatively constant rate by a utilities provider. The price of hog fuel, on the other hand, varies depending on the source. Hog fuel is typically produced internally by the mill, but may be supplemented by

[1]Portions of this chapter have been accepted for publication. Marshman, D.J., Chmelyk, T., Sidhu, M.S., Gopaluni, R.B., and Dumont, G.A. (2010) Energy optimization in a pulp and paper mill cogeneration facility. Applied Energy. doi:10.1016/j.apenergy.2010.04.023

purchasing from other pulp mills. The price of fuels and cost of water treatment will likely need to be entered and adjusted manually based on the conditions at the time of operation.

$$C_t = \sum_{i=1}^{n^{boi}} \left(\sum_{j=1}^{n^{sup}} \left(c^j_{hog} h^{i,j}_t \right) + c_{ng} g^i_t \right) + c_w m^w_t \tag{7.1}$$

Although the objective of the EMS is to maximize profitability, the primary objective of a cogeneration facility is to generate heat. This is especially true in a pulp and paper mill application, where most cogeneration systems in the industry are modified process heating systems. For this reason, the pulp mill and the cogeneration facility have a master-slave relationship in reference to heat production. Although there may be contractual obligations associated with electricity production, there is usually a large degree of flexibility when it comes to the rate of power generation in day-to-day operation. Therefore, plant heat demand does not appear in the objective function of the profitability optimization problem, but rather as a constraint that must be satisfied. The required heat demand can be expressed as a linear function of heat demands from the pulp and paper mill at each header pressure level as per (7.2).

$$Q_t = \sum_{i=1}^{n^{sh}} q^i_t. \tag{7.2}$$

The rate of electricity production, on the other hand, is a defining component of the EMS objective function along with operating costs. Since the rate of electricity production from a pulp and paper mill is relatively small compared to overall grid demands, the relationship between power generation and plant profitability is defined by the contractual agreement between the cogeneration facility and a larger regional power provider. These contracts can be extremely complex in nature, and the sale pricing method for electricity can vary significantly between facilities. Prices may fluctuate with the market, making online automatic updates of pricing profiles a necessary component of an effective EMS. In an extreme alternative, electricity prices may be fixed for an entire year. For this reason the algorithm horizon, iteration period length, and pricing structure have not been fixed. Due to the assumption of linearity for individual unit models, the rate of electrical power generation can be expressed as a linear function of steam flow rate between each extraction point within a turbine at steady state, as shown in (7.3).

$$P_t = \sum_{i=1}^{n^{tur}} \sum_{j=1}^{n^{tur_i,sta}} \left(\epsilon^{tur_i,sta_j} \left(H_{in}^{tur_i,sta_j} - H_{out}^{tur_i,sta_j} \right) m_t^{tur_i,sta_j} \right). \tag{7.3}$$

The energy optimization problem can now be defined by equations (7.4) - (7.10). The objective function in (7.4) denotes the overall cost of operation, which is obtained by subtracting the revenue of electricity sales from the cost of operation. The problem constraints are represented by the inequalities in (7.5)-(7.7) and the equalities such as the mass and energy balances seen in (7.8)-(7.10). More specifically, (7.5) represents a limitation on hog fuel supply from each supplier over the entire optimization horizon, (7.6) constrains a steam flow rate $m_t^{X_i,Y_j}$ to physically realizable values for unit X_i (and/or the corresponding subunit Y_j), and (7.7) is a rate of change limitation to steam flow through unit X_i (and/or the corresponding subunit Y_j), where $\delta m_{MAX}^{X_i,Y_j}$ is the corresponding maximum physically allowable change in steam flow rate from one time period to the next. $\delta m_{MAX}^{X_i,Y_j}$ can be specified using a discrete form of the transfer function of the corresponding unit. (7.8) enforces enthalpy balance around a PRV. (7.9) represents an energy balance around boiler i where steam is potentially produced using both natural gas and hog fuel from various different suppliers. The left hand side of (7.9) represents the energy input to the boiler through hog fuel and natural gas and the right side represents the enthalpy of steam generated. (7.10) enforces mass balances around a medium pressure header. It is straightforward to write mass balances around other pressure headers as well.

$$Min \sum_{t=1}^{tmax} (C_t - c_{e,t} P_t) \tag{7.4}$$

$$s.t. \sum_{t=1}^{tmax} \sum_{i=1}^{n^{boi}} h_t^{i,j} \leq s_j \quad j = 1 \text{ to } n^{sup} \tag{7.5}$$

$$0 \leq m_t^{X_i,Y_j} \leq m_{MAX}^{X_i,Y_j} \quad \text{for all } X_i \text{ and all } Y_j \tag{7.6}$$

$$m_{t-1}^{X_i,Y_j} - \delta m_{MAX}^{X_i,Y_j} \leq m_t^{X_i,Y_j} \leq m_{t-1}^{X_i,Y_j} + \delta m_{MAX}^{X_i,Y_j} \quad \text{for all } X_i \text{ and all } Y_j \tag{7.7}$$

$$H_{in}^{PRV_i} m_t^{PRV_i} = H_{out}^{PRV_i} \left(m_t^{PRV_i} + \Delta m_t^{PRV_i} \right) \quad i = 1 \text{ to } n^{PRV} \tag{7.8}$$

$$\epsilon^{boi_i} \left(\beta \sum_{j=1}^{n^{sup}} \left(h_t^{i,j} \gamma^j \right) + \phi g_t^i \theta \right) = H_{out}^{boi_i} m_t^{boi_i} \quad i = 1 \text{ to } n^{boi} \tag{7.9}$$

$$m_t^{tur_1,sta_1} + m_t^{PRV_1} + \Delta m_t^{PRV_1} = \frac{q_t^2}{H_{out}^{tur_1,sta_1}} + m_t^{tur_1,sta_2} + m_t^{PRV_2} + m_t^{ven_2} \tag{7.10}$$

The constraints in the optimization problem shown above are representative of typical mass and energy balance constraints in the cogeneration facility. There are many other similar constraints that are not shown due to space limitations. While these other constraints are not shown above, they are used in the energy optimization problem during implementation. A simplified representation of the optimization procedure is shown in Fig. 7.1. In order to solve the above optimization problem, optimal values for all hog and natural gas fuel combustion rates, and all steam mass flow rates through each unit within the system must be chosen. The final optimization problem contains $tmax\,(2n_{boi}n_{sup} + n)$ optimization variables subject to $n_{sup} + tmax\,(4n + n_{boi}n_{sup} + 2n_{sh})$ constraints, several of which may become redundant depending on the complexity of the system under investigation. For a mill similar to those under investigation in this work, an optimization problem with a 24 hour horizon involves approximately 1000 optimization variables subject to approximately 2500 constraints. Despite the large size of the problem, its convex nature results in reasonable solution times with a standard convex optimization tool. The CVX toolbox for Matlab developed by Michael Grant and Stephen Boyd was used for this work.

Online implementation of the energy management optimization strategy in a real facility requires regular updates to ensure that continuously optimal operating conditions are maintained, as well as to update and revise forecasts. Minor disturbances and regular process noise will slowly drive conditions away from optimality, but under short time frames

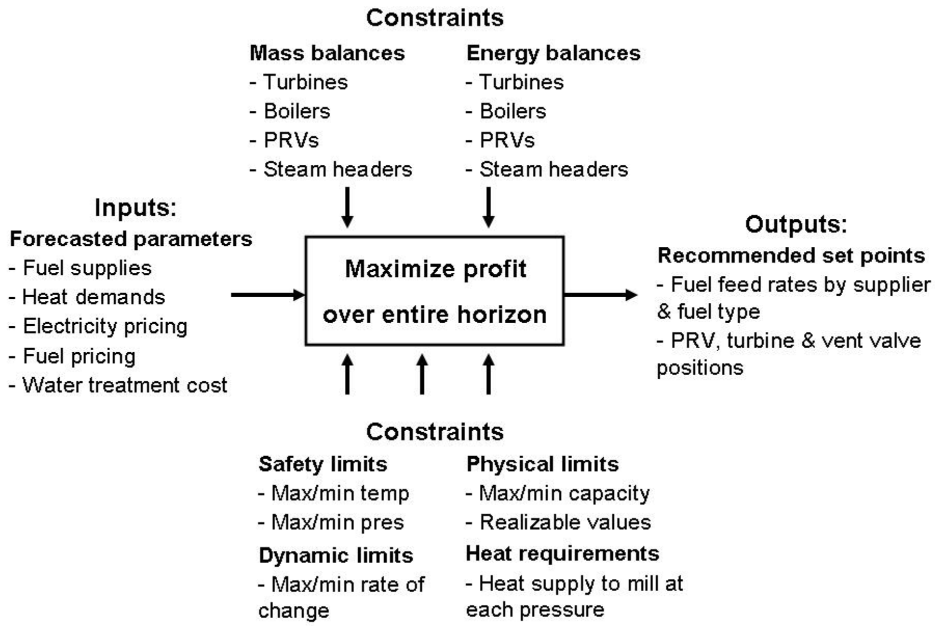

Figure 7.1: Summary of EMS optimization algorithm

local unit control strategies should sufficiently negate such effects. However, more significant disturbances including, but not limited to, unit start-up and shut down, mill production variations, significant process disturbances, etc. will have a more severe impact on maintaining optimality. Frequency of such events varies greatly between facilities, so the trade-off between maintaining optimality and frequency of optimization calculations should be assessed on a case by case basis. Generally, it is recommended that the energy management optimization problem is revised and resolved every 1-10 minutes, with increased solution frequency during periods of known significant disturbances or start-up/shutdown.

7.1 Special cases of energy management

The most well intended, advanced control strategies may be hindered by unexpected obstacles observed only through practical application. For example, one of the mill cogeneration facilities investigated in this work had a sufficiently profitable energy management system in place that managed the cogeneration operation. For the majority of the year this EMS worked effectively. However, when the weather became too warm the rate of evaporation of the cooling reservoir, which is used to absorb heat from the condensed water (see Fig. 5.1), increased significantly, jeopardizing the sustainability of the pond, and the pump returning water to the mill would begin to fail. The only feasible solution when this temperature threshold was exceeded was to cease power generation, allow the pond to cool, then resume operation. Such measures usually required shutting down power generation until the following morning.

One proposed solution was to introduce a basic feedback control strategy based on the pond temperature, and to cut back production as temperature approached a critical point. Although this approach would allow sustained power generation, the profitability of the system would be drastically reduced. Power generation during a high-sell price period would be treated no differently than during a period of marginal profitability. The basic feedback method also failed to incorporate significant, predictable, and sometimes obvious temperature trends. Such trends include nightly temperature drops, early afternoon temperature peaks, and short term weather forecasting.

Rather than introducing a supervisory control loop, a forecasting algorithm was developed to operate in parallel with the mill EMS. By combining readily available meteorological data/forecasts with thermal modeling techniques for small bodies of water, the production scheduling algorithm proposed in the previous sections of this thesis was modified to check for future critical temperature violations and, if necessary, take economically efficient corrective action.

This general strategy provides an effective and efficient solution to dealing with unique, model-friendly processes with no direct impact on the energy management objective function. By taking this optimization based approach to unique constraint handling, cogeneration facilities can readily customize energy management solutions to their specific needs without having to compromise safety/quality or resort to costly, brute force failsafe methods.

7.1.1 Reservoir temperature forecasting

For a given power production schedule and weather forecast, it is possible to use the developed process model, (5.2), in order to predict the peak reservoir temperature. If the peak forecasted temperature exceeds the operating limit at any point over the optimization horizon, it is possible to adjust the cogeneration plant operation schedule in order to stay below the critical pond temperature depending on the severity of the climate at the mill reservoir. By incorporating the forecasting technique into the economic optimizer, a safe pond temperature profile may be achieved while minimizing lost revenue.

7.1.2 Reservoir temperature limited production scheduling

One major challenge that must be overcome when addressing the co-ordination of production scheduling with reservoir thermal energy forecasting is the unconventional relationship between cooling rate, time of day, and peak temperature. On a normal day, an undisturbed pond will typically experience a peak temperature in the late afternoon. The exact time that the pond hits this peak temperature is dependent on the weather conditions and the residence time of water in the pond (assuming that the pond is not isolated from other natural water sources). Therefore, a different peak temperature may be achieved depending on the time of day that the reservoir contacts the mill's condensed stream. It is entirely possible that depending on whether the pond absorbs 30kJ of heat at 9am, 2pm, or 8pm, it may reach a daily peak temperature of 18C, 24C, or 22C respectively.

The important conclusion from the above observation is that the relationship between peak reservoir temperature and power generation scheduling is both non-trivial and non-convex. Due to the need for online implementation, however, a non-convex optimizer may not be practical for an industrial application. The proposed solution is therefore an algorithm that determines the cogeneration operation schedule using convex optimization techniques, but which undergoes an iterative (but still convex) optimization process in the event of reservoir temperature constraint violation.

The proposed solution begins by posing an optimization problem in the form of equations

(7.4-7.10). The resulting production schedule is used to determine the mill contribution to the reservoir inlet energy flow over the optimization horizon. By combining reservoir cooling requirements with meteorological forecasting, the difference equation (5.2) can be used to determine the reservoir temperature profile, and consequently the peak temperature, over the horizon.

If the solution of (5.2) yields a peak temperature below the maximum allowable limit, then the overall profitability of the plant is not jeopardized and no corrective action needs to be taken. On the other hand, if the peak reservoir temperature is greater than the upper limit, then some corrective action must be taken in order to avoid the last minute safety measure of shutting down power generation. In this temperature limiting case, an additional constraint in the form of (7.11) can be added to the overall optimization problem, where $w_{f,t}$ is the fuel usage weight factor, k_f is a total fuel scaling factor, f_t is the energy content of fuel used during time period t, and f_o is the total energy content of fuel used in the solution to the original optimization problem in the form of equations (7.4-7.10).

$$\sum_{t=1}^{tmax} f_t w_{f,t} \leq \frac{f_o}{k_f} \tag{7.11}$$

The weights, $w_{f,t}$ are calculated using the following method:

1. Solve for the maximum allowable heat exchange (using (5.2)) with reservoir during the first optimization period such that the temperature is still below the threshold, assuming no heat is exchanged for the rest of the time periods. Then $w_{f,t}$ is assigned the inverse of the maximum allowable heat exchange.

2. Find $w_{f,t}$ for every optimization period in the horizon.

3. Rescale the weight factors by dividing each weight factor with the sum of all weight factors and thus ensuring that each weight factor satisfies $0 < w_{f,t} < 1$.

The vector $w_{f,t}$ effectively redistributes the usage of fuel in a way that allows for sustainable power production by exploiting the degree to which thermal energy is retained by the pond depending on the ambient conditions throughout the day. For example, heat typically dissipates readily into the environment in the cool, early morning, so large cooling duties can be offset. However, the rate of transfer from the pond to its surroundings slows as the air temperature and humidity increases throughout the day. Other factors such as precipitation, cloud cover, solar radiation, etc. also contribute to the ability of the pond to reject heat. By incorporating the fuel weighting vector into the original problem, time periods where thermal energy transferred to the reservoir is easily dissipated are favoured and allotted additional fuel, whereas periods where thermal energy is retained are penalized and therefore allotted less fuel. However, such penalties may still be offset by significantly high sale prices during those periods. The end result is an economically efficient, sustainable production schedule.

Once the values of the vector $w_{f,t}$ are known, the fuel scaling factor (k_f) is assigned a value of 1 and an iterative process used to lower the maximum pond temperature in the most cost effective way possible begins. The fuel usage weighting vector is incorporated into the scheduling problem as additional constraints in the form of (7.11), the original scheduling optimizer is re-run, and the maximum observed reservoir temperature is again noted. If it still exceeds the upper limit, k_f is increased, and the optimizer is run again. By increasing the value of k_f, the total fuel usage will gradually decrease until the reservoir temperature is maintained below its limit. This process is depicted by the flow chart shown in Fig. 7.2.

In the event of temperature constraint violations the solution time of the EMS optimizer is increased, typically by a factor ranging from 2 to 20, due to the iterative nature of the solution. However, online solution time may be minimized by infrequent updating of the fuel scaling factor (k_f) and the fuel weighting factors ($w_{f,t}$). Since these variables will only change with varying weather conditions, the iterative procedure only needs to be carried out a few times per hour, depending on the climatic conditions at the facility. Additionally, minor changes in the weather forecast require very few iterations given a reasonable step size. In any event, the implementation of this iterative convex procedure is more practical than its highly non-convex counterpart.

It should also be noted that the ability of the EMS to handle potential reservoir tem-

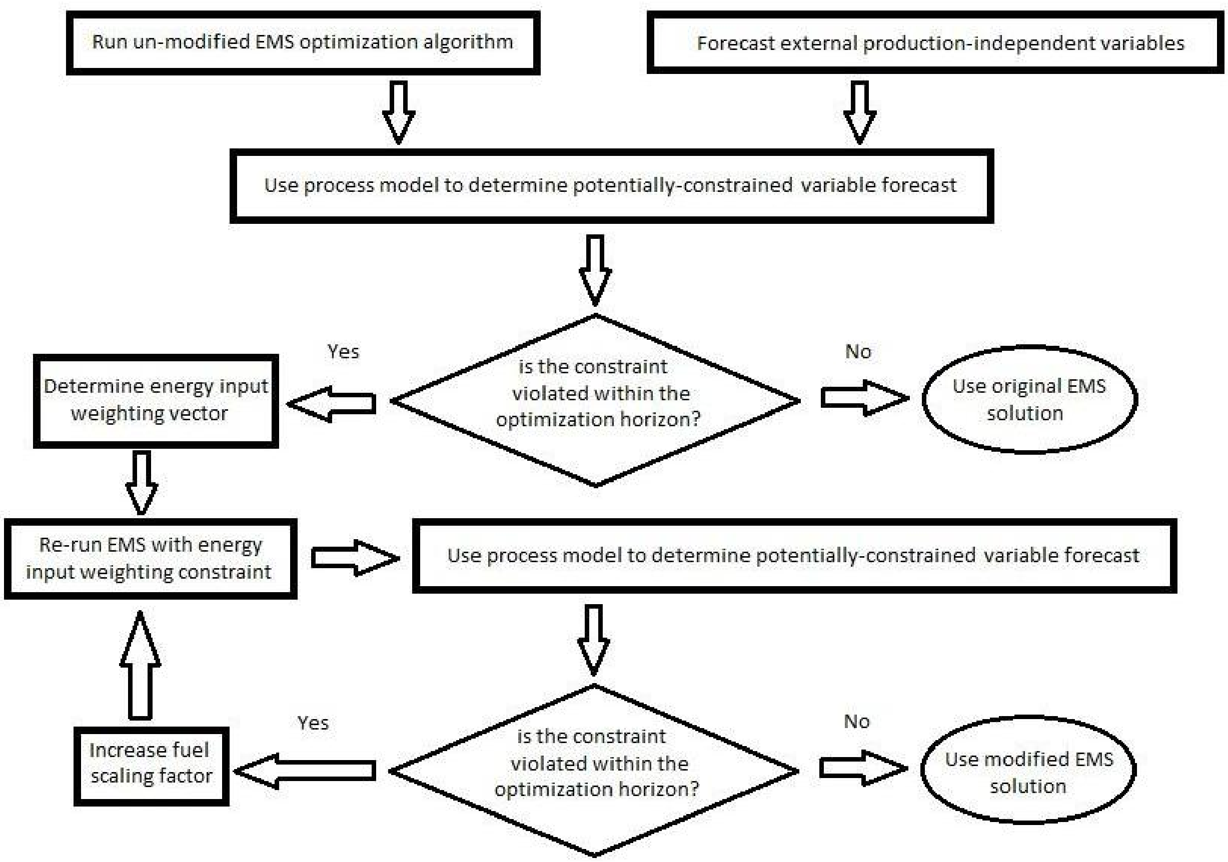

Figure 7.2: Modified EMS algorithm flow chart

perature violations is highly dependent on weather forecasting accuracy. For best results, it is recommended that on-site temperature, pressure, wind speed and humidity readings are used whenever possible. Local weather forecasting can be adjusted based on discrepancies between on-site and weather station readings.

The validity of the uniform pond temperature assumption should be analyzed on a case by case basis. For small, round, shallow ponds the approximation should hold reasonably well. However, as the pond increases in depth and length, temperature gradients will likely grow. In any case, temperature readings should be taken near the surface, downstream from the mill heat exchanger exhaust.

The generic application of this strategy follows a similar path. The value of a unique, constrained variable must be modeled as a function of both a significant plant operation metric (such as production rate) and an external variable set (such as temperature, pressure, etc.). After solving for the ideal unique-constraint-free operation of the process using the EMS and forecasting the required external variable set, the model must be used to determine whether or not the variable in question exceeds a limit. In the case where the constraint is violated, some corrective action must be taken. A vector representing the susceptibility of the constrained variable to overall production over the optimization horizon must then be solved using the three step approach outlined above in this section. By constraining overall production rate using a key process input similar to equation 7.11 and then iteratively increasing the scalar k_f, the production rate will be decreased until the constraint is satisfied. Conversely, if the constraint violation requires *increased* production, two slight alterations are required. First, in step 1 when solving for the vector $w_{f,t}$, the values should not be inverted. Secondly, the scalar k_f should be decreased with each iteration.

Chapter 8

Case Studies[1,2]

The objectives of this thesis were to develop an economic performance assessment method and an energy management system, as stated in chapter 4. These objectives were achieved in the previous two chapters of this thesis. The following chapter covers two case studies of the developed EPA algorithm and three case studies of the EMS, one of which includes the expanded version of the EMS from Chapter 7.1 that accounts for a unique, production limiting constraint.

8.1 Steady state performance assessment

The performance assessment method, as described in the chapter 6, was applied to two unit operations. The first case study is based on the simulated operation of a multi-stage, counter-current evaporator. The second case study is based on the operation of an industrial condenser unit in a pulp and paper mill.

[1]Portions of section 8.1 from this chapter have been accepted for presentation at DYCOPS-9. Marshman, D.J., Chmelyk, T., Sidhu, M.S., Gopaluni, R.B., and Dumont, G.A. (2010) Economic performance assessment with optimized LQG benchmarking in MIMO systems.

[2]Portions of sections 8.2 & 8.3 from this chapter have been accepted for publication. Marshman, D.J., Chmelyk, T., Sidhu, M.S., Gopaluni, R.B., and Dumont, G.A. (2010) Energy optimization in a pulp and paper mill cogeneration facility. Applied Energy. doi:10.1016/j.apenergy.2010.04.023

For each study, the mean observed values of each variable during normal operation were assumed to be the current setpoint. All noise was approximated as Gaussian for the purposes of model generation and simulation. Correlations between manipulated and disturbance variables were analyzed, and redundant variables were removed from the models. Finally, MATLAB's identification toolbox was used to generate first order transfer function models for each unit operation from the processed data.

8.1.1 Multi-stage evaporator

Process description

A multi-stage, counter current evaporator, based on a mathematical model developed by Kaya and Sarac [44], was used for the first case study. Such units are applied in large scale industrial processes requiring significant changes in solution concentration where the solute and solvent have considerably different vapourization temperatures. Multiple stages are generally used to reduce waste heat, and therefore reduce energy consumption.

The unit investigated in this work consists of four stages of evaporation set up in counter-current operation. The solution is fed into stage four, and flows through each stage to stage one. The desired product is the concentrated liquid phase solution extracted from stage one.

Pressurized steam is fed into stage one from a boiler unit. The evaporated solvent from stage one is used to heat stage two, the evaporated solvent from stage two is used to heat stage three, and the evaporated solvent from stage three is used to heat stage four.

Operation of the evaporator system is controlled by three critical manipulated variables: inlet flow rate, steam flow rate, and steam pressure. However, overall plant operation dictates that inlet flow rate is determined by upstream production rate. Although a limited amount of upstream solution can be stored momentarily, its average operating flow rate cannot be changed without major changes to overall plant operation. Therefore, inlet flow rate, although essential to the unit model, will not be a variable for optimization.

Operation is also dictated by two monitored disturbance variables: inlet stream heat

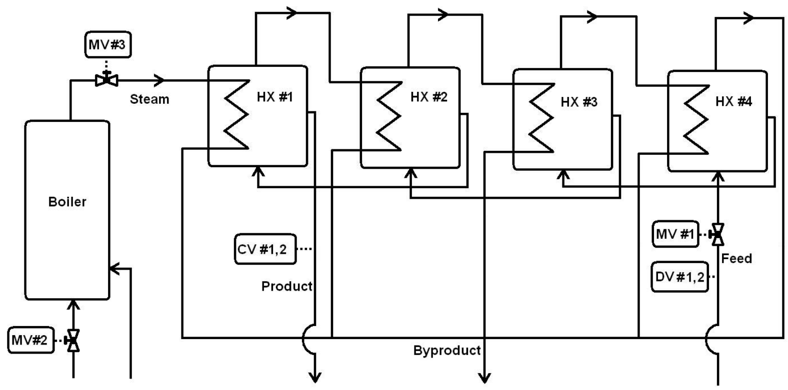

Figure 8.1: Multi-stage, counter-current evaporator schematic

content (or temperature), and inlet concentration. The two controlled variables of the process are product concentration and flow rate. A generalization of the process schematic can be seen in Fig. 8.1.

The only significant process constraints were upper limits on product and steam flow rates, steam pressure, and a useful range for product concentration. A minimum back-off of 1.5σ was desired for each constraint. The current control scheme involves a simple PID control strategy with key controller pairings.

The cost function for the evaporator involved a benefit associated with production rate and concentration, and a lesser cost penalty associated with steam flow rate and pressure. All other variables were considered cost-neutral.

Economic performance assessment

Results are summarized in Table 8.1. Financial results according to the given cost function are summarized in Fig. 8.2.

The first stage of performance assessment, the setpoint shift optimization, revealed a potential 2.15% increase in profitability without changes to the current control strategy. The most notable change recommended during this step is a 0.1 bar decrease in steam pressure. Although this adjustment reduces the product concentration, it also increases the product

Table 8.1: Evaporator steady state property values

Variable	Current value	SP shift	LQG with sp shift [94]	LQG with sp shift (this work)
Product conc. [% TDS]	0.6907	0.6885	0.6852	0.6864
Product flow rate [kg/h]	21793	22168	24209	24284
Inlet flow rate [kg/h]	101000	101000	101000	101000
Steam flow rate [kg/h]	24487	24401	23774	23618
Steam pres. [bar]	1.3998	1.2638	1.2816	1.2795

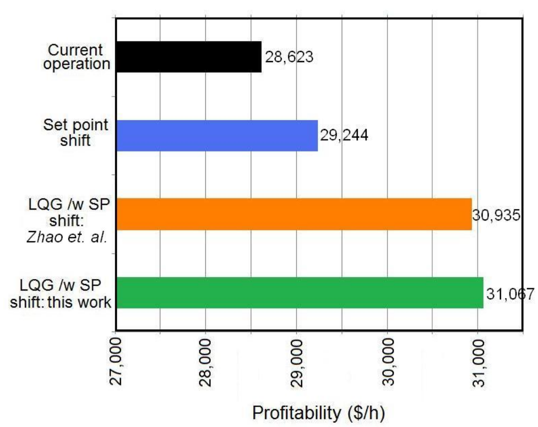

Figure 8.2: Evaporator hourly profit based on current operation, setpoint shift, and LQG benchmarking methods with setpoint shift

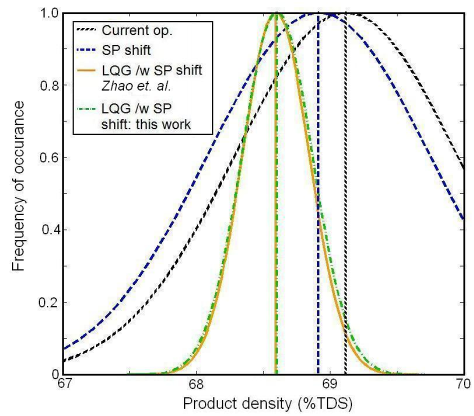

Figure 8.3: Product density operation distribution curves for various stages of economic performance analysis

flow rate due to a slight reduction in heat transferred, and consequently evaporation rate.

The performance assessment with LQG benchmarking using a cost function-based controller weighting, as recommended by Su *et. al.* [94], resulted in a 8.10% improvement over the current control method. However, by optimizing the controller weighting vector independently of the cost-function, a potential 8.53% improvement was revealed. The net difference between the two methods is $122.40/h, or $88,128/month. Although seemingly insignificant at first, this may be the difference between the approval of financing for a project, or the winning of a contract.

The difference between the two methods can be highlighted by closely examining Fig. 8.3. Product density is nowhere near the constraints, and therefore not limited directly by back-off from a constraint. Nonetheless, due to its high contribution to the cost function, the method in [94] focuses on reducing the variability of product density. The method presented in this paper, however, weights product density variability relatively low and focuses instead on constrained variables. The controller configuration in [94] is therefore not optimal for the current objective.

8.1.2 Industrial Case Study: Three-stage condenser

The method outlined in this paper has been applied to several industrial systems based on large sets of operational data. For reasons of confidentiality, only one of the several real applications is presented in this paper.

Process description

This study is based on the operation of a three-stage condenser represented by the process schematic shown in Fig. 8.4. The condensing system is used in a pulp and paper mill to convert black liquor, which is an otherwise useless byproduct of pulp production, into a concentrated, combustible fuel source. The concentrated black liquor is then used as an inexpensive alternative to natural gas in order to generate heat for further pulp production.

The condenser itself is fed by upstream pulp production units. The quality and flow rate of the feed stream are considered to be disturbance variables, as the production of black liquor is essentially a slave process to the operation of the mill as a whole. The feed stream is split into two parallel streams passing through two separate heat exchangers, recombined and temporarily stored in a holding tank, then fed through a final heat exchanger unit. A portion of the outlet stream from the final heat exchanger is recycled back to the holding tank, and the rest is sent to the boilers for combustion. Manipulated variables of this process include solution flow rates, steam flow rates, and steam pressures. The controlled variables are properties of the final product. Cost function parameters were selected by mill engineers.

Economic performance assessment

The first stage of performance assessment, the setpoint shift optimization, revealed a potential 9.43% increase in profitability without changes to the current control strategy. The majority of the increased profit was a result of an improved product quality through simple adjustments to key process variables. The recommended changes are more aggressive than current operating conditions, but still maintain the required 1.5σ back off from constraints.

The second step of LQG benchmarking resulted in a further 1.21% improvement using

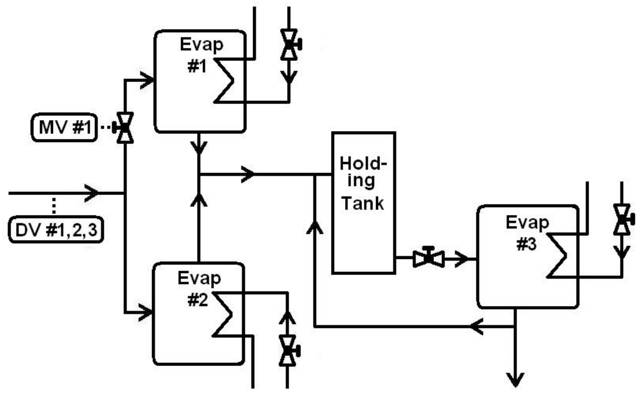

Figure 8.4: Black liquor condensing system schematic

a cost function-based controller weighting, as recommended by Su *et. al.* [94], and a 1.40% improvement using optimized controller weighting vectors. Both LQG benchmarking methods recommended control strategies that would make significant changes to the distribution of variability between key operating variables. These results are represented in Fig. 8.5.

As was the case in the previous two case studies, there were discrepancies between controller weighting methods. Once again the method proposed by Su *et. al.* [94] placed excessive emphasis on reducing the variability of unconstrained variables, whereas the method proposed in this work focused specifically on those variables at the minimum back-off from an active constraint.

8.2 Mill energy management

The case studies presented below are based on real power plant models and power generation contracts. Process gains, dynamic constraints and mill heat demands have been approximated from extensive sets of industrial data. Fuel and electricity prices have been estimated based on historical trends.

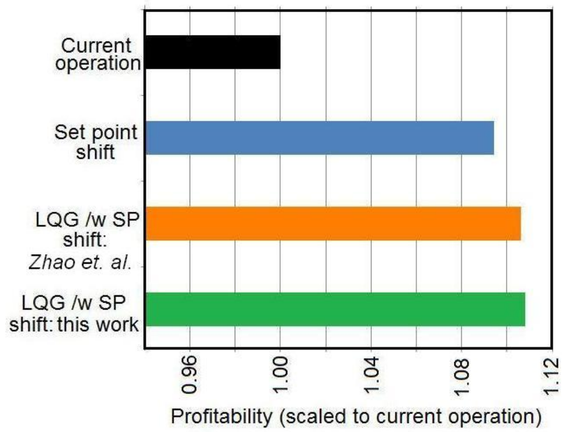

Figure 8.5: Condenser estimated profitability relative to current operating conditions

8.2.1 Case I: Daily Production Scheduler

The first case study involves an hourly optimization over a 24 hour horizon. Electricity sale prices are assumed to fluctuate hourly over the course of the day in a standard manner according to market demand. Fuel prices are fixed for the course of the day. It is assumed that an unlimited supply of natural gas is available for use, but that the hog fuel supply is limited. The optimization procedure is carried out assuming hog fuel supplies of 0, 30, 50, 75 and 100 metric tonnes (T).

Fig. 8.6 shows the rate of optimal electrical power generation (to maximize the revenue) by the facility for the five different amounts of hog fuel supplies. The electricity price profile is also included on a second axis for reference.

In the case of no hog fuel availability (see 0 tonne profile in Fig. 8.6), the algorithm assumes only natural gas is available for use. Due to the high cost of natural gas relative to the sale price of electricity, the rate of steam production over the course of the day is limited to rates sufficient to satisfy mill heat demands. The steam generated can be sent through the turbines and/or through the PRVs as it descends to lower pressure (see Fig. 5.1). The proposed algorithm suggests that the path that steam follows as it descends to satisfy low pressure heat demands should depend on the price of electricity at a given time. When the sale price is low the algorithm sends steam through PRVs (from about 3.5hr to 6hr in Fig.

8.6), where the steam is contacted with a water source as it expands (de-superheating). As a result, energy is transferred to the water supply, and thus decreases the steam enthalpy on a per unit mass basis but increases the flow rate through PRV. When the sale price is sufficiently high, the steam passes through the turbines instead, generating power (from about 6hr to 24hr in Fig. 8.6).

As hog fuel becomes increasingly available, the proposed algorithm uses it to first replace natural gas, then increase steam production in order to generate more power. Between the 50 and 75 tonne supply profiles in Fig. 8.6, a shift in maximum electrical generation is observed (from about 9MW to 11.5MW). This shift represents a decision by the algorithm to alter the plant configuration by opening a vent in plant 1, and a PRV in plant 2 (see Fig. 8.7). Steam flowing through the PRV is sufficient to satisfy the mill heat demands, so no mid pressure extraction is required from the turbine, and more steam may be forced to the back of the condensing turbine. A similar situation can be seen in plant 1, where the steam flow rate through the turbine units is restricted by the exhausting capabilities of the low pressure (LP) line. Initially, the only outlet for steam in the LP line is the mill heat demand; but when it becomes economically feasible to open the vent to provide further exhaust, significantly more steam can flow through the plant. These alterations increase the steam requirement and subsequently operation costs, but the peak sale prices and abundance of cheap fuel make it economically feasible. Fig. 8.7 breaks down the individual unit inlet valve setpoints within the system over the course of the day for the 100 tonne hog supply case. Multiple profiles in each plot represent the setpoints for valves controlling fuel streams, turbines, PRVs and vents within each of the two plants.

This case study was compared to an energy management algorithm currently being used in a very similar pulp and paper mill in British Columbia. The method in use essentially involved proposing a predefined setpoint increase and decrease to every system variable and relating that change back to overall mill profitability using a cost function. If the change was economically advantageous (beyond a preset deadband) then it was implemented, otherwise operation continued unchanged. The mill using this method is frequently faced with limited

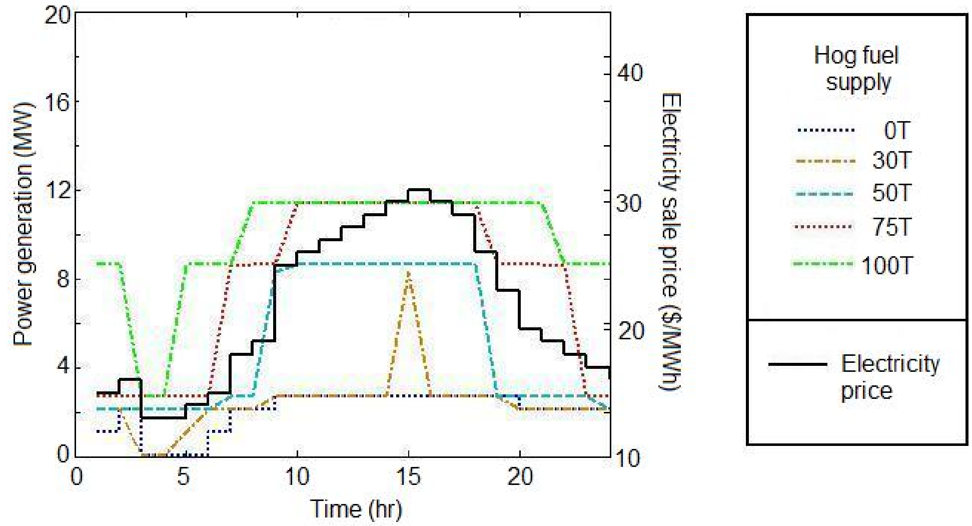

Figure 8.6: Electricity production schedule for limited hog fuel supplies over a 24 hour period with hourly market-based sale prices

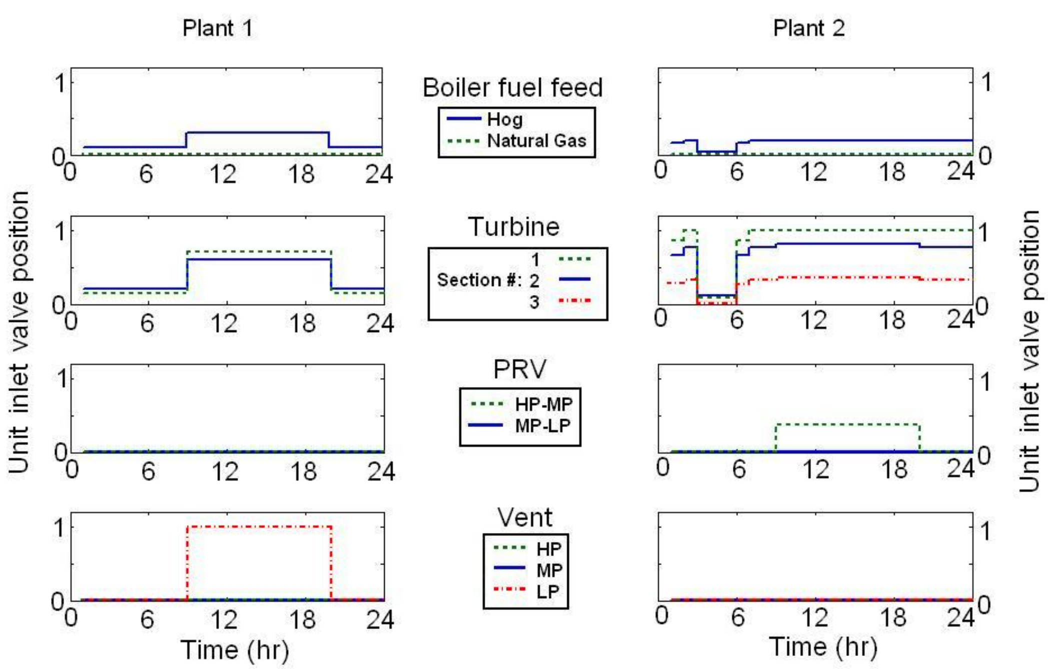

Figure 8.7: Optimized unit inlet valve positions over 24 hours for a 100 tonne hog fuel supply

hog fuel supplies, making this case study especially applicable.

For the comparison, a 40 tonne supply of hog fuel was assumed (again with an unlimited supply of natural gas) over the 24 hour horizon, and the same electricity price profile was used. Optimal electrical power generation and the corresponding profit (or loss) with the current energy management system is compared with those of the proposed algorithm in Fig. 8.8 and Fig. 8.9.

The method currently implemented in the facility begins to force power generation early in the day, and quickly depletes the supply. The cheap price of hog fuel relative to the sale price of electricity makes it advantageous to force production (see Fig. 8.8) despite thin profit margins (see Fig. 8.9). There is no consideration of future sale prices, which predictably peaks in the early afternoon well in excess of the prices early in the morning. Once the hog supply is depleted, only the more expensive natural gas remains to satisfy mill heat demands for the rest of the day, and the algorithm is left trying to minimize losses. The result is a net loss of approximately $20-40 per MW of electricity produced with natural gas, depending on the sale price at the time, which brings the overall daily profitability of the plant to a net loss of $629.65.

The method presented in this paper exploits the sale price trend by reserving the majority of the hog fuel supply and only forcing steam production during the peak hours. The difference in performance over the optimization horizon is substantial, as the method presented here results in a net profit of $666.81; or in other words, a total of $1296.46 more than the previous method. This amount may appear to be relatively insignificant for an entire mill, but amounts to an annual difference of $473,279. It is also important to note that the turbine units in this case study peaked at roughly 12 MW, but units double and triple that size are not uncommon in pulp and paper applications. Therefore, the proposed algorithm will likely result in significant yearly profits in larger cogeneration facilities.

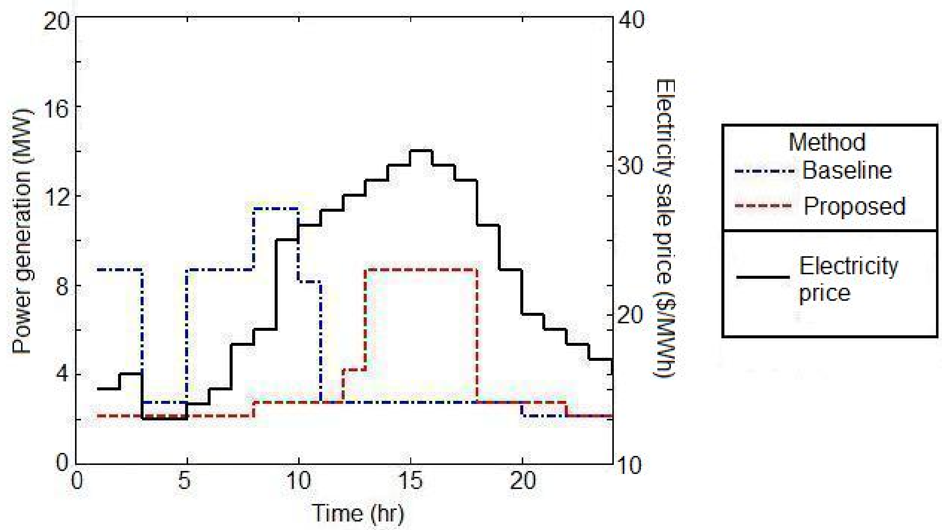

Figure 8.8: Comparison of electricity production schedules for 40 tonne hog fuel supply over a 24 hour period with hourly market-based sale prices

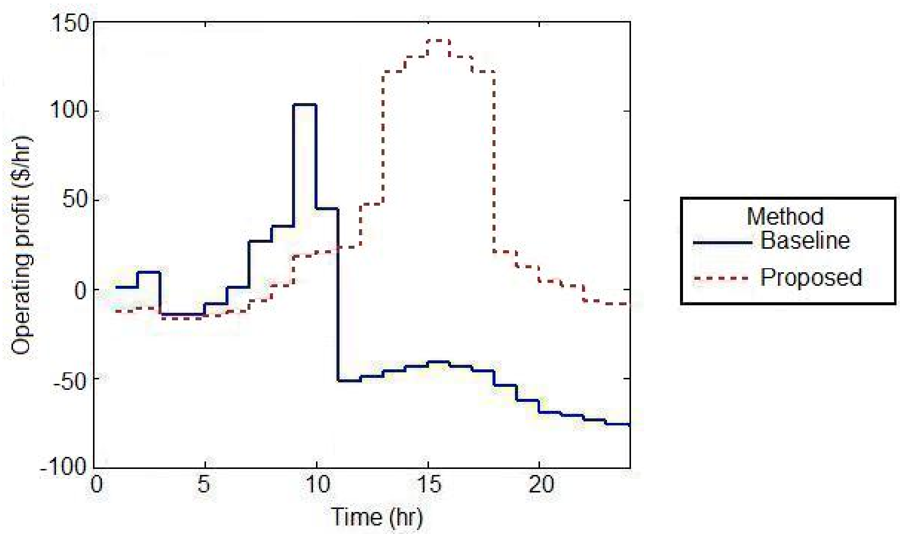

Figure 8.9: Comparison of profitability for 40 tonne hog fuel supply over a 24 hour period with hourly market-based sale prices

8.2.2 Case II: Weekly Production and Purchasing Scheduler

The second case study involves an hourly optimization over a 168 hour period (1 week). Electricity sale prices are assumed to be under contract at distinct but constant peak (high) and off-peak (low) values. The peak price is applied to power generated between the hours of 8am and 8pm, and the off-peak price is applied to power generated between the hours of 8pm and 8am, daily. Natural gas is available at a fixed price and in unlimited quantity. Hog fuel is available from three suppliers, each with a different total amount available at a unique price as outlined in Table 8.2.

The optimal power generation and fuel usage results highlight one significant feature: the power generation schedule is coordinated with the purchasing schedule, making strategic long-term planning possible where shortsighted decisions would have previously been made. The results account for not only current fuel prices, but future prices that will be paid once the current stock is depleted. Several other algorithms, such as the pre-existing one, use only current fuel prices to determine profitability. This distinction will not likely have any short-term impact, but may decrease profitability over a longer time frame. For example, a decision that requires 30% more fuel to increase overall profitability by 10% would be deemed reasonable by the pre-existing algorithm, regardless of other vendor supply prices and quantities. The algorithm presented in this paper, on the other hand, may reject a temporary 10% increase in profitability in order to make a cheap fuel last 30% longer if the only other available hog fuel is from a supplier with double the price.

Fig. 8.10 shows the results from this case study by comparing the power generation profiles using the existing method from the previous case study with the new method developed in this paper. The electricity price profile is also included for reference. Financial results over the one week period are presented in Table 8.3. It is evident that the existing method makes inefficient use of the cheap fuel, and is left with only the final, more expensive supplier of hog fuel at roughly the 130 hour mark. By instead rationing the fuel supply for the entire week, the new method achieves a sustainable level of profitability and earns in excess of $2000 more over the one week period.

Table 8.2: Case II: hog fuel suppliers

Supplier #	Available Amount [T]	Price per Tonne [$/T]
1	375	39.10
2	300	34.21
3	750	56.70

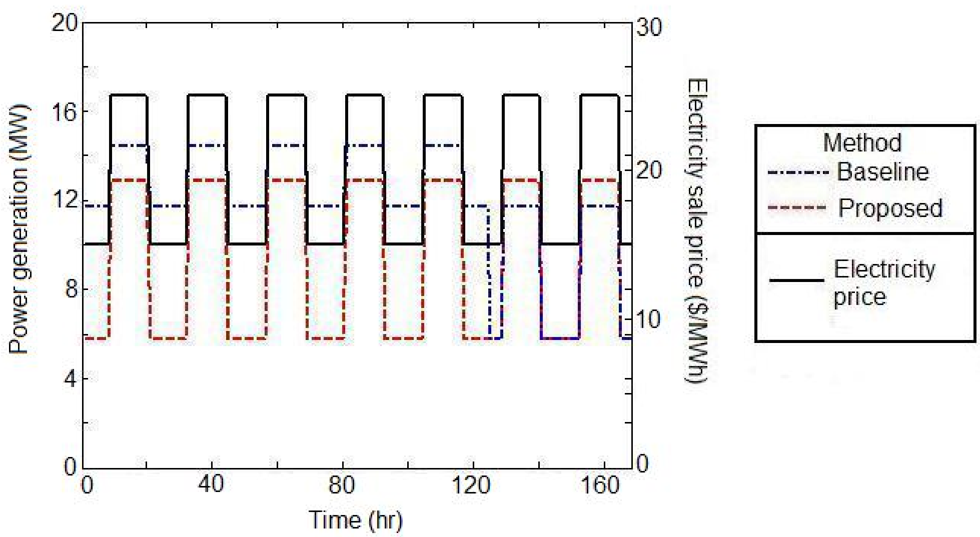

Figure 8.10: Comparison of electricity production schedules over a seven day period under a two tier electricity sale price contract

Table 8.3: Case II: economic results

Method Used	Hog Used [T]	Total Fuel Cost [$]	Total Revenue [$]	Net Profit [$]
Existing	844.85	34555.78	41623.17	7067.39
New	675.00	24926.25	34223.52	9297.27

8.3 Mill energy management: thermal reservoir-limited case

The case study presented in this section is based on a real power plant model and power generation contract. The general structure of the mill is depicted in Fig. 5.1. Unit gains, dynamic constraints and mill heat demands have been approximated from extensive sets of industrial data. Fuel and electricity prices have been estimated based on historical trends. A set of recorded weather data from July 2009 local to the mill in question was also used.

The study involves an hourly optimization over a 24 hour horizon. Electricity sale prices are assumed to fluctuate hourly over the course of the day in a standard manner according to market demand. Fuel prices are fixed over the course of the day. It is assumed that an unlimited supply of natural gas is available for use, but that the hog fuel supply is limited to a maximum of 20 tonnes. Ambient atmospheric conditions are assumed to behave according to the recorded historical data set. During practical application, a forecasted set of data would be used instead. The optimization algorithm would be updated hourly according to fluctuations in both weather and market electricity prices.

In this instance, the reservoir is a 600m^3 pond with a surface area of 400m^2. A river flowing at an average rate of 4.3m^3/hr and an average temperature of 11.2C feeds into the pond. Water exits the pond at a similar rate and at the mean pond temperature, which is assumed to be uniform throughout. Current operating procedure calls for the cessation of power generation if the pond temperature exceeds 21.7C at any point.

Using only the EMS schedule optimizer presented in at the start of chapter 7, and not the modified version presented in chapter 7.1, operation of the cogeneration facility results in a violation of the pond temperature limit at approximately 6pm. Continued operation for the remainder of the day results in a final pond temperature of 23.8C.

As mentioned previously, current operating procedure in place at the mill calls for power generation to be stopped in the event of a reservoir temperature violation, but the entire pulp mill cannot be shut down. Therefore, the cogeneration facility will stop generating steam for power production, but will continue to produce heat to satisfy the mill demand. Under these guidelines a final temperature of 21.8C would be achieved, but the peak temperature would still reach 22.03C at approximately 9pm due to steam production in order to satisfy mill heat demands.

The unique constraint modification to the EMS (see chapter 7.1) was then used in place of the original optimizer. As expected, no violation of the pond temperature occurred over the optimization horizon. A peak temperature of 21.6C was observed at the end of the day. A plot comparing the reservoir temperature profiles that result from the original and modified versions of the EMS over the course of the 24 hour period can be seen in Fig. 8.11.

The unmodified EMS, if allowed to run for the full 24 hour period regardless of pond temperature, would produce 250.8MWh over the period for a total profit of \$1,653.03. In practice, however, power generation would be shut down at approximately 6pm after generating a total of 179.2MWh of electricity for a total profit of \$1,290.35.

By applying the reservoir temperature constraint modification to the EMS, a total of 203.0MWh would be produced for a net profit of \$1,378.69. More importantly, however, is that this profit would be achieved while maintaining a pond temperature below the 21.7C limit. A plot comparing the power generation profiles that result from the original and modified versions of the EMS over the course of the 24 hour period can be seen in Fig. 8.12. A summary of financial results can be found in Table 8.4.

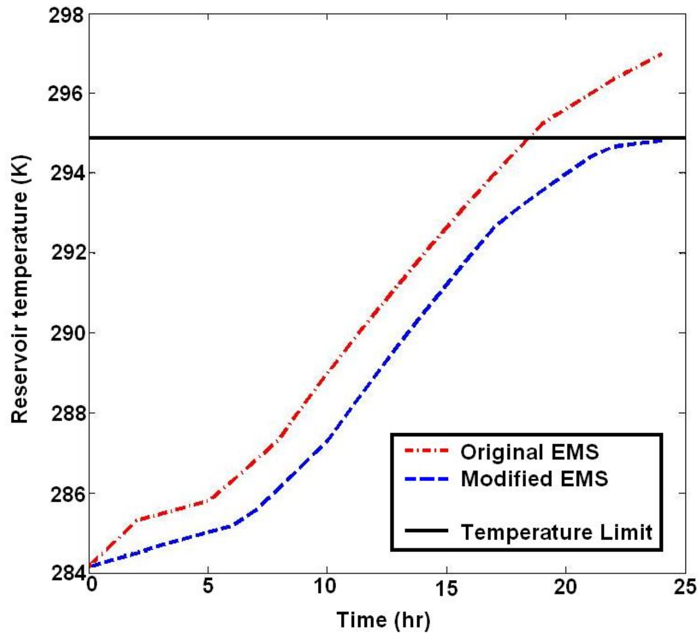

Figure 8.11: Thermal reservoir temperature profile over a 24 hour period for the original EMS and the temperature constraint modified version of the EMS

Table 8.4: Thermal reservoir-limited case: results summary

EMS Version	Max. res. temp [C]	Final res. temp [C]	Total power gen. [MWh]	Net Profit [$]
Unmodified (temp ignored)	23.8	23.8	250.8	1653.03
Unmodified (with shut down)	22.0	21.8	179.2	1290.35
Modified	21.6	21.6	203.0	1378.69

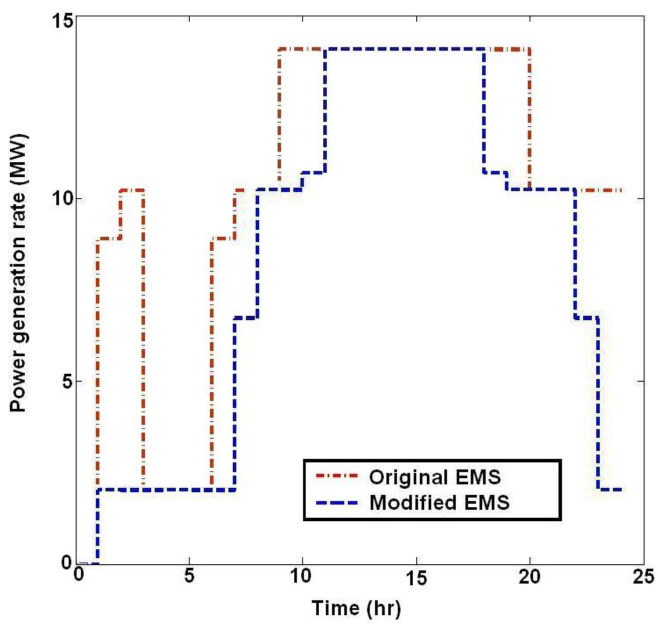

Figure 8.12: Power generation profile over a 24 hour period for the original EMS and the temperature constraint modified version of the EMS

Chapter 9

Conclusions and Future Work

Effective process control and optimization is vital for the economic health of a pulp & paper mill due to factors such as large capital costs, low profit margins, and high levels of competition. The constant replacement of mill equipment with new, more efficient versions thereof is an impractical goal. Consequently, the sustainable operation of existing units at their full potential is a primary concern for mill process engineers. It is in these areas that this work has made the following contributions:

1. The economic performance assessment strategy proposed by Zhao et al. [94] has been improved to provide a more comprehensive assessment of current and potential process performance by exploring a wider variety of possible controller tuning parameters, as described in Chapter 6.

2. An energy management system optimization algorithm for a pulp and paper cogeneration facility has been developed to address the objectives listed in Chapter 4.2 through the effective optimization of a complex array of process variables, as described in Chapter 7.

3. The EMS optimization algorithm has been expanded to address a special class of performance constraining processes as defined in Chapter 4.2. The scenario of thermal reservoir temperature-limited cogeneration was used to develop this class of problems

through the incorporation of a reliable reservoir model into the original optimization algorithm, as described in Chapter 7.1.

9.1 Summary of contributions

Zhao *et. al.* [94] have made significant contributions to the field of controller assessment over the past decade. Their approach using an LQG controller as a benchmark for performance assessment in an economic framework provides an accurate, relevant and realistic estimate of achievable performance through advanced process control. This work has modified the controller formulation method proposed by Zhao *et. al.* for MIMO process assessment to achieve a more economically advantageous controller weighting strategy for economic performance assessment. Rather than using a cost function-based weighting parameter or matrix, an iterative approach is proposed to optimize each parameter within the weighting matrix concurrently with the input-output variability relationship. By doing so, the proposed solution provides a more comprehensive analysis of possible system behaviour, which usually results in a more economically optimistic solution as demonstrated by several case studies. Although more computationally expensive, this new approach is especially useful for the assessment of complex system control strategies in an economic framework.

A practical energy management system optimization algorithm for use in a pulp and paper mill cogeneration plant has been developed. The proposed approach is applicable to a wide range of mills in the industry, with the potential to address a variety of plant configurations and power contracts over a given horizon due to a relatively flexible problem structure. By coordinating fuel pricing and availability with electrical price forecasts over the optimization horizon subject to constraints dictated by a complete cogeneration plant model, an economically efficient plant management strategy is obtained. This strategy provides significant economic benefits over classical methods that make use of basic current-state optimization, as demonstrated by several case studies. The magnitude of the aforementioned benefits varies significantly from case to case, but increased profit in the range of 10-50% has been regularly observed. Additionally, since the optimization problem is posed in a convex format, solution times are relatively fast making online implementation feasible.

The proposed EMS optimization algorithm was modified to incorporate a special class of constraints. This class of constraints represents unique, mill-specific challenges to energy management that have an occasional indirect impact on system performance, that can be accurately modeled, and that are dependent on at least one variable external to the system and at least one variable internal to the system. One such case that was used for the development of the solution in this thesis is a cogeneration cooling reservoir temperature constraint. By implementing a thermal energy forecaster based on operational and meteorological data in parallel with the original algorithm, operational-limiting thermal constraints can be satisfied in an economically feasible way, without needing to resort to extreme safety measures such as complete cessation of power generation. This was demonstrated in a case study dealing with thermal reservoir limitations. Solution time increased with the additional thermal constraint, but convexity of the optimization problem was preserved through the utilization of an iterative optimization strategy, which made online implementation possible.

9.2 Future research

The following is a list potential research subjects based on the work described by this thesis:

1. The development of an economic performance assessment algorithm using LQG control with the ability to distinguish between hard input constraints and soft output constraints. This would require a non-Gaussian input noise distribution, which is used in the back-off approach to constraint handling. An alternative method of constraint handling would therefore be required.

2. The incorporation of fault detection and/or unit performance analysis components into the energy management system. By using redundant measurements (possible attained through relatively simple unit models) the EMS may be able to recognize

malfunctioning sensors and equipment, recommend maintenance in the event of fouling, or simply give advanced warnings of otherwise undetected problems.

3. The application of this energy management strategy, including the aforementioned special case of constraints (where applicable), to other industries.

Bibliography

[1] J. M. Arroyo and A. J. Conejo. Optimal response of a thermal unit to an electricity spot market. *IEEE Transactions on power systems*, 15(3):1098–1104, August 2000.

[2] K. Astrom. *Introduction to stochastic control theory*. Academic Press, 1970. New York.

[3] D. S. Bernstein and W. M. Haddad. Lqg control with an H_{inf} performance bound: A Riccati equation approach. *IEEE Transactions on Automatic Control*, 34(3):293–305, 1989.

[4] S. Boyd and C. Barratt. *Linear control design*. Prentice Hall, Eaglewood Cliffs, NJ, 1991.

[5] S. Boyd and L. Vandenberghe. *Convex optimization*. Cambridge University Press, New York, 2004.

[6] L. Changliang, L. Jizhen, N. Yuguang, and L. Weiping. Nonlinear boiler model of 300MW power unit for system dynamic performance studies. *IEEE International Symposium on Industrial Electronics*, 2:1296–1300, June 2001.

[7] B. Chen and C. Hong. Optimum operation for a back-pressure cogeneration system under time-of-use rates. *IEEE Transactions on Power Systems*, 11(2):1074–1082, May 1996.

[8] C. S. Chen, C. T. H. Y. D. Less, and C. K. Chen. Transient response of an incinerator plant by considering boiler model with dynamic steam variation. *IEEE Transactions on Power Systems*, 23(1):92–99, February 2008.

[9] S. Chen, M. Tsay, and H. Gow. Scheduling of cogeneration plants considering electricity wheeling using enhanced immune algorithm. *International Journal of Electrical Power & Energy Systems*, 27(1):31–38, January 2005.

[10] R. Cheng. *Decomposition of coordination of large-scale operations optimization*. Doctor of philosophy in process control. Department of chemical and materials engineering, University of Alberta, Edmonton, 2007.

[11] R. Childress. Closed-loop energy management control of large industrial facilities. Technical report, Dynamic Energy Systems, LLC, April 2002.

[12] C. H. Cho. Energy management applications for the steel industry. *Iron Steel Eng.*, 58(4):54–60, 1981.

[13] A. I. Cohen and V. R. Sherkat. Optimization-based methods for operations scheduling. *Proceedings of the IEEE*, 75(12):1574–1591, December 1987.

[14] A. I. Cohen and S. H. Wan. An algorithm for scheduling a large pumped storage plant. *IEEE Transactions on Power Apparatus and Systems*, 104(8):2099–2104, 1985.

[15] J. C. W. Denholm-Price and J. M. Rees. A practical example of low-frequency trend removal. *Boundary-Layer Meteorology*, 86(1):181–187, 1997.

[16] L. Desborough and T. Harris. Performance assessment measure for univariate feedback control. *Canadian Journal of Chemical Engineering*, 70:1186–1197, 1993.

[17] T. Edgar. Control and operation: when does controllability equal profitability? *Computers and Chemical Engineering*, 29:41–49, 2004.

[18] P. Eriksson and A. Isaksson. Some aspects of control performance monitoring. In *Proceedings from the 3rd IEEE Conference on Control Applications*, Glasgow, Scotland, pages 1029–1034, 1994.

[19] J. W. Evans. Energy management system survey of architectures. *IEEE Computer Applications in Power*, 2(1):11–16, 1989.

[20] G. Ferrari-Trecate, E. Gallestey, P. Letizia, M. Spedicato, M. Morari, and M. Antoine. Modeling and control of co-generation power plants: a hybrid system approach. *IEEE Transactions on Control Systems Technology*, 12(5):694–705, September 2004.

[21] J. Figueroa, P. Babri, J. Bandoni, and J. Romagnoli. Economic impact of disturbance and uncertainty parameters in chemical process - a dynamic back-off analysis. *Computers and Chemical Engineering*, 20:453–461, 1996.

[22] M. Forbes, M. Guay, and J. Forbes. Control design for first-order processes: shaping the probability density of the process state. *Journal of Process Control*, 14:399–410, 2004.

[23] U. Forssell and L. Ljung. Closed-loop identification revisited. *Automatica*, 35:1215–1241, 1999.

[24] D. Forsyth and B. Ahmad. The importance of energy management systems in the deregulated power market. *Pulp & Paper Canada*, pages 23–26, 2009.

[25] D. W. Francis, M. T. Towers, and T. C. Browne. Energy cost reduction in the pulp and paper industry - an energy benchmarking perspective. Technical report, Pulp and Paper Research Institute of Canada, 2009.

[26] J. Gao and N. P. Merrick. Simulation of temperature and salinity in a fully mixed pond. *Environmental Software*, 11(1-3):173–178, 1996.

[27] C. E. Garcia, D. M. Prett, and M. Morari. Model predictive control: Theory and practice-a survey. *Automatica*, 25(3):335–348, 1989.

[28] M. Gilli and P. Winker. A review of heuristic optimization methods in econometrics. *Finance Institute Research Paper*, 8(12):1–44, 2008.

[29] R. Gopaluni, H. Raghavan, R. Patwardhan, S. Shah, and G. Dumont. Identification of delay dominant recycle systems. *Journal of Process Control*, 16:903–912, 2006.

[30] J. Gruhl, F. Schweppe, and M. Ruane. Unit commitment scheduling of electric power systems. *System Engineering for Power: Status and Prospects*, 1975.

[31] Y. Gu, C. Zhao, H. Su, and J. Chu. A pragmatic approach for assessing the economic performance of model predictive control systems and its industrial application. *Chinese Journal of Chemical Engineering*, 17:241–250, 2009.

[32] T. Harris. Assessment of closed loop performance. *Canadian Journal of Chemical Engineering*, 67:856–861, 1989.

[33] W. F. Helwig. Energy management system. Patent 4180744, Avtec Industries Ind, 1979.

[34] B. Huang. A pragmatic approach towards assessment of control loop performance. *International Journal of Adaptive Control and Signal Processing*, 17:589–608, 2003.

[35] B. Huang and S. Shah. Limits of control loop performance: practical measures of control loop performance assessment. In *AIChE Annual Meeting*, Chicago, IL, 1996.

[36] B. Huang and S. Shah. The role of the unitary interactor matrix in the explicit solution of the singular lq output feedback control problem. *Automatica*, 33:2071–2075, 1997.

[37] B. Huang and S. Shah. *Performance Assessment of Control Loops: Theory and Applications*. Springer, 1999. New York.

[38] B. Huang, S. Shah, and E. Kwok. Good, bad or optimal? Performance assessment of multivariable processes. *Automatica*, 33:1175–1183, 1997.

[39] G. Huang, B. W. Baetz, and G. G. Patry. A grey linear programming approach for municipal solid waste management planning under uncertainty. *Civil Engineering and Environmental Systems*, 9(4):319–335, 1992.

[40] P. J. Immonen. Mathematical models in cogeneration optimization. Technical report, ABB Automation, Inc., December 2000.

[41] International Association for the Properties of Water and Steam, Lucerne, Switzerland. *Revised release on the IAPWS industrial formulation 1997 for the thermodynamic properties of water and steam*, if97 edition, August 2007.

[42] R. E. Kalman. Contributions to the theory of optimal control. *Bulletin de la Societe Mathematique de Mexicana*, 5:102–119, 1960.

[43] R. E. Kalman. A new approach to linear filtering and prediction problems. *Transactions of ASME, Journal of Basic Engineering*, 87:35–45, 1960.

[44] D. Kaya and H. I. Sarac. Mathematical modeling of multiple-effect evaporators and energy economy. *Energy*, 32:1536–1542, 2004.

[45] D. Kozub and C. Garcia. Monitoring and diagnosis of automated controllers in the chemical process industries. In *AIChE Annual Meeting*, St Louis, MO, 1993.

[46] P. Latour. Process control: Clifftent shows it's more profitable than expected. *Hydrocarbon Processing*, 75:75–80, 1996.

[47] W. L. Leyde. Digital load control circuit and method for power monitoring. Patent 4064485, Pacific Technology, 1977.

[48] C. Loeblein and J. Perkins. Economic analysis of different structures of on-line process optimization systems. *Computers and Chemical Engineering*, 22:1257–1269, 1998.

[49] C. Loeblein and J. Perkins. Structural design for on-line process optimization: 1. dynamic economics of mpc. *AIChE Journal*, 45:1018–1029, 1999.

[50] K. Lucas. On the thermodynamics of cogeneration. *International Journal of Thermal Sciences*, 39(9-11):1039–1046, October 2000.

[51] C. Lynch and G. Dumont. Closed loop performance monitoring. In *Proceedings from the 2nd IEEE Conference on Control Applications*, Vancouver, Vancouver B.C., pages 835–840, 1993.

[52] R. Madlener and C. Schmid. Combined heat and power generation in liberalised markets and a carbon-constrained world. *GAIA - Ecological Perspectives for Science and Society*, 12(2):114–120, June 2003.

[53] S. Makkonen and R. Lahdelma. Non-convex power plant modelling in energy optimisation. *European Journal of Operational Research*, 171(3):1113–1126, June 2006.

[54] T. Marlin, G. Barton, M. Brisk, and J. Perkins. Advanced process control: Project report and technical papers. Technical report, Warren Centre for Advanced Engineering, Sydney, 1987.

[55] D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Economic performance assessment with optimized LQG benchmarking in MIMO systems. In *DYCOPS-9*, 2010.

[56] D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Energy management optimization in a pulp and paper mill cogeneration facility. In *ACC 2010*, 2010.

[57] D. J. Marshman, M. S. Sidhu, T. Chmelyk, R. B. Gopaluni, and G. A. Dumont. Energy optimization in a pulp and paper mill cogeneration facility. *Applied Energy*, 2010.

[58] G. Martin, L. Turpin, and R. Cline. Estimating control function benefits. *Hydrocarbon Processing*, 69:68–73, 1991.

[59] K. I. M. McKinnon. Convergence of the Nelder-Mead simplex method to a nonstationary point. *Society for Industrial and Applied Mathematics, Journal of Optimization*, 9(1):148–158, December 1998.

[60] T. Miao and D. Seborg. A monitoring strategy for flow and pressure control loops. In *2nd Asia-Pacific Conference on Control and Measurement*, Chongqing, China, 1995.

[61] W. Morton. Modelling utility systems. ECOSSE Technical Report 14, University of Edinburgh, Department of Chemical Engineering, 1994.

[62] K. Moslehi, M. Khadem, R. Bernal, and G. Hernandez. Optimization of multiplant cogeneration system operation including electric and steam networks. *IEEE Transactions on Power Systems*, 6(2):484–490, May 1991.

[63] L. Narraway, J. Perkins, and G. Barton. Interaction between process design and process control: Economic analysis of process dynamic. *Journal of Process Control*, 1:243–250, 1991.

[64] R. S. Patwardhan. *Studies in the synthesis and analysis of model predictive controller*. PhD thesis, University of Alberta, 1999.

[65] R. E. J. Putman, T. Allen, J. J. Novacek, and F. G. Huff. Optimization of a plurality of multiple-fuel fired boilers using iterated linear programming. Patent 5259562, Westinghouse Electric Corp., October 1992.

[66] S. J. Qin and T. A. Badgwell. A survey of industrial model predictive control technology. *Control Engineering Practice*, 11:733–764, 2003.

[67] C. C. A. Rajan and M. R. Mohan. An evolutionary programming based simulated annealing method for solve the unit commitment problem. *International Journal of Electrical Power & Energy Systems*, 29(7):540–550, September 2007.

[68] R. Rhinehart. A watch dog for controller performance monitoring. In *Proceedings from the American Control Conference*, Seattle, WA, pages 2239–2240, 1995.

[69] J. Richalet, A. Rault, J. L. Testud, and J. Papon. Algorithmic control of industrial processes. In *Proceedings of the 4th IFAC symposium on identification and system parameter estimation*, pages 1119–1167, 1976.

[70] M. A. Rodriguez-Toral, W. Morton, and D. R. Mitchell. The use of new sqp methods for the optimization of utility systems. *Computers and Chemical Engineering*, 25:287–300, 2001.

[71] A. Rong, H. Hakonen, and R. Lahdelma. A variant of the dynamic programming algorithm for unit commitment of combined heat and power systems. *European Journal of Operational Research*, 190:741–755, 2008.

[72] A. Rong, R. Lahdelma, and M. Grunow. An improved unit decommitment algorithm for combined heat and power systems. *European Journal of Operational Research*, 195(2):552–562, June 2009.

[73] R. N. Sampson, L. L. Wright, J. K. Winjum, J. D. Kinsman, J. Benneman, E. Krsten, and J. M. O. Scurlock. Biomass management and energy. *Water, Air, & Soil Pollution*, 70(1-4):139–159, October 1993.

[74] H. K. Sarimveis, A. S. Angelou, T. R. Retsina, S. R. Rutherford, and G. V. Bafas. Optimal energy management in pulp and paper mills. *Energy Conversion and Management*, 44:1707–1718, 2003.

[75] W. D. Schmitz, R. H. Turpin, R. A. Dashiell, and C. L. Hadley. Energy management system. Patent 4153936, Reliance Electric Company, 1979.

[76] D. E. Seborg, T. F. Edgar, and D. A. Mellichamp. *Process dynamics and control.* John Wiley & Sons, Inc., 2 edition, 2004.

[77] S. Skogstad and I. Postlethwaite. *Multivariable feedback control: analysis & design.* John Wiley & Sons, Inc., 2 edition, 1996.

[78] C. A. Snow and M. J. Realff. Mill steam and power optimization in a real-time pricing environment. *Tappi Journal*, 81(12):142–152, December 1998.

[79] N. Stanfelj, T. Marlin, and J. MacGregor. Monitoring and diagnosing process control performance: the single-loop case. *Industrial & Engineering Chemistry Research*, 32:339–347, 1993.

[80] M. Sudhakaran and S. M. R. Slochanal. Integrating genetic algorithms and tabu search for combined heat and power economic dispatch. *Conference on Convergent Technologies for Asia-Pacific Region*, 1:67–71, October 2003.

[81] E. Thorin, H. Brand, and C. Weber. Long-term optimization of cogeneration systems in a competitive market environment. *Applied Energy*, 81(2):152–169, June 2005.

[82] C. L. Tseng, S. S. Oren, A. J. Svoboda, and R. B. Johnson. A unit decommitment method in power system scheduling. *Electrical Power and Energy Systems*, 19:357–365, 1997.

[83] C. Tsiligiannis and S. Svoronos. Dynamic interactors in multivariable process control-2. Time delays and zeros outside the unit circle. *Chemical Engineering Science*, 44:2041–2047, 1989.

[84] M. Tyler and M. Morari. Performance monitoring of control systems using likelihood methods. In *Proceedings from the American Control Conference*, Seattle, WA, pages 1245–1249, 1995.

[85] M. A. VanBuren, W. E. Watt, J. Marsalek, and B. C. Anderson. Thermal balance of on-stream storm-water management pond. *Journal of Environmental Engineering*, 126(6):509–517, June 2000.

[86] A. Vasebi, M. Fesanghary, and S. M. T. Bathaee. Combined heat and power economic dispatch by harmony search algorithm. *International Journal of Electrical Power & Energy Systems*, 29(10):713–719, December 2007.

[87] J. Williams, F. C. Huff, and P. Francino. Islands of optimization: a web-based economic optimization tool. White paper, Emerson Process Mangement, 2005.

[88] P. Winker and D. Maringer. *The threshold accepting optimisation algorithm in economics and statistics*, volume 9 of *Advances in Computational Management Science*. Springer, Berlin, 2007. pp. 107-125.

[89] A. C. W. Wong and A. T. P. So. Building automation in the 21st century. *Advances in Power System Control, Operation and Management*, 2(4):819–824, 1997.

[90] F. Xu, B. Huang, , and S. Akande. Performance assessment of model predictive control for variability and constraint tuning. *Industrial and Engineering Chemistry Research*, 46:1208–1219, 2007.

[91] J. Young, C. Swartz, and R. Ross. On the effects of constraint economics and uncertain disturbances on dynamic operability assessment. *Computers and Chemical Engineering*, 20:667–682, 1996.

[92] S. H. Zanakis and J. R. Evans. Heuristic "optimization": why, when and how to use it. *Interfaces*, 11(5):84–91, October 1981.

[93] C. Zhao, H. Su, and B. Huang. Economic control performance assessment with lqg benchmarking. In *Proceedings from the American Control Conference*, Seattle, WA, pages 11–13, 2008.

[94] C. Zhao, Y. Zhao, H. Su, and B. Huang. Economic performance assessment of advanced process control with lqg benchmarking. *Journal of Process Control*, 19:557–569, 2009.

[95] Y. Zhou and J. Forbes. Determining controller benefits via probabilistic optimization. *International Journal of Adaptive Control and Signal Processing*, 17:553–568, 2003.