Development of a Supervisory Control for a Kraft Pulp Mill Steam and Power System

Using PCA and PLS

by

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ABSTRACT

Steam and power systems in kraft pulp mills can be complex and difficult to optimize. Supervisory controls can facilitate the optimization if the appropriate weightings and time delays are applied. The focus of this thesis is to: create models of the steam and power systems of a kraft pulp mill, to evaluate the models, and to develop a control system based on those models. A system involving a kraft recovery boiler, two turbo generators, a batch cooking plant and multiple process users is examined. Partial Least Squares (PLS) and Principal Component Analysis (PCA) are used to develop models that are utilized to develop factors that will be employed in the supervisory controls. Mass and energy balances are completed to validate measurements. A thorough understanding of the system, including the delays associated with changes to the variables, is required to ensure that the supervisory controls improve the responses. As a result, these objectives were satisfied resulting in an increase of 2.2 MWh (21%) of hog fueled power produced, no interruption of process steam users, and statistically significant reductions in steam venting.

DEDICATION

I dedicate my thesis to my family; Patti, Kaitlyn and Emily, who have sacrificed time with me and supported me throughout this process. I also dedicate this to my parents, Diane and Rick, who taught me the value of lifelong learning.

ACKNOWLEDGEMENTS

I acknowledge the help, patience and support of my professor, Dr. Yonghao Ni for his guidance and support throughout the time it took to complete my thesis.

I would also like to thank Dean Ferguson for his patience and his help to understand the concepts and his guidance in the use of the software.

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List of Symbols, Nomenclature or Abbreviations

DCS	Distributed Control System
kpph	Thousand Pounds per Hour
LAN	Local Area Network
MACS	Multivariable Advanced Control System
OPC	Interoperability Standard for the Secure and Reliable Exchange of Data in the Automation Space
PCA	Principal Component Analysis
PLS	Partial Least Squares

Chapter 1

Introduction

1.1 Efficiency in the Forest Products Industries

The forest products industry is highly integrated and a significant component of Canada's economy. "The $58-billion-a-year forest products industry represents 2% of Canada's GDP and is one of Canada's largest employers operating in hundreds of communities and providing 230,000 direct jobs across the country."[1] This industry is comprised of lumber, tissue and papermaking as well as the different forms of pulp manufacture. This industry makes use of the whole tree, from the boards milled out of the trunk, the sawmill residuals and tops that are sent for pulping, to the bark that is used in power generation for the mills.

Energy has become a key driving force behind the profitability of mills. Examples include the tradeoff between basis weight and drying technologies, such as through air drying in tissue manufacture, minimizing costs of drying in papermaking, optimizing the refining process to improve quality and reduce specific energy costs in thermomechanical pulping, and the converting of waste and byproduct generation streams to maximize the utilization of energy in pulp manufacture. Making kraft pulp results in lower pulp yields than making mechanical pulp, however, it results in an available energy source that, when utilized appropriately, makes the process more cost effective.

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[1] Murray, S. (2015, December 4). *Canada's Forest Sector: Here To Help Government Meet It's Environmental And Economic Goals.* Retrieved from http://www.fpac.ca/canadas-forest-sector-here-to-help-government-meet-its-environmental-and-econmic-goals/

Thus, as Salmenoja and Nymen (2010) discuss, optimizing the energy management components can be the difference between economic success and failure of a kraft pulp mill. Between 2005 and 2009 the chemical pulp production in Canada declined by 36%.[2] Inefficient mills have been shut down; therefore, high availability and cost efficiency are vitally important for the survival of the pulp mill.[3] Once the mills have been constructed, certain parameters regarding the energy footprint are firmly established and are unlikely to change without significant additional capital expenditures. However, there is the opportunity to optimize the system.

Automatic controls work particularly well when many adjustments are required to keep the system in control. Operators can be distracted by other events and it is difficult for them to maintain focus on a single control that requires constant attention. Automatic controls "removes [the] drudgery of performing [the] same task again and again."[4] Typically, many of the parameters to be optimized are controlled using single loop closed loop control. While this was a tremendous leap forward when it was initially implemented[5], it is limited in that there is little, if any, interaction between the loops towards an overarching strategy. The ultimate goal is the implementation of an advanced control that can tie these loops together, allowing the mill to run closer to the constraints, thereby optimizing the desired outcomes (e.g.: increased production, better efficiency, improved quality, reduced waste, and meeting environmental obligations).

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[2] Poon, J. (2010), Wood Market Statistics Including Pulp and Paper in Canada, Pointe Claire, Quebec: FP Innovations

[3] Salmenoja, K., & Nyman, M., Optimizing Kraft Pulp Mill Material Flows to Reduce Fossil Fuel Use, 2010 TAPPI/PAPTAC International Chemical Recovery Conference, Williamsburg, Virginia, Mar 29-Apr1, 2010, TAPPI

[4] Jagan, N. C. (2008). *Control systems*. Hyderabad: BS Publications. Page 1

[5] Jagan, N. C. (2008). *Control systems*. Hyderabad: BS Publications

The focus of this thesis is to:

- create models of the steam and power systems of a kraft pulp mill
- to evaluate the models
- and to develop a control system based on these models.

The focus of this thesis is two-fold. Principal Component Analysis (PCA) and Partial Least Squares (PLS) methods are used to determine the relationships between the variables and develop control strategies to maximize power generation and minimize losses. This paper is not an exhaustive analysis of PCA and PLS. It, however, discusses some of the limitations of the techniques. This also evaluates the analysis and modeling of a kraft pulp mill energy system for the purpose of maximizing the economic advantage using an advanced supervisory control system. This system incorporates a batch digester system, recovery boiler, hog (and alternate) fueled boiler as well as steam turbines for power generation. Data is drawn from the distributed control system (DCS). The analysis involves modelling based on Principal Component Analysis (PCA) and Partial Least Squares (PLS). It should be noted that the tools used have applications beyond the steam and power systems and beyond kraft pulp mills.

1.2 Background

In a kraft pulp mill, chips are conveyed to the digester(s) where cooking liquor is added. The pulp and spent liquor are then separated in the brown stock washing sequence. The pulp continues on to the bleaching process (for bleached kraft mills) and then to finishing where it is formed into bales for transport as pulp or is converted into other product(s) as in the case with integrated mills. The spent liquor (black liquor) is separated out of the brown stock process and then concentrated to the point where it can be burned. The concentrated liquor is fed to the recovery boiler where the organic portion is burned and the inorganic portion, primarily smelt, is combined with water. This green liquor is mixed with reburned lime (also called reactive lime) to create white liquor. The solids are separated out (lime mud) and the white liquor is ready to be reused in the cooking process. The lime mud is dried and then burned to regenerate the reburned lime for reuse to make more white liquor.[6] These recycle loops reduce the need for chemical make-up and waste processing or disposal. They are also consumers of energy and in the case of the recovery boiler, is a significant source of steam. An overall general flow diagram for the major process streams for a kraft pulp mill follows in Figure 1.1 below:

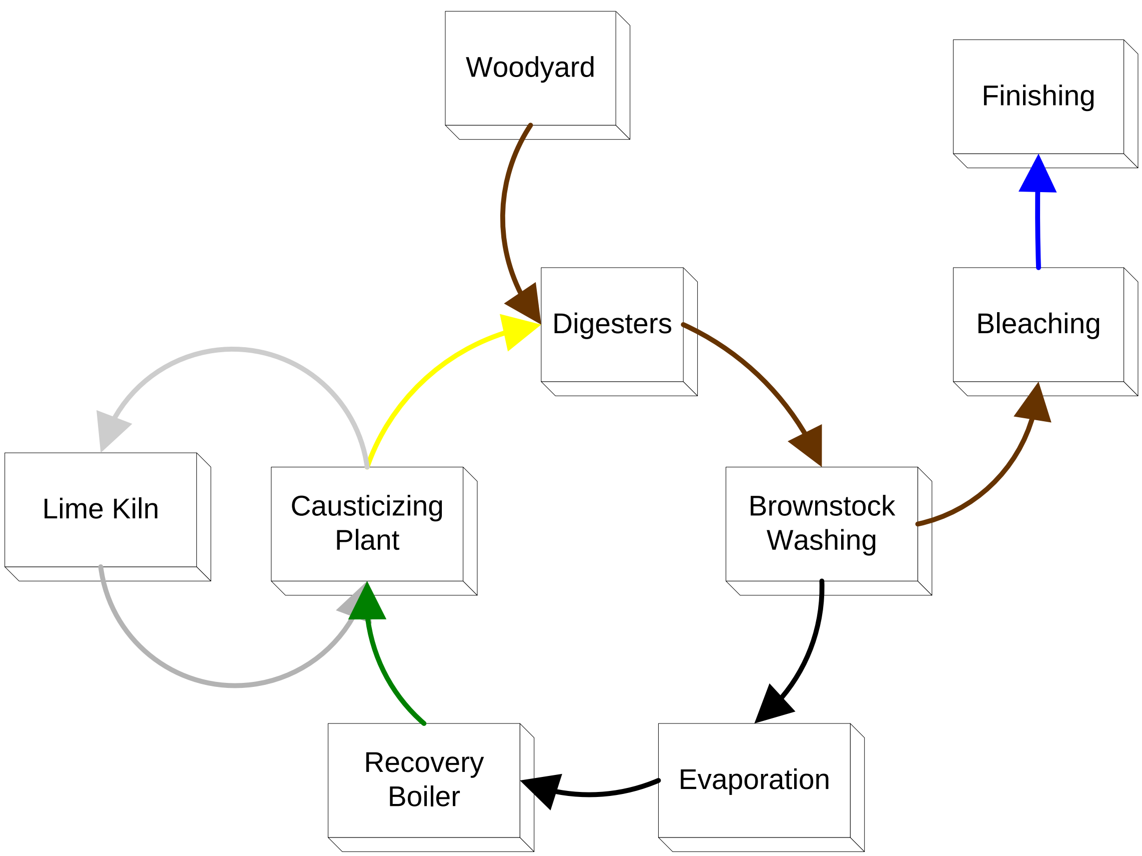

Figure 1.1 Major Process Flows in a Kraft Mill

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[6] Smook, G.A. (1992). *Handbook for Pulp & Paper Technologists*. Vancouver: Angus Wilde Publications

Although the above diagram highlights the gross chemical flows, it does not capture the energy cycles, and it is a simplification of the process.

Many kraft mills have supplementary boilers to ensure there is sufficient steam to provide for the process loads. Many also have some form(s) of turbines to maximize the energy that can be extracted from the process as well as pressure reducing stations to provide additional lower pressure steam as can be seen in Figure 1.2. The operation of each of the parts of this system has impacts on the others.

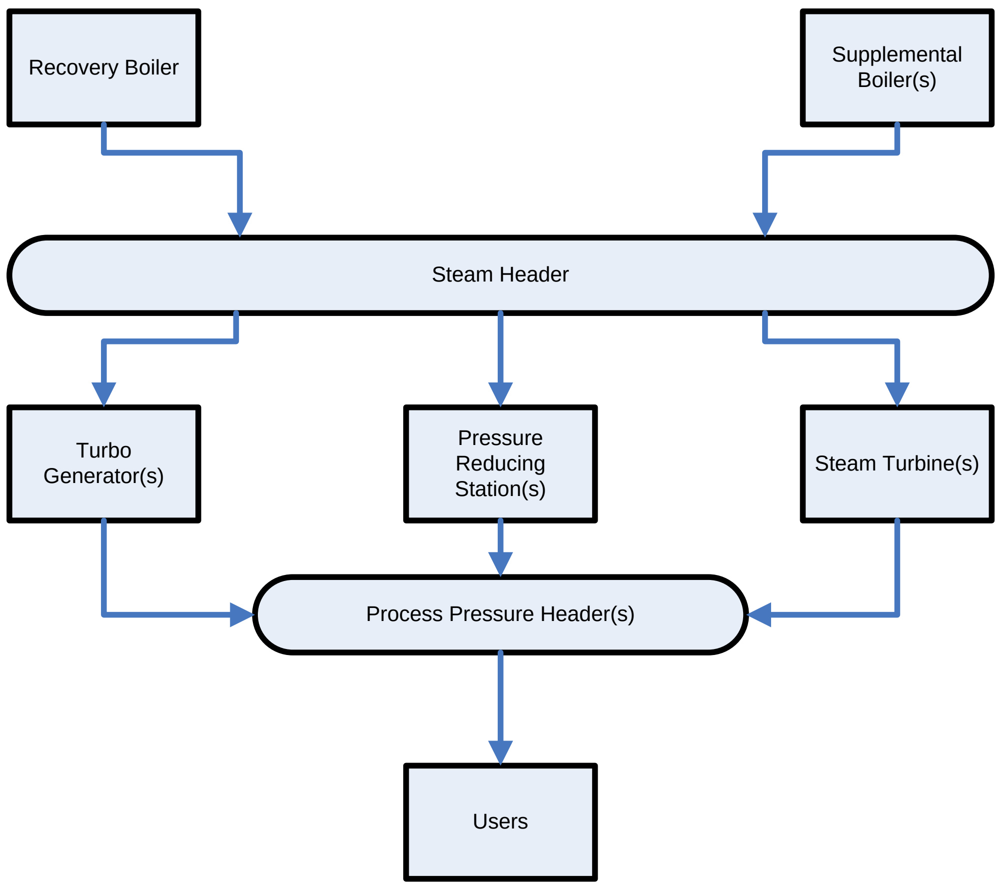

Figure 1.2 Typical Kraft Mill Steam System

1.3 Project Objectives

Using the fixed assets in a kraft pulp mill, the goal of this study is to develop a system that optimizes power generation while providing a stable steam supply to the process to maximize the economic advantage.

In order to maximize the economic advantage to kraft pulp mills, the objectives are to achieve the following:

- maximize the hog fuel boiler firing rate on biomass
- minimize steam header venting
- optimize the turbo generator settings to maximize the power production and satisfy the steam demands

The controller is used when it is economical to make power using hog fuel. Therefore, maximizing the firing rate provides for the maximum amount of biomass generated steam available to produce power. Steam header venting represents a waste of thermal energy. The steam is not progressing through the complete turbo generator steam path and therefore is not converted to electrical power. Finally, the turbo generator must be primarily set up to satisfy the process steam demands and also maximize the power production.

Chapter 2

Literature Search

2.1 Principal Components, Partial Least Squares and Practical Applications

While the literature reveals little research done to use PCA/PLS in kraft mills steam and energy systems, there has been research in other industrial applications. Principal component analysis was utilized extensively in the field known as "Chemometrics", "which employs multivariate statistics, applied mathematics, and computer science via using methods frequently employed in core data-analytic, in order to address problems in chemistry, biochemistry, medicine, biology and chemical engineering".[7] The development of new sensors and wide availability of highly correlated data provided the low rank linearity required for a PCA analysis.

PLS can be used with near infrared data to predict batch quality in textile production and it has been used for organizational performance, pharmaceutical manufacture, mining, and wastewater treatment. Tenkeu, Vermaak, Kamatou, and Viljoen (2014) have demonstrated that it can be used to predictively model the quality of tea tree oil, as a replacement for a more expensive and time consuming test.[8] It was determined with a high degree of correlation that mid-infrared and near-infrared could be

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[7] Khanmohammadi, M. (2014). *Current Applications of Chemometrics*. Hauppauge, New York: Nova Science Publishers, Inc.

[8] Tankeu, S., Vermaak, I., Kamatou, G., & Viljoen, A. (January 01, 2014). Vibrational spectroscopy as a rapid quality control method for Melaleuca alternifolia cheel (tea tree oil). *Phytochemical Analysis : Pca, 25,* 1.

used as a fast and cost effective method to evaluate the quality of tea tree oil. Using these testing techniques allows a non-destructive test to be completed in a minute to substitute for a time consuming and expensive gas chromatography coupled to mass chromatography test that requires skilled personnel to execute the tests.

Kourti (2005) discusses the applications of PCA and primarily PLS as tools that are used in statistical quality control. [9] The differences between univariate and multivariate charts are discussed and the implications in earlier problem detection as well as the detection of changes in the covariance structure are named as potential advantages of multivariate charts. She also discusses the use of PLS to fill in missing data and to identify when sensors are not giving accurate results. In most cases in practice, changes in the covariance structure precede detectable deviations from nominal trajectories. This was the problem that univariate monitoring approaches for batch processes could not address. In most process upsets it is the correlation among the monitored variables that changes first, and later, when the problem becomes more pronounced, the monitored variables deviate significantly from their nominal trajectories. There are cases where a process upset will change dramatically only the correlation among the variables without causing any of the variables involved to deviate significantly from its nominal trajectory. These particular cases, although rare, can result to significant cost to a company since they can go unnoticed for long periods of time[10]

[9] Kourti, T. (May 01, 2005). Application of latent variable methods to process control and multivariate statistical process control in industry. *International Journal of Adaptive Control and Signal Processing, 19,* 4, 213-246.

[10] Kourti, T. (May 01, 2005). Application of latent variable methods to process control and multivariate statistical process control in industry. *International Journal of Adaptive Control and Signal Processing, 19,* 4, 232.

Krause, Birle, Hussein and Becker (2011) use PLS to compensate for sensor error and to predict parameters that are not easily measured such as sugar and alcohol contents during yeast cultivation.[11] Krause et al. (2011) discussed these applications in brewing applications. The lack of abundant sensors that provide discrete accurate data that would provide a complete assessment of the current conditions was cited as a constraint; however, coupling ultrasonic sensors with a PLS calibration would provide an improvement.

Ristolainen, Alén, and Toivanen (1999) use PCA and PLS as an analysis tool when characterizing total chlorine free bleach plant effluents.[12] Gabrielson and Trygg (2006) discuss PLS applications using PLS to predict the biological oxygen demand in a pulp mill lagoon, NIR spectroscopy for optical and mechanical properties of kraft pulps, as well as using NIR spectroscopy data to predict moisture and pine contents.[13] Reis and Saraiva (2005) discuss using PLS among other techniques as a tool to address measurement error, noise, and missing data. While their analysis focuses on steady state situations, they believe that the applications would include dynamic systems as well using lagged variables.[14] PCA can also be used to determine when one of the sensors may not be performing as expected. Soft sensors can be developed using PCA to approximate the values prior to the repair or replacement of the sensors.[15]

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[11] Krause, D., Birle, S., Hussein, M. A., & Becker, T. (August 01, 2011). Bioprocess monitoring and control via adaptive sensor calibration. *Engineering in Life Sciences, 11,* 4, 402-416.

[12] Ristolainen, M., Alén, R., & Toivanen, J. (January 01, 1999). Characterization of totally chlorine-free effluents from kraft pulp bleaching III:Analytical pyrolysis of high-molecular-mass hardwood-derived material. *Journal of Analytical and Applied Pyrolysis, 52,* 2, 225-237.

[13] Gabrielsson, J., & Trygg, J. (January 01, 2006). Recent Developments in Multivariate Calibration. *Critical Reviews in Analytical Chemistry, 36,* 3-4.

[14] Reis, M. S., & Saraiva, P. M. (November 01, 2005). Integration of data uncertainty in linear regression and process optimization. *Aiche Journal, 51,* 11, 3007-3019.

[15] Winchell, P. (July 01, 2005). Using multivariate data analysis for process troubleshooting. *Pulp & Paper Canada, 106,* 29-32.

Malkavaara, Harjula, Alén, and Knuutinen (2000) use PCA and PLS analysis to evaluate structural changes in kraft pine lignin during pulping.[16] They successfully apply PCA to classify the lignin samples and also use PLS as part of their analysis toolkit to provide an indirect measure of pulp properties. Again, this represents the use of these tools to analyze the data from a discrete set of samples to make predictions, not for closed loop control.

Silverio et al. (2011) also evaluate samples for research purposes. They use PCA to determine the effects of wood storage on the potential for pitch formation. Using these techniques when coupled with data on yield and pulp properties; a projected optimal wood chip storage time was selected.[17] Pu, Ragauskas, Lucia, Naithani, and Jameel (2008) use PCA and PLS with near infrared spectroscopy to predict kraft pulp yields across oxygen delignification stage(s). The PLS model that they develop has a high correlation between predicted and measured pulp yield.[18]

Within the experimental work that we have examined, it can be seen that PCA and PLS have applications to predict outcomes and to detect and compensate for sensor error. Further, there are applications within pulp and paper industries; however, most of the examples cited above are focused on sample analysis. This thesis seeks to expand on these techniques to apply them to kraft pulp mill steam and power systems.

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[16] Malkavaara, P., Harjula, P., Alén, R., & Knuutinen, J. (January 01, 2000). Chemometric investigation on structural changes in pine kraft lignin during pulping. *Chemometrics and Intelligent Laboratory Systems, 52*, 2, 117-122.

[17] Silverio, F., Barbosa, L., Fidencio, P., Cruz, M., Maltha, C., & Pilo-Veloso, D. (January 01, 2011). Evaluation of Chemical Composition of Eucalyptus Wood Extracts after Different Storage Times Using Principal Component Analysis. *Journal of Wood Chemistry and Technology, 31,* 1, 26-41.

[18] Pu, Y., Ragauskas, A., Lucia, L., Naithani, V., & Jameel, H. (January 01, 2008). Near-Infrared Spectroscopy and Chemometric Analysis for Determining Oxygen Delignification Yield. *Journal of Wood Chemistry and Technology, 28,* 2, 122-136.

2.2 Using PCA and PLS in a Kraft Pulp Mill

Kraft pulp mills are complex systems where the interactions between many of the different parts of the process impact each other. These interactions typically require detailed models to predict process outcomes. Much of the data is correlated allowing for simplified PCA and PLS models that provide adequate prediction of the process outputs without the requirement of the development of detailed process models.

2.3 Processes

Because it is essential to understand how the components interact, it is necessary to build a model to predict power generation and determine the factors. Once these factors have been established the model can be used to maximize the power generation and minimize venting without violating any constraints.

Fortunately, in many pulp and paper mills there is a wide availability of data. Typically mills are quite complex and there is a requirement to control many parameters relating to safety, environmental compliance, quality, production, and cost to ensure that the respective goals are met. It is essential to understand the constraints and variables associated with the process to maximize their positive impact on the process. Consider a simple boiler coupled to a turbo generator with a condenser under steady state condition (Figure 2.1). In this case all of the parameters would be related. The fuel and air are coupled to provide the appropriate rate for combustion. This ratio and flow also provide the constituents and flow of the stack gas. Combustion releases a certain amount of heat. This causes an amount of water to boil at the desired pressure. This steam is fed to the turbine, producing an amount of power and condensate. Thus, it can be seen that by knowing any one of these parameters would allow the calculation of all of the other ones.

In this case maximizing the fuel flow to the constraint would allow for maximum power production.

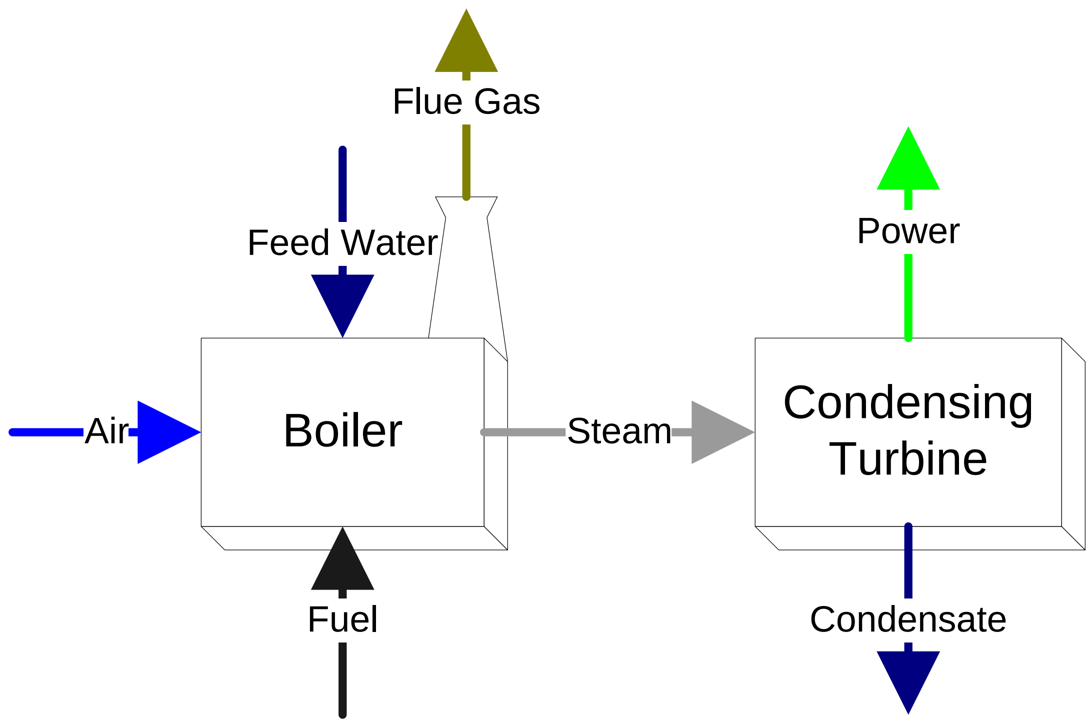

Figure 2.1 Simplified Coupled Boiler and Turbo generator

Most industrial systems are much more complex. Kraft mills include one or more boilers coupled with multiple users. There is typically more than one fuel available to be fired and each fuel and boiler may differ in their efficiencies. Headers may experience pressure and temperature variability. Users may be constant, may vary with operating rate, or may be intermittent.

Table 2.1 provides examples of some of the parameters that may be known or monitored. Some of the parameters would be highly correlated, while others may not be correlated at all. For example, the flow of steam through a pressure reducing valve (PRV) would be highly correlated with the valve output assuming that both are sized and ranged properly. The more the valve opens the more steam is expected to pass through it. Alternatively, the steam flow from a base loaded boiler would not correlate with the steam demand of a minor user. Generating a PCA model will identify which parameters are influencing the desired outcomes in this kraft pulp mill.

Table 2.1 Steam Generation and Consumer Parameters

Headers and Consumers	Generation
Steam Header(s) Pressure	Steam Flow off of the Recovery Boiler
Pressure Reducing Station(s) Flows	Steam Flow off of the Supplemental Boiler(s)
Pressure Reducing Station(s) Outputs	Steam Temperatures
Extraction Steam Flow(s)	Furnace Temperatures
Extraction Steam Valve Output(s)	Fuel Flow
Power Generation	Fuel Cost(s)
Turbine Efficiencies	Fuel Efficiencies of Conversion
Turbine Valve Positions	Enthalpy of Boiler Feedwater
Condenser Flows	Air Flow(s)
Condenser Vacuum	Fan Speed(s)
Safety Set-points	Stack Gas Analysis
Steam Flow by User	Fan/Pump Amps
Steam Quality by User	Safety Set-points

In kraft mills a common constraint is the firing rate of the recovery boiler. Therefore, it is typically base loaded at its maximum firing rate, assuming there is fuel available. This can provide a relatively stable steam supply and quality to the headers. Typically there is an alternate fuel source available (albeit less desirable).

Supplementary fueled boilers may use solid, liquid and/or gaseous fuels as a supply. Each fuel type has different operating characteristics including response rate, pricing, and steaming rate. For this evaluation hog fuel is the primary fuel source for the auxiliary boiler. This imparts a considerable lag between the application of the fuel and the increase in steaming rate. This additional hog fuel may reduce the steaming rate until the new steady state is reached because the increased hog fuel fed to the boiler must first be heated to the ignition temperature. As well, hog fuel typically has some variation in moisture content which imparts an additional complication. The moisture swings may be exacerbated by weather conditions and external storage which is normally the case. These swings result in variation in the steam production on a fuel mass flow basis. Figure 2.2 represents moisture variation in the hog fuel over a two year span.

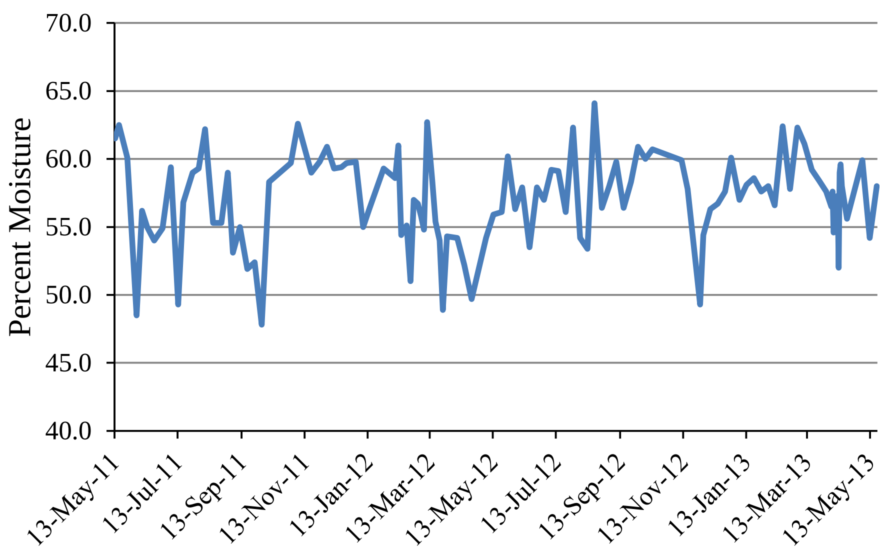

Figure 2.2 Hog Fuel Moisture Variation

Turbo generators are used to convert the energy in the steam to electrical energy. They can be base loaded or partially loaded. Operating at partial load is generally less efficient due to a reduction in the feed pressure to the turbine and the associated throttling of one of the inlet valves on the valve train. The reduction of the inlet pressure is translated across the turbine, thereby providing less potential energy to be translated into less mechanical energy and therefore less power.[19] Thus, for the purposes of this analysis, we will be utilizing a single turbine at partial load and assuming the other turbine is loaded to the maximum.

Using batch digesters imparts variability in the steam demand. Digesters require steam for chip packing, heating to get the digester contents up to the desired temperature, and finally maintaining that temperature throughout the cooking phase. This can impart significant variability in steam demand, particularly with large steam demands during the heating phase as there is a large thermal mass to be brought up to the cooking temperature.

The pulp dryers also represent a significant steam load variability, albeit (hopefully) on a much less frequent basis. The variation would occur during machine outages and breaks. It would typically represent an on/off situation with small rate changes having less impact on the overall steam demand variability over the longer term.

Typically, most of the remainder of the steam users in the pulp mill would represent small users or users that would not vary significantly over time and would represent a smaller impact on any modeling on steam demand.

[19] Embleton, W., & Jackson, L. (2003). *Reed's Applied heat for engineers*. London: Adlard Coles Nautical

Chapter 3

Methodology

The objectives of this thesis are to:

- develop models of the steam and power systems of a kraft pulp mill,
- evaluate the models,
- and develop a control system based on those models.

PCA and PLS methods are used to determine the relationships between the variables and develop control strategies to maximize power generation and minimize losses. These models are assessed to ensure that they will meet the objectives. Time lags are calculated for use within the control environment. The advanced controls algorithm is created and put on line. These controls are compared to the normal operations.

3.1 Modelling Overview

The components of the kraft mill that are analyzed in the energy model are the following: fourteen batch digesters of four different sizes, a kraft recovery boiler, a hog fuel boiler used for supplemental steam generation, and two turbo generators, one of which has a condenser.

The batch digesters are sequentially filled with chips, charged with white liquor and topped up with black liquor. They are then brought up to temperature and cooked to an H-factor target and then are blown to the blow pits. Digester steam consumption is the largest variable steam user in the mill.

Approximately 70% of the steam is generated from the recovery boiler. The boiler is typically base loaded; however, in the event there is insufficient concentrated black liquor available, it may be cut back. Bunker C is the alternate fuel available. The remaining steam load is made up by the power boiler. This boiler is capable of burning hog fuel, natural gas and/or Bunker C. Hog fuel is typically the fuel of choice.

There are two turbo generators as well; one is a back pressure turbine that is typically maximized, and the other has a condenser and its output is varied to control the process. There are also steam vents that may be used to control the steam headers as well.

There are other steam users in the process including the pulp dryers, the bleach plant, oxygen delignification, evaporation, boiler feed water preparation, condensate stripping, and heating (process and area heating) among others. These users tend to be more stable in their steam demands over time with the only variability typically due to rate changes and unit area shut downs or breaks.

3.2 Principal Component Analysis

PCA is a tool that can be used to explain the maximum amount of variance with the minimum number of principal components (linear combinations of the original variables). We can consider a data set made up of a series of variables that may possibly be correlated:

$$x_1, x_2, x_3, \ldots, x_n$$

From the variables a series of principal components can be created (eq. 1, 2 and 3), such that the first principal component has the maximum variance and each succeeding principal component has the maximum variance possible, provided that it is orthogonal to all preceding components. Each of these components should provide the best description of the remaining error. They are written as follows:

$$y_1 = v_{11}*x_1 + v_{12}*x_2 + v_{13}*x_3 \ldots v_{1n}*x_n \quad \text{(eq. 1)}$$

$$y_2 = v_{21}*x_1 + v_{22}*x_2 + v_{23}*x_3 \ldots v_{2n}*x_n \quad \text{(eq. 2)}$$

to:

$$y_n = v_{n1}*x_1 + v_{n2}*x_2 + v_{n3}*x_3 \ldots v_{nn}*x_n \quad \text{(eq. 3)}$$

This enables the maximum amount of data captured with the minimum number of principal components. When the model provides the appropriate approximation of the system (by determining how close the model must match reality), no further components are required. The model can only have a maximum number of components equal to the number of variables. With the first principal component as the best descriptor of the data set and each subsequent principal component as the best orthogonal descriptor of the remaining error, the model requires less than the maximum number of components to adequately describe it as otherwise it is of little value.

As an example we will use a two dimensional representation of the data set that is graphically represented in Figure 3.1.

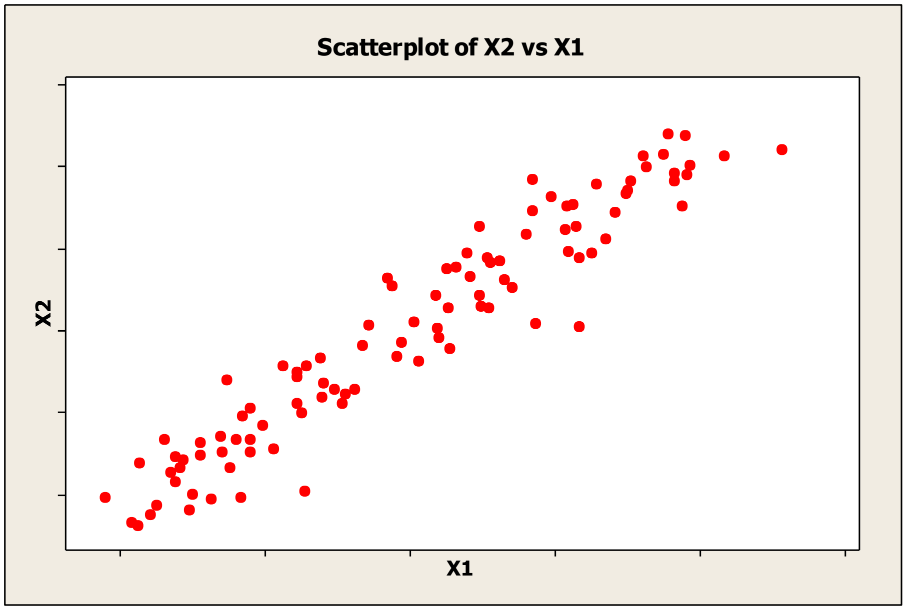

Figure 3.1 Two Dimensional Representation of a Correlated Data Set

It can be seen that the majority of the data can be described along the long axis of the data cloud as shown below in Figure 3.2.

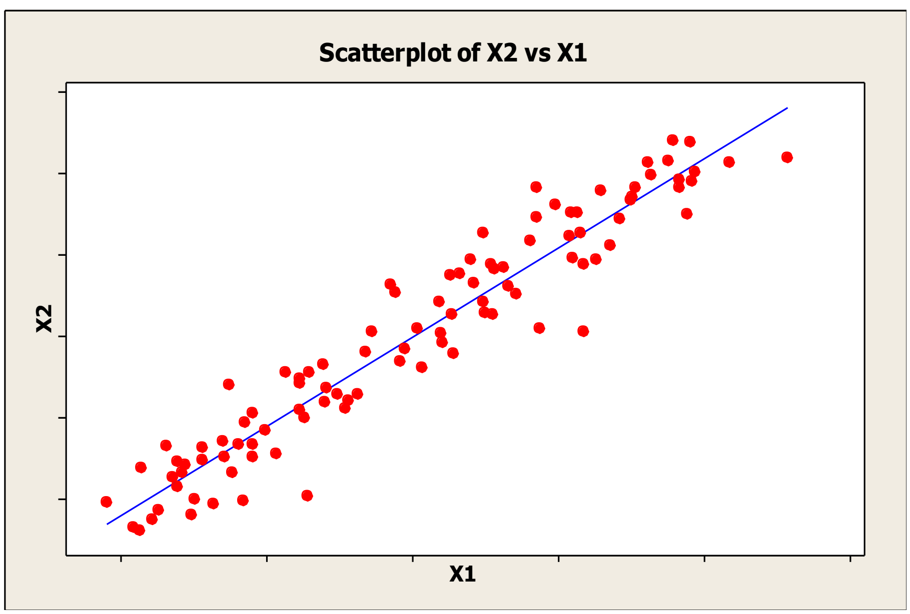

Figure 3.2 Two Dimensional Representation of a Correlated Data Set with Best Liner Fit Line

If further resolution is required, a second axis, orthogonal to the first, would be used to capture the error remaining after the first principal component's approximation. This can be repeated in n dimensional space until a suitable model is developed. Understanding of the variables involved allows for interpretation of the results.

Some limitations of the PCA analysis are as follows:

- Directions with the largest variance are assumed to be of the most interest; however, there may be a special circumstance where this is not the case;
- PCA only uses orthogonal transformations;
- Analysis is based on the mean vector and the covariance, which does not characterize all systems;
- PCA is only advantageous if the original variables are correlated, otherwise no reduction is possible;
- PCA assumes real and continuous data; and
- Scaling is a factor with PCA.

PCA can be used in industrial processes for control and as a virtual sensor[20]. In this application PCA is used to generate models to describe the relationships required to maximize power generation and minimize costs.

3.3 Partial Least Squares

PCA differs from PLS in that in PCA the model is developed such that the covariance between the different data sets is maximized. In maximizing the covariance between the first and second data sets, we are able to use the data obtained in the first data set to predict the responses in the second. In this application partial least squares is

[20] Wise, B.M. and Ricker, N.L.(1991) Recent Advances in Multivariate Statistical Process Control: Improving Robustness and Sensitivity, Seattle: www.eigenvector.com

used to develop a predictive tool to optimize the process. By predicting data that involves significant time lag, the process can be optimized such that, for example, the steam is available when it is required and it is not vented when it is not required.

3.4 Integration of the Models into the Controls

To develop an advanced method of controls it is first necessary to understand how the various process parameters interact, in this case with the focus being power generation. This data is used to build a model. Once a model is developed it must be evaluated to ensure that the model meets the system requirements. As well, it is necessary to determine if any lag exists between the various parameters and, if so, to quantify it.

Phase one is the development of the model. Phase two involves the evaluation and phase three includes a transition to controls and the necessary adjustments.

3.5 Experimental

Data was collected from the Distributed Control System (DCS) for the parameters that could have influence on the ability to maximize power generation and minimize fuel costs. These would represent parameters that could be adjusted to obtain the desired results, called manipulated variables, variables that set the window of desired operation called constraint variables, and variables that are indicators or predictors of process performance.

These include the parameters around generator power production, valve positions on the stages of generator inlet valve trains, extraction steam flow, air and fan speeds for the auxiliary boiler, vent positions steam pressure relieving, steam pressures at the headers, auxiliary boiler furnace temperatures, variable steam demand, hog fuel flow, and feed characteristics.

A depiction of the system is included in Figure 3.3. The base loaded and auxiliary boiler feed steam into a common high pressure header system. The high pressure steam is fed to a condensing and an extraction turbine for power generation and pressure reduction. There are also pressure reducing valves that control down to medium and low pressure steam headers. The headers all feed the appropriate steam consumers.

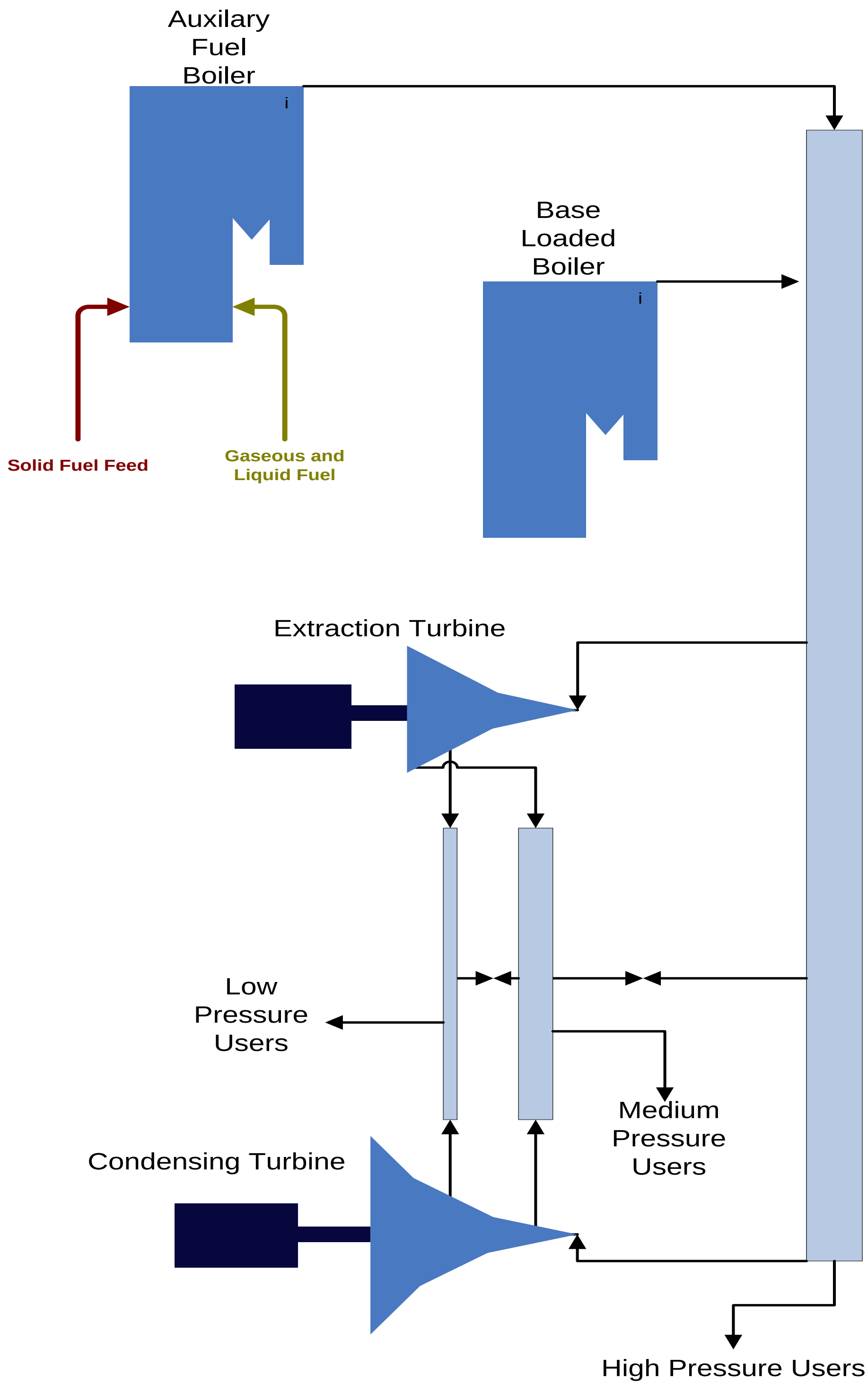

Figure 3.3 Model Steam System Diagram

The base loaded boiler is fired on black liquor and is fully loaded provided there is adequate supply. The auxiliary boiler is fed with hog fuel, natural gas or Bunker C. Hog fuel is the primary fuel with either natural gas or Bunker C as the backup, depending on the relative fuel costs at the time. This boiler is loaded according to the steam demand.

Due to the nature of turbine efficiencies[21], it is more efficient to keep one of the turbo generators fully loaded to maximize the steam to electrical power efficiency. In this case, due to the ability of the condensing turbo generator to utilize steam without dumping it into a header, it is set up to deal with the swings in steam supply and demand.

Steam is consumed by the high pressure, medium pressure, low pressure consumers as well as the condenser on the turbo generator. The majority of the high pressure users will be relatively stable, including the feed to the extraction turbine as well as the turbines being used as prime movers. The low pressure users on aggregate show a relatively stable demand as well (See Figure 3.4). The flow of steam from the extraction stage is relatively stable showing a standard deviation of 11 kpph on an average of 262 kpph (including the low spikes). However, when there is a decrease in the steam extracted from the turbo generators, the pressure reducing valve between the medium and low pressure headers opens to compensate.

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[21] Foresthoffer, W.E. (2005), Foresthoffer's Rotating Equipment Handbooks, :Elsever Science

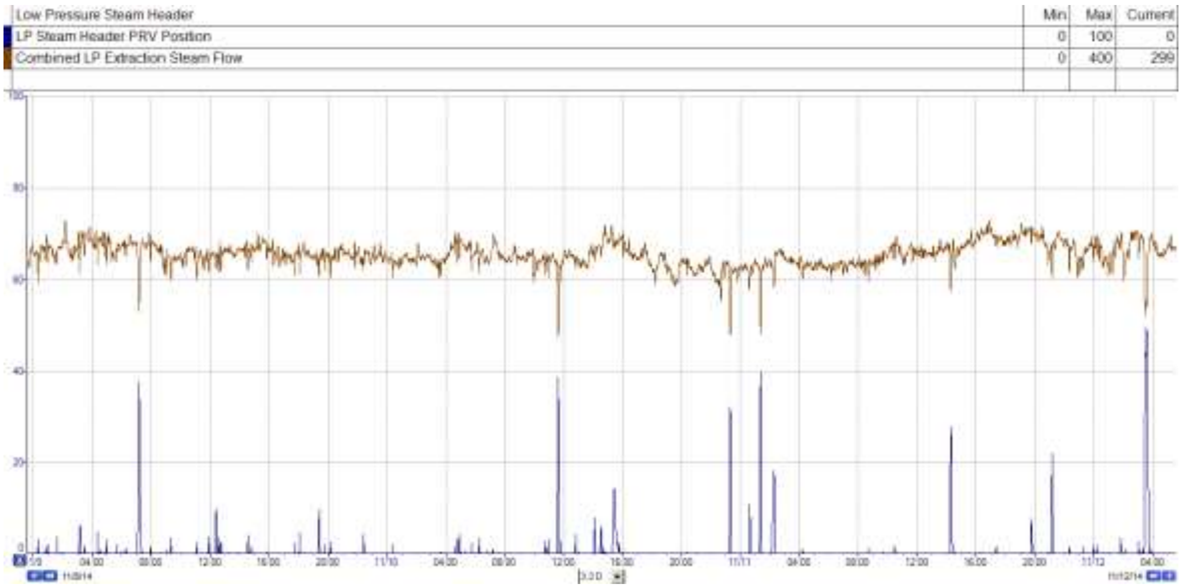

Figure 3.4 Low Pressure Steam Flows

The objectives are to maximize power generation on the condensing turbine, to minimize venting out of the steam headers, and to minimize the amount of steam that goes through the pressure reducing valves. The bark flow would be the main variable that would be manipulated with the valves around the turbo generator constrained within their operating ranges. The vent openings and pressure reducing valve openings would also be constraints.

3.6 Bump Testing

It is important to compensate for the time lags within the system, both to improve the precision of the model and to ensure that when operating under control, the lags are taken into account. If each of the inputs are varied in a controlled manner across as wide a range as possible and with varying timescales, the data can be manipulated to provide a gain and delay. Figure 3.5 shows a typical turbo generator inlet valve response to an increase in natural gas to the furnace.

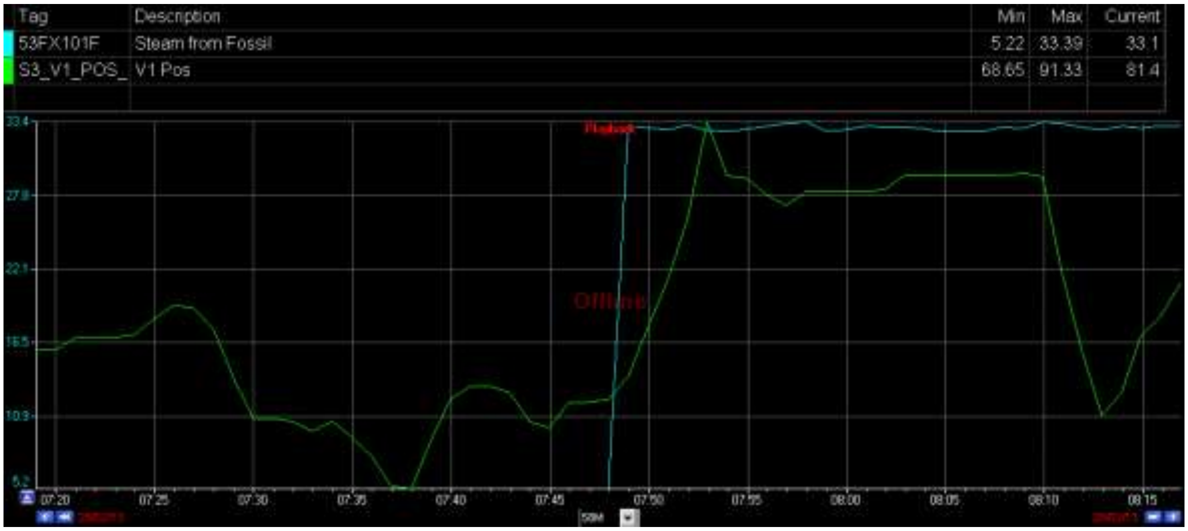

Figure 3.5 Inlet Valve Response to a Change in Gas Flow

It can be noted in Figure 3.6 that the duration between step changes as well as the amplitude of the step change were varied over the range. This figure also shows the response of steam out of the boiler as well as the power produced when step changes to the bark feed are implemented.

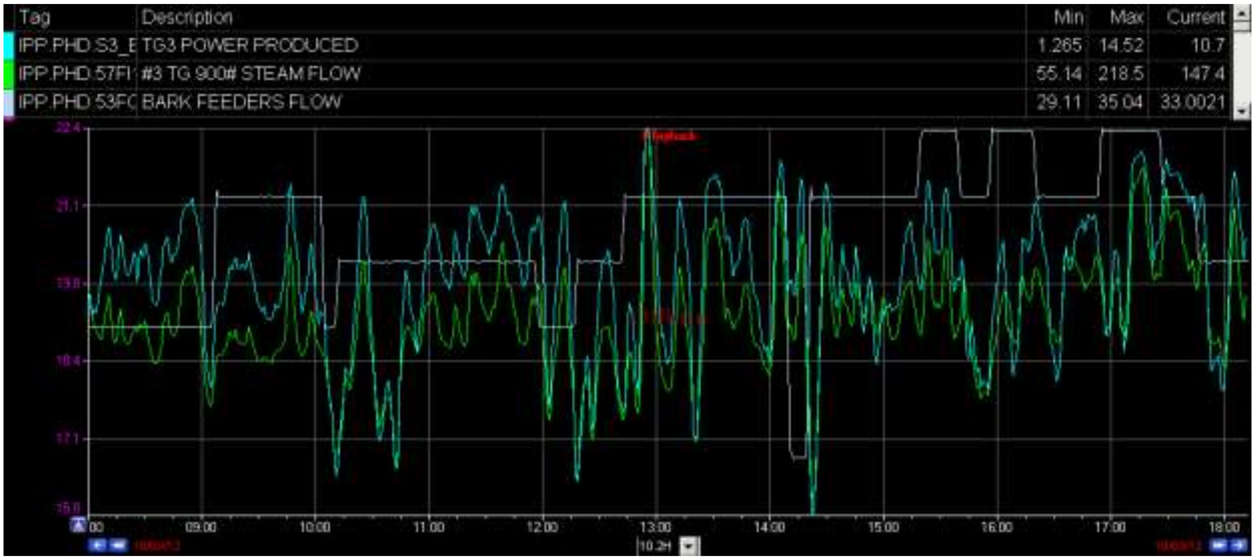

Figure 3.6 Response of Steam Production and Power Production to Changes in Hog Fuel Feed.

More layers of related inputs and outputs can be added that would give a much more complete picture of the situation; however, the added parameters increase the complexity of the trend and can make it difficult to interpret. This can be seen in Figure 3.7. It can be seen that for interpretation, it is logical to evaluate a few parameters at a time or use software to obtain the relationships.

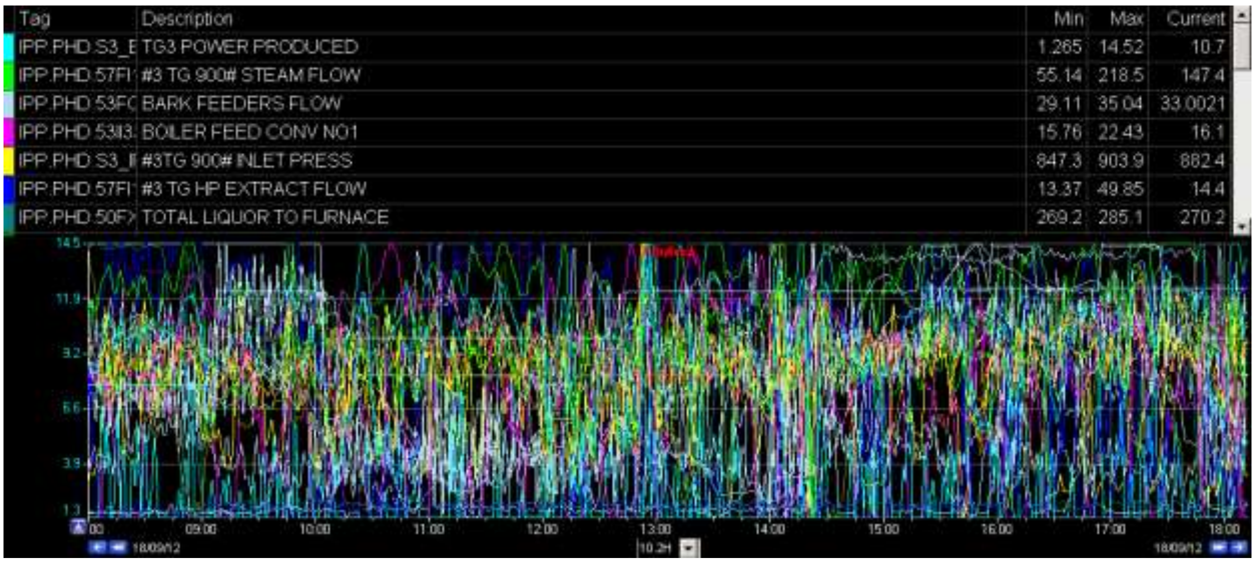

Figure 3.7 Responses to Changes in Hog Fuel Feed.

The time delay was manually adjusted to give the best model fit with the minimum manipulation. Figure 3.8 shows the model for the relationship between the fossil fuel to the boiler and the turbine's inlet valve position.

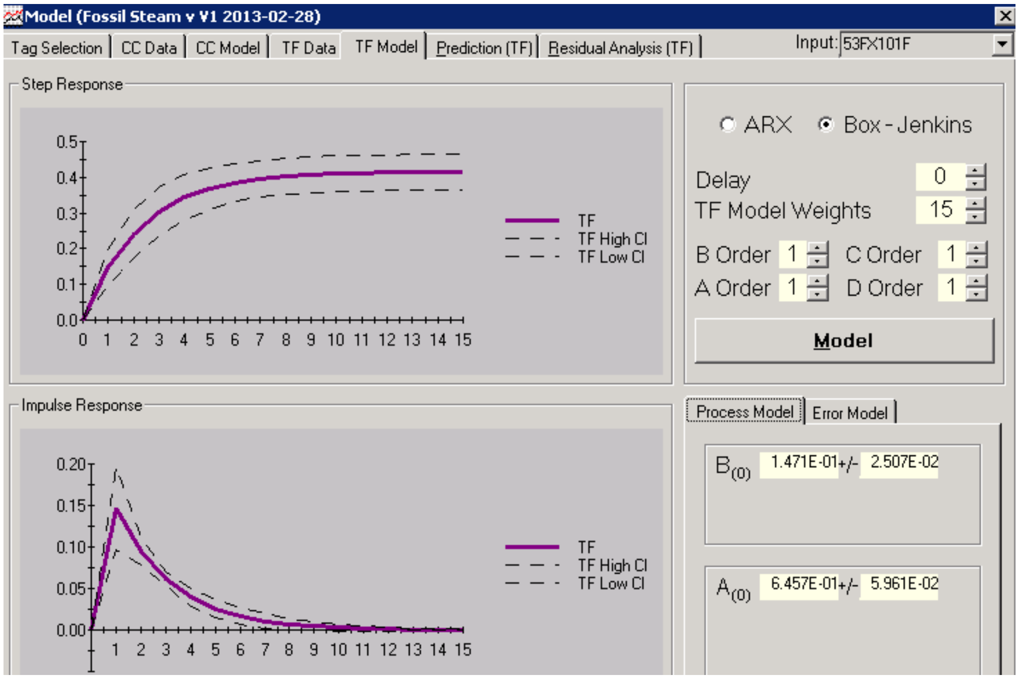

Figure 3.8 Step Response between Fossil Fuel to the Boiler and Turbine Inlet Valve Position

Some parameters respond quite quickly (e.g.: the relationship between a valve position and fluid flow), while others may have a much slower response (e.g.: the relationship between a wet solid fuel entering the boiler and the condensing power produced). The primary purpose of these evaluations for this project is to determine when the process re-stabilizes after a disturbance. The disturbance may be external to the controls, a control response to another disturbance, or an operator initiated response.

3.7 Model Generation

The main parameters that are affected and manipulated are listed in Table 3.1. The target is to maximize the power generation. Therefore, a target power production is selected to maximize this and minimize the risk of venting unused steam. The other variables are constrained by economics or process conditions for stable operation of the systems. A positive relationship would mean that as the manipulated variable is increased, the variable in question would also increase after whatever time delay is defined by the system. As an example, increasing the flow of hog fuel to the boiler would be expected to increase the power production.

Table 3.1 Process Variables

Variables:	**Manipulated Variable:**
Control Variable:	Hog flow to Boiler
Power Generation	Positive
Constrained Variables:	
Generator Input Valve Position	Positive
Medium to Low Pressure Turbine Valve Train Position	Positive
Low Pressure to Extraction Valve Train Position	Positive
Medium Pressure Vent Valve Position	Positive
Low Pressure Vent Valve Position	Positive
High to Medium Pressure Pressure Reducing Valve	Positive
Medium to Low Pressure Pressure Reducing Valve	Positive

Figure 3.9 shows the condensing turbine with the two extraction stages and the condensing stage.

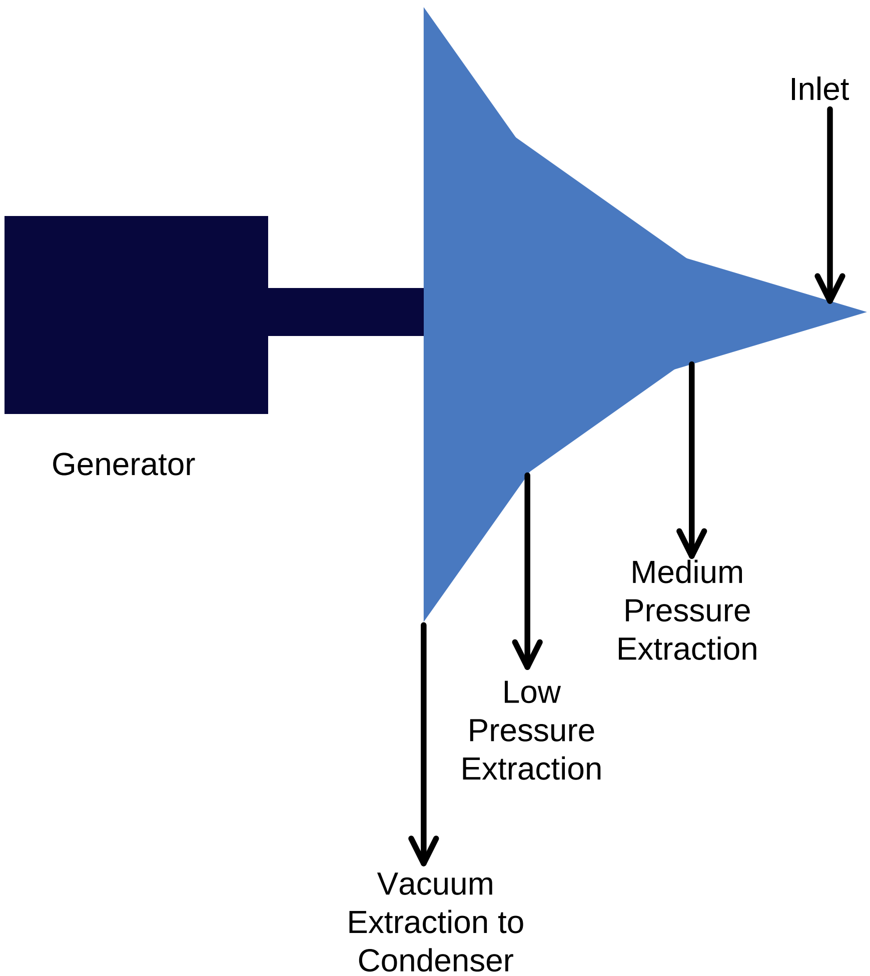

Figure 3.9 Condensing Steam Turbine

A mass balance is completed across the turbine. This ensures that the data set is valid. The mass flow of steam entering the turbine must equal the sum of the extraction and condensing steam flows (eq. 4), where M_I represents the inlet steam mass flow, M_M represents the medium pressure steam mass flow, M_L represents the low pressure steam mass flow and M_V represents the mass flow of steam to the condenser as follows:

$$M_I = M_M + M_L + M_V \quad \text{(eq. 4)}$$

As well, an energy balance should also be completed. The power produced divided by the turbo generator efficiency is equal to the energy entering the turbine minus the energy leaving in the medium pressure, low pressure and vacuum condensing stage (eq. 5). P represents the power produced, Ƞ the turbine and generator efficiency, h_I , h_M , h_L and h_v the respective inlet, medium pressure, low pressure and vacuum enthalpies:

$$P/\eta = M_I h_I - M_M h_M + M_L h_L + M_V h_v \qquad \text{(eq. 5)}$$

The mass and energy balances are generated and validated with process data within the meter tolerances. Compensated steam flows were used when possible.

Subsequently, a PLS model can be created around the condensing turbine. The following variables are evaluated : the power produced by the generator, the valve positions of the inlet, medium pressure extraction, low pressure extraction, and the vacuum extraction as well as the steam flow and pressure to the turbine. Table 3.2 lists the variables.

Table 3.2 Condensing Turbine Model

Var	Description	Avg	StdDev	Min	Max
Y	TG3 POWER PRODUCED (MWh)	12.806	1.925	4.745	16.66
X1	ACTUAL V1 VALVE POSITION (%)	74.528	9.403	43.556	96.8
X2	ACTUAL V2 VALVE POSITION (%)	81.137	13.596	18	99
X3	ACTUAL V3 VALVE POSITION (%)	50.982	19.41	23	90
X4	#3 TG 900 LB STEAM PRESSURE (psi)	838.888	3.317	823.341	855.652
X5	#3 TG 900# STEAM FLOW (kpph)	215.176	33.938	101.02	302

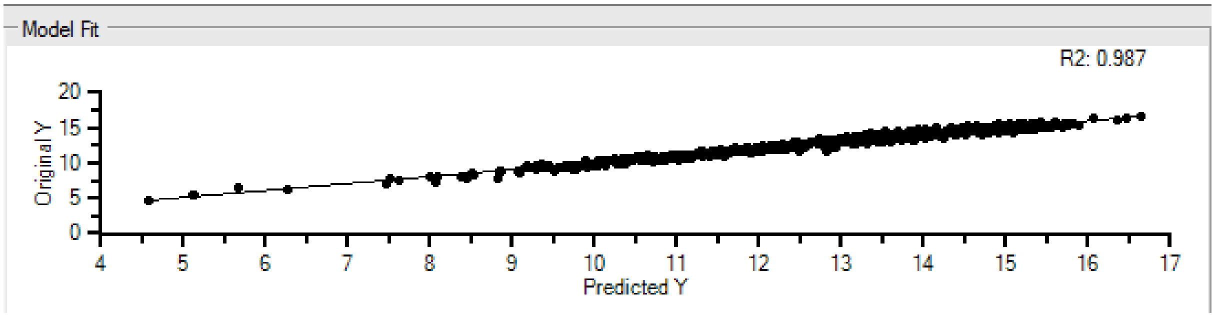

Figure 3.10 Condensing Turbine PLS Model Fit

Figure 3.10 is a graphical representation of the data as compared to the model fit line. In this case there is an R^2 of 98.7%.

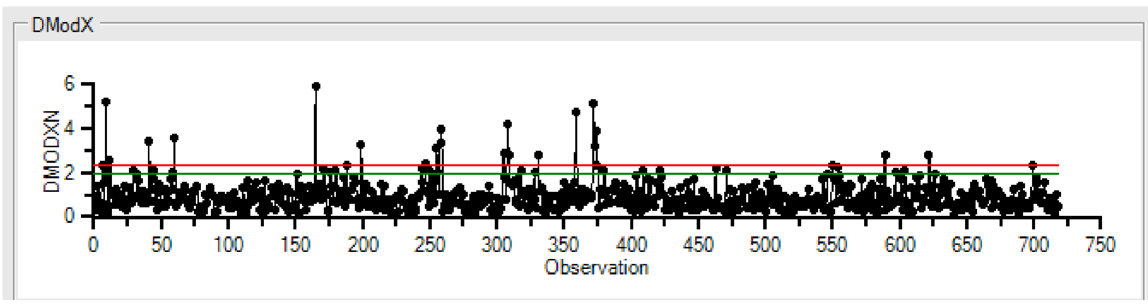

Figure 3.11 Condensing Turbine PLS Model Distance to the Model for X values

Figure 3.11 is a graphical representation of the normalized sum of differences between the predicted X values and the actual X values.

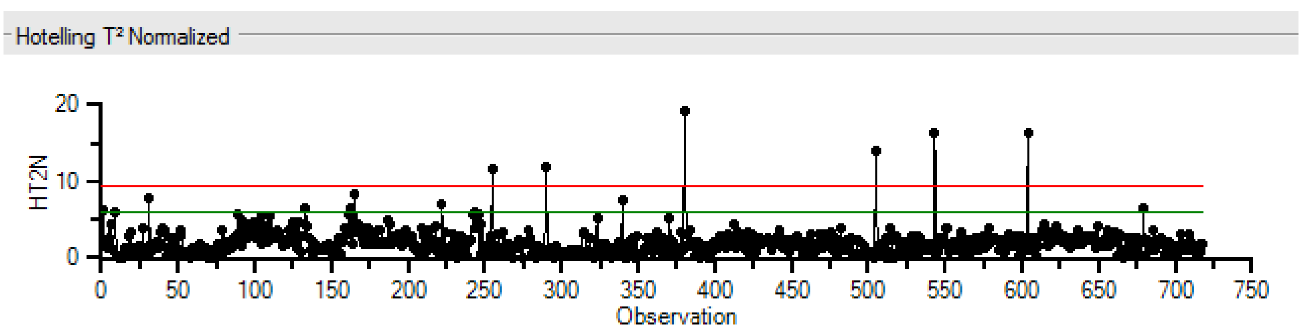

Figure 3.12 Condensing Turbine PLS Model Fit Deviation from Average Values

Figure 3.12 is a graphical representation of the normalized T Scores. T Scores represent deviation from average across all of the X values. Larger values represent more deviation from average values.

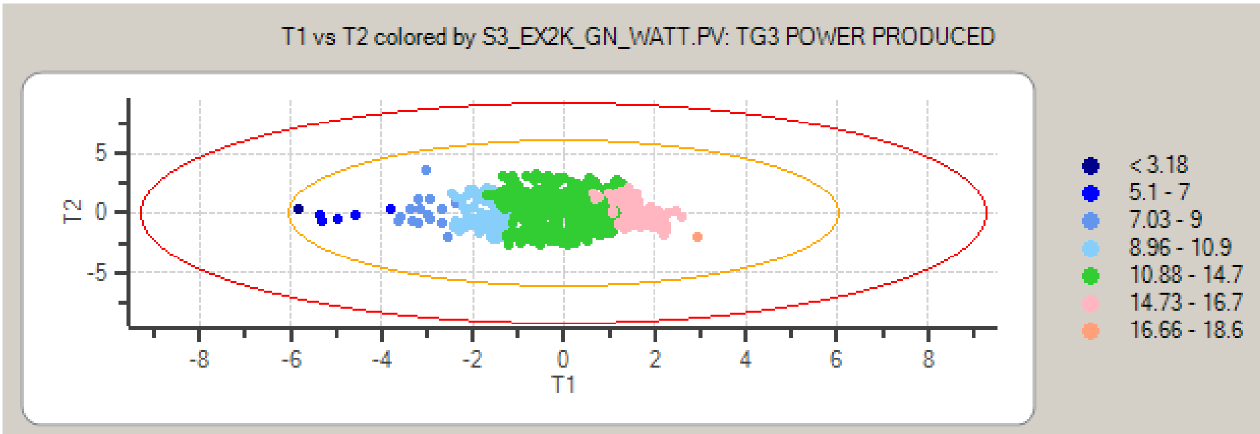

Figure 3.13 Condensing Turbine PLS Model Fit Two Dimensional Representation of the Deviation off of the Model

Figure 3.13 is a graphical representation of the model power produced represented in two dimensions. The representation is as if the observer is looking in line with the major axis and represents the deviation off of the model.

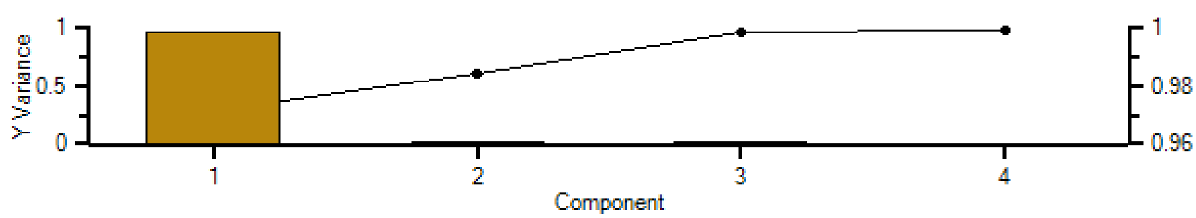

Figure 3.14 Condensing Turbine PLS Model Fit

Figure 3.14 is a graphical representation of the vectors and their relative weightings to explain the data. In this case it can be seen that the first order vector represents over 97% of the variation. Vectors 2 and 3 represent just over 1% variation and the final vector represents less than 0.1 %. Therefore, in this case, the first vector represents a good approximation of the data.

The PCA model represents the equations necessary to predict the generator output based on the other X variables. Although using a similar data set, the parameters do not appear identical to those generated by the PLS model since the PCA model focuses on the interrelationships between the variables (what is different than normal), while the PLS model predicts an output.

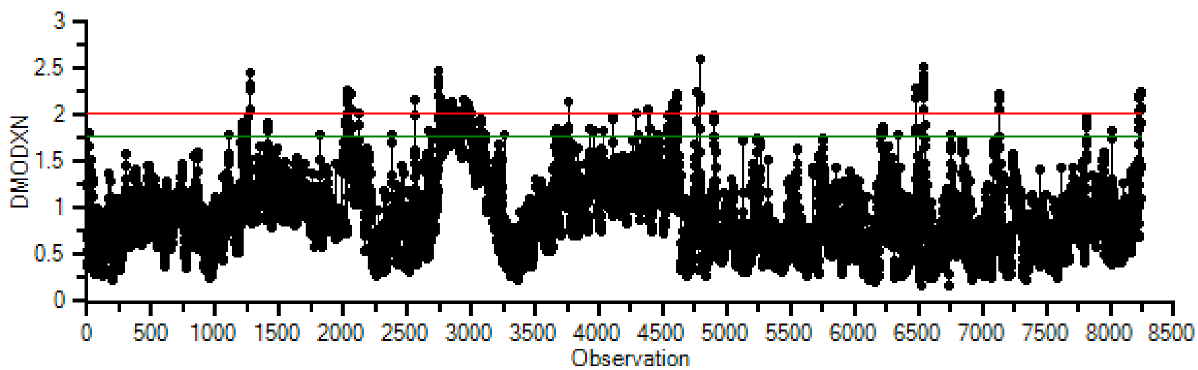

Figure 3.15 Condensing Turbine PCA Model Distance to the Model for X values

Figure 3.15 is a graphical representation of the distance to the model for the data points. DMODXN represents the normalized difference between the predicted X values and the actual X values.

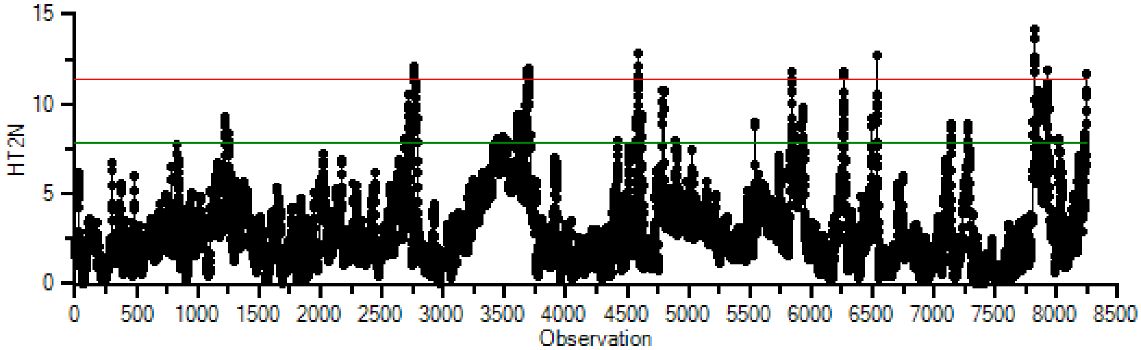

Figure 3.16 Condensing Turbine PCA Model Fit Deviation from Average Values

Figure 3.16 is a graphical representation of the normalized T scores from the average.

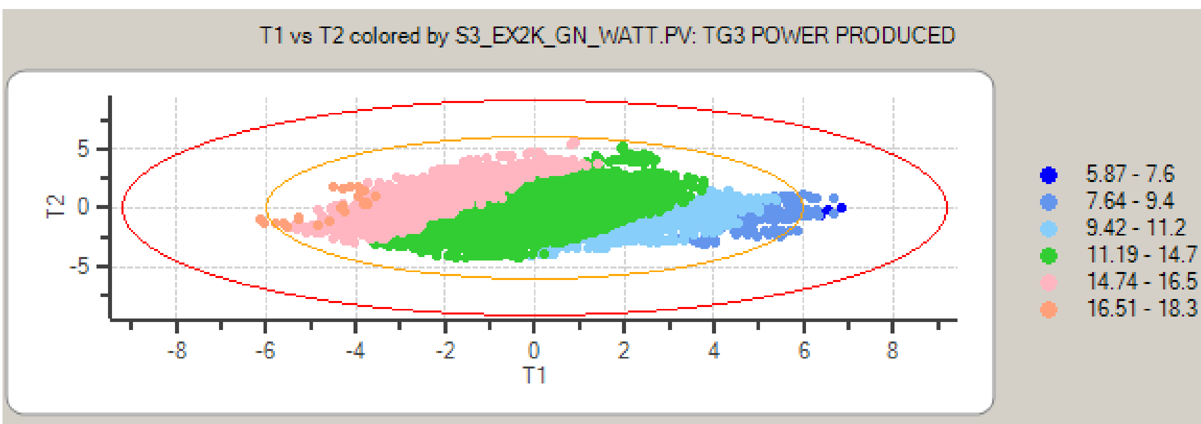

Figure 3.17 Condensing Turbine PCA Model Fit Two Dimensional Representation of the Deviation off of the Model

Figure 3.17 is a graphical representation of the model power produced represented in two dimensions. The representation is as if the observer is looking in line with the major axis and represents the deviations off of the model.

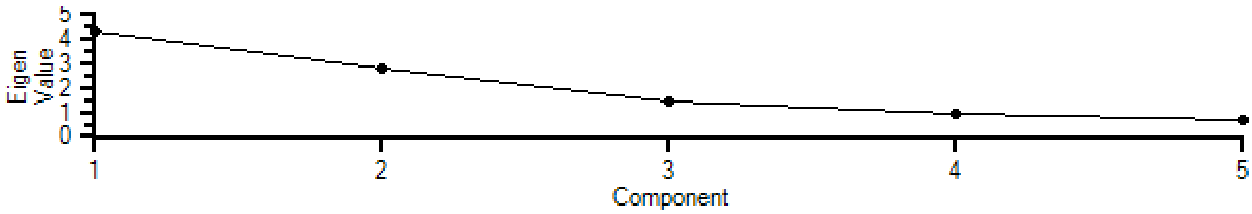

Figure 3.18 Eigen Values for the PCA analysis around the Condensing Turbine

Figure 3.18 shows the eigen values for the first five principal components. Component 1 is equal to 4.33 down to component 5 at 0.70. The eigen values represent the relative magnitude of the vectors in the principle directions.

Using the models generated above coupled with the mass and energy balance gives the factors necessary for supervisory control over the turbine. Now the complete balance may be calculated. The PCA and PLS models were created for the variables that would have an effect on the power generation, pressure control, and steam venting. The sum of the factors for each variable for each of the components is used as a starting point for the factors that are used for the controls. The overall factors are listed in Table 3.7 (page 49).

The PLS models are developed for the systems. We will examine the turbo generator. The model for the high pressure steam valve position going into the generator is shown in Table 3.3 below. Figure 3.19 indicates the correlation between the model predictor and the values indicated. The correlation has an R^2 of 96.6%.

Table 3.3 PLS Model for High Pressure Steam Inlet Valve Position

Description	Units	Coefficient
Constant		16.1509
Condensing Turbine Power Produced	W	1.40996
MP to LP Steam Valve Position	%	0.0763985
LP Steam to Condensing Valve Position	%	-0.0119151
MP Steam Extraction Flow	kpph	0.102914
LP Steam Extraction Flow	kpph	0.0876838
Exhaust Flow to Condenser	kpph	-0.0028
Inlet Steam Flow	kpph	0.124267

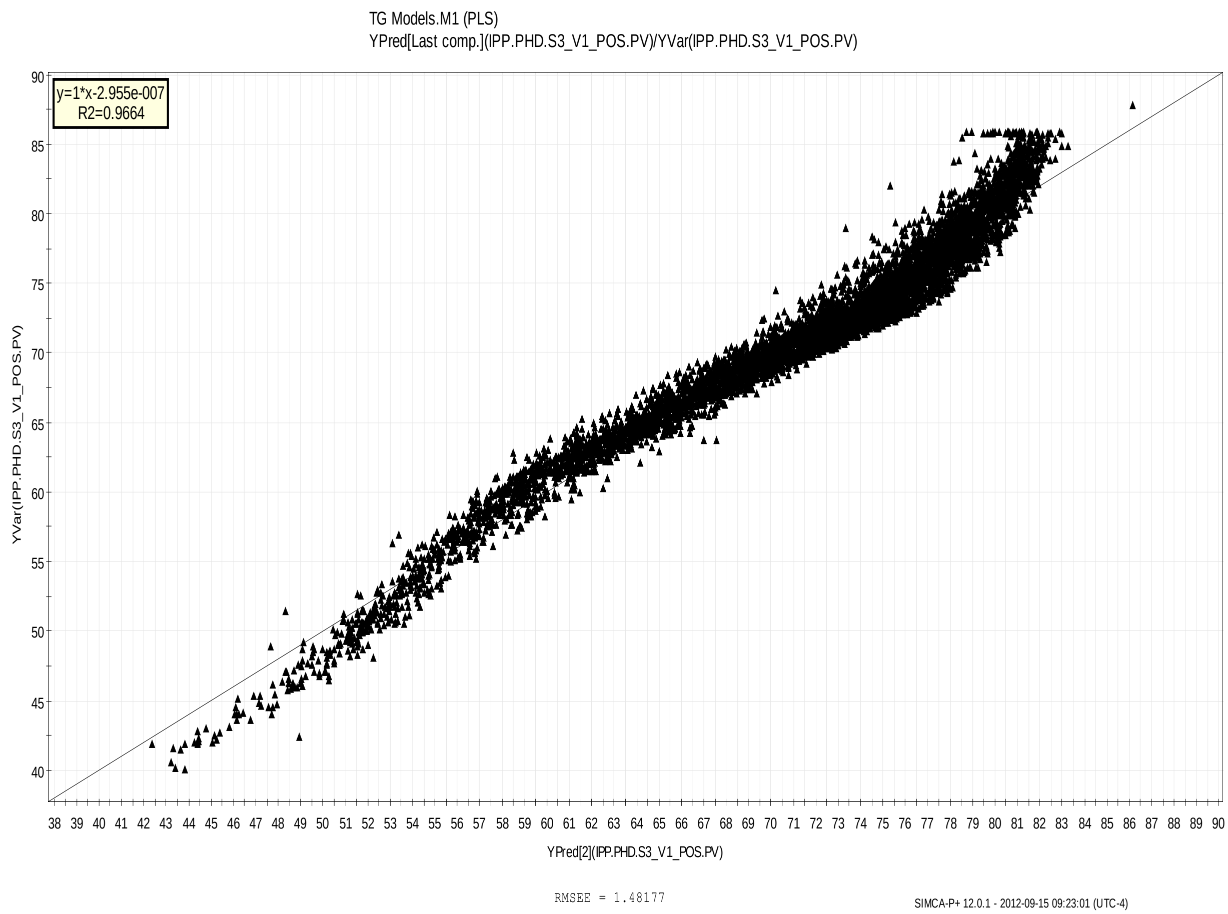

Figure 3.19 PLS Model for High Pressure Steam Inlet Valve Position

The model for the rack for the medium pressure steam valve position is shown in Table 3.4. Figure 3.20 indicates the correlation between the model predictor and the values. The line represents the prediction and the triangles represent the values observed. The correlation has an R^2 of 98.0%.

Table 3.4 PLS Model for Medium Pressure Steam Valve Position

Description	Units	Coefficient
Constant		18.8309
Condensing Turbine Power Produced	W	1.77982
Inlet Steam Valve Position	%	0.0795539
LP Steam to Condensing Valve Position	%	0.132002
MP Steam Extraction Flow	kpph	-0.138415
LP Steam Extraction Flow	kpph	0.380284
Exhaust Flow to Condenser	kpph	0.121333
Inlet Steam Flow	kpph	0.0156918

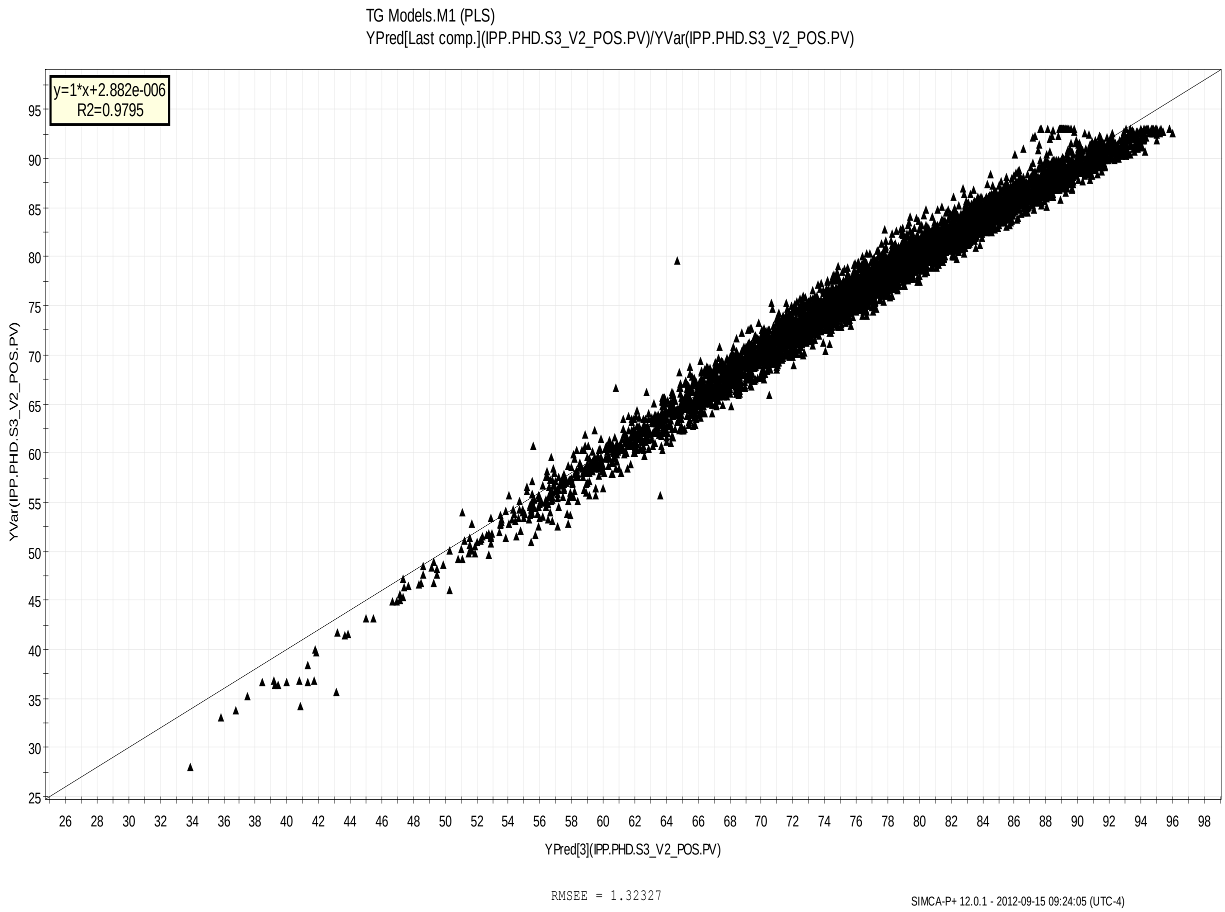

Figure 3.20 PLS Model for Medium Pressure Steam Valve Position

The model for the rack for the low pressure steam valve position is shown in Table 3.5. Figure 3.21 indicates the correlation between the model predictor and the values. The correlation has an R^2 of 98.4%.

Table 3.5 PLS Model for the Low Pressure Steam Valve Position

Description	Units	Coefficient
Constant		11.0019
Condensing Turbine Power Produced	W	2.57207
Inlet Steam Valve Position	%	-0.0312803
MP to LP Steam Valve Position	%	0.447266
MP Steam Extraction Flow	kpph	-0.106653
LP Steam Extraction Flow	kpph	-0.425585
Exhaust Flow to Condenser	kpph	0.392674
Inlet Steam Flow	kpph	-0.0139332

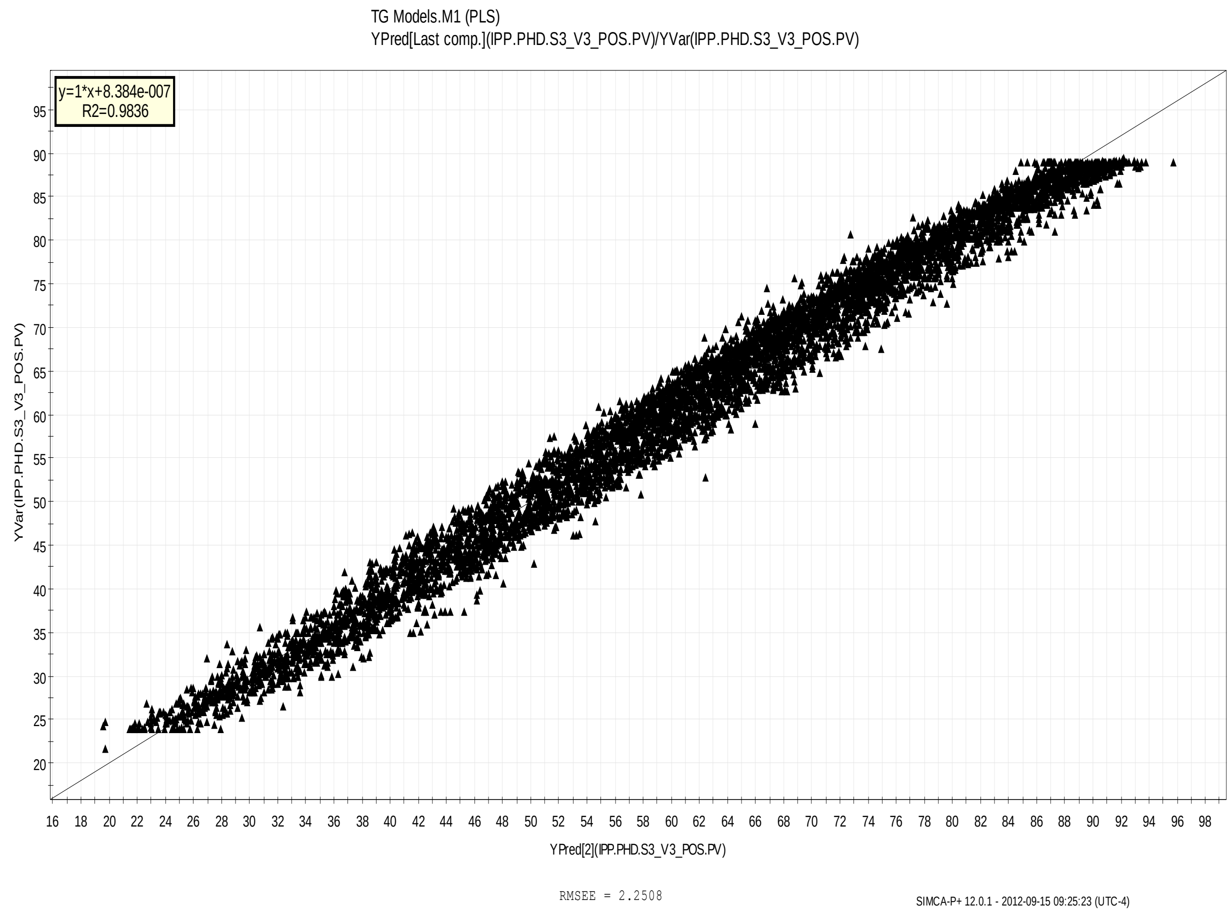

Figure 3.21 PLS Model for Low Pressure Steam Valve Position

The model for the power generated is shown in Table 3.6. Figure 3.22 indicates the correlation between the model predictor and the values. The correlation has an R^2 of 95.6%.

Table 3.6 PLS Model for Power Generation

Description	Units	Coefficient
Constant		-5.3753
Inlet Steam Valve Position	%	0.0648009
MP to LP Steam Valve Position	%	0.0630317
LP Steam to Condensing Valve Position	%	0.0246526
MP Steam Extraction Flow	kpph	0.00343281
LP Steam Extraction Flow	kpph	0.0112779
Exhaust Flow to Condenser	kpph	0.0232239
Inlet Steam Flow	kpph	0.0185729

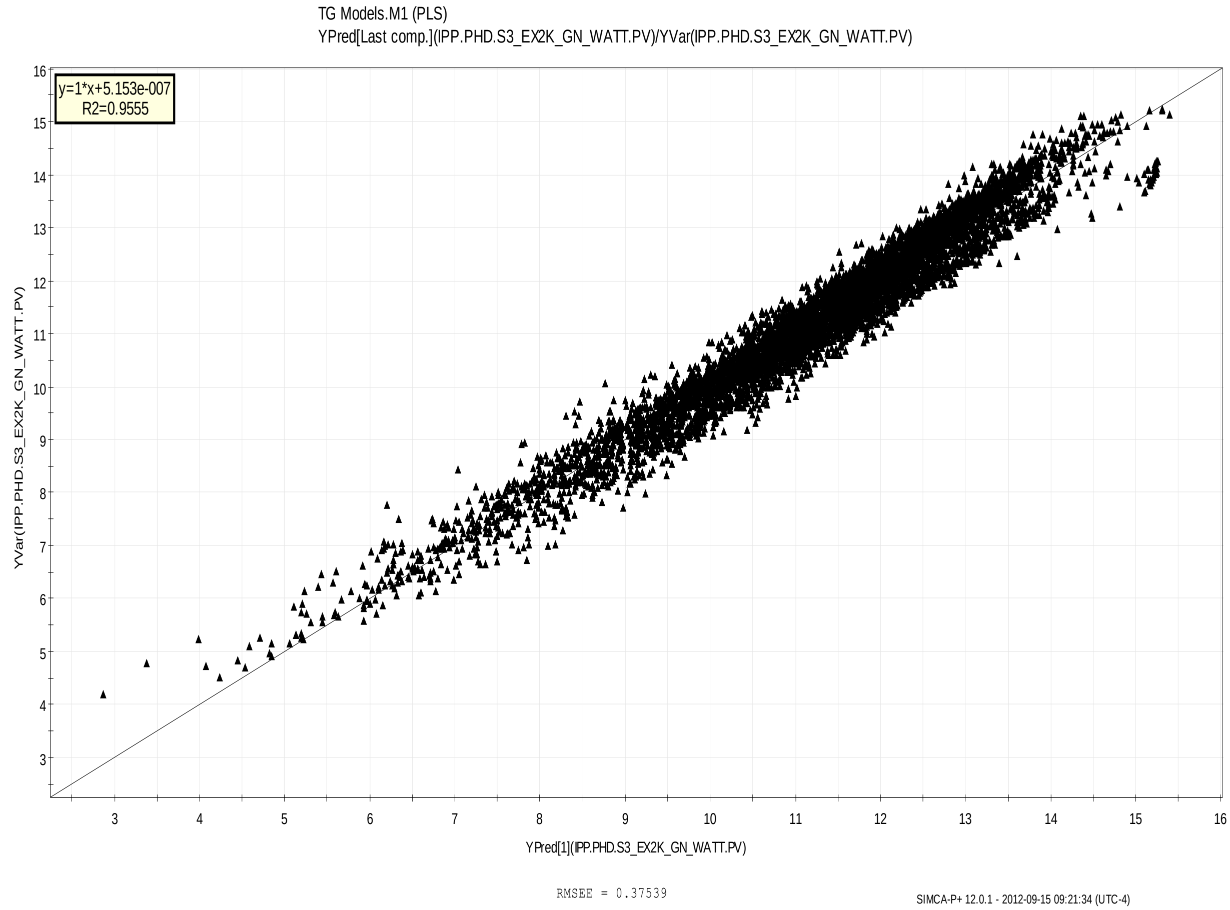

Figure 3.22 PLS Model for Power Generation

The data from the modelling is used to generate the factors that are applied to the variables to validate that the models can be used in the control environments. As well, the model must be constrained so that the process does not operate outside of the normal operating windows as this could have impacts on the safety, stability, or economic viability of the project. As this will be operated as a supervisory control, the interlocks and other safety protocols will be maintained.

The lags in the various components of the systems are taken into account in the modelling as well. Some factors have very short response times (e.g.: near instantaneous low pressure steam extraction valve position and power generation), whilst other components exhibit a considerable lag as in the case of increasing the hog fuel feed rate, which sees an eleven minute delay before increasing steam production.

The model predictive control is set up to handle constraints on manipulated and controlled variables. The model is set up with a set of dynamic models representing the process to predict the effects of future control moves on both the controlled and constraint output variables. An optimization routine is run to satisfy the process constraints and simultaneously minimize the performance index.

Control moves are set up for each of the control intervals; however, only the calculated move for the present is implemented. Process feedback is used to correct for any unmonitored and unmodeled process disturbances.

The model used for control is detailed in equation 6 below. The algorithm calculates a series of m future control actions at each control interval: in this case, one, two, three, five and ten minutes. These times represent the control horizon. The responses are calculated over the two hour prediction horizon and the process is optimized to minimize the error over the complete prediction horizon.

$$\min J = \begin{array}{l} \sum_{m\epsilon\{1,2,3,5,10\}} \left\{ \alpha_{BarkMasterOP} \left(\Delta BarkMasterOutput(t+m) \right)^2 \right\} \\ + \sum_{k=1}^{120} \left\{ \begin{array}{c} \beta_{MW} \left(MWTgt(t) - MW(t+k) \right)^2 \\ +\beta_{V1Limit} \left(V1Limit(t) - V1\,(t+k) \right)^2 \\ +\beta_{V2Limit} \left(V2Limit(t) - V2\,(t+k) \right)^2 \\ +\beta_{V3Limit} \left(V3Limit(t) - V3\,(t+k) \right)^2 \\ +\beta_{MWLimit} \left(MWLimit(t) - MW\,(t+k) \right)^2 \\ +\beta_{900\#Limit} \left(900\#Limit(t) - 900\#\,(t+k) \right)^2 \end{array} \right\} \end{array} \quad (eq. 6)$$

The equation above (eq. 6) sums the squares of the manipulated variables multiplied by the respective manipulated variable tuning weights added to the sum of the squares of the errors between the controlled and constraint variables multiplied by their respective tuning weights. One sided limits are also expressed in the same manner; however, the equation only manages the errors if they are outside the limit.

Tuning is accomplished by adjusting the individual weighting coefficients α and β. As α is increased the penalty associated with adjusting the manipulated variable increases; thus, decreasing the tendency for it to be moved. As β is increased, there is more impetus to get the controlled variable to target (because the associated error has a higher weighting) and therefore has a larger impact on the performance index (*J*).

A simplified demonstration is shown below. Figure 3.23 shows the manipulated variable. The control horizon is shown in green. The control horizon is the time in which the manipulated variable moves are projected. The dark blue vertical line indicates the current time. Figure 3.24 shows the output horizon for the predictive control in light blue. The output horizon is the timespan that the model projects the output. Again, the dark blue represents the current time. The lines before the current time represent both the actual variables values and the red lines represent the control limits or constraints.

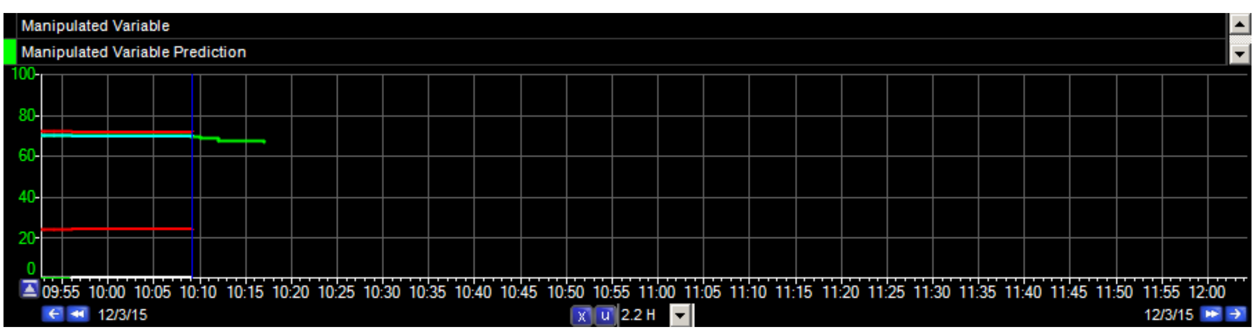

Figure 3.23 Manipulated Variable

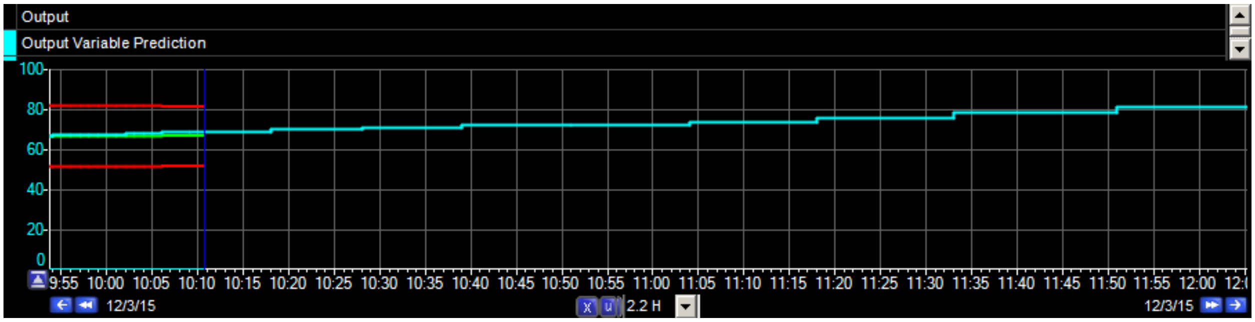

Figure 3.24 Output Variable

The controller in Figure 3.25 is set up with a number of inputs including the power generation target, the upper and lower pressure limits on the high pressure steam system, the limits on the medium and low pressure steam pressure reducing valves, the limits associated with venting the medium and low pressure steam, and the upper limits on the throttling valve trains in the generator (high pressure inlet, medium to low pressure rack and the low pressure to condenser rack) that will all drive the hog fuel master air flow. The controller is set up to recalculate every minute.

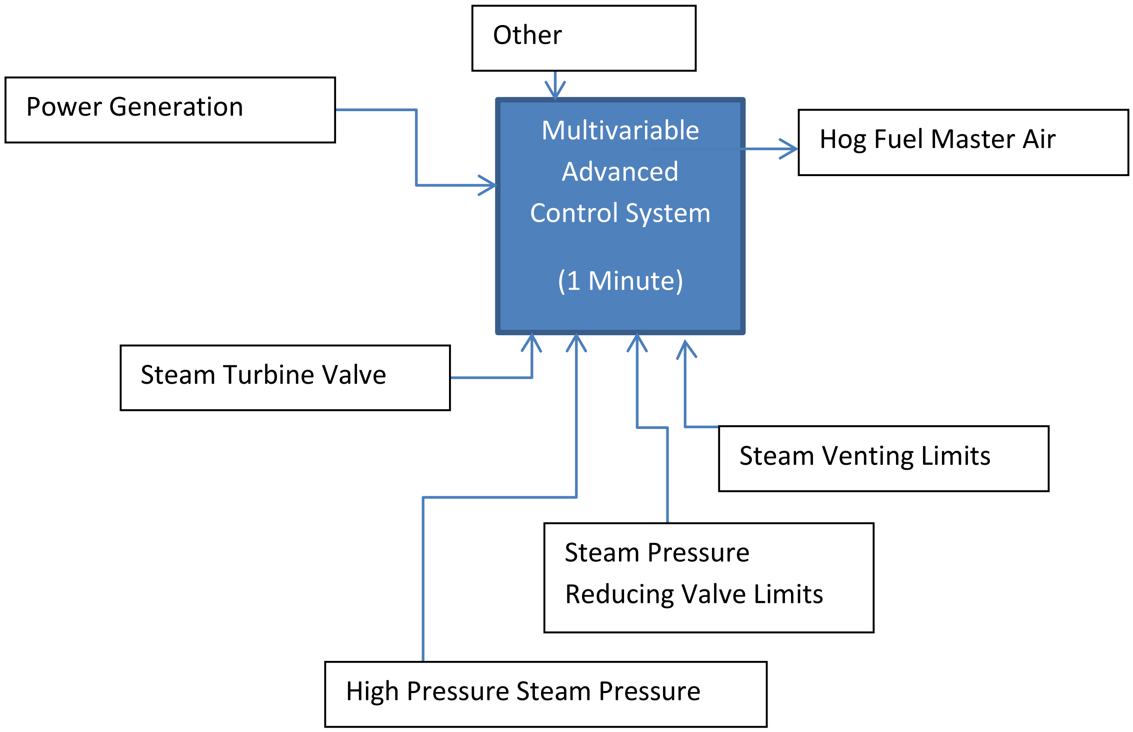

Figure 3.25 Multivariable Advanced Controller set up

The multivariable advanced controller uses two matrices to control and predict the output variables. The prediction matrix projects the future process responses based on the historical inputs. It calculates the optimal set of manipulated variable set-point changes to improve the predicted future response of the matrix. The represented matrix is shown in Table 3.7 below.

Table 3.7 Controller Model Matrix

Relationships for the hog fueled boiler		**Manipulated Variable**	**Feed Forward Variables**		
		Bark Boiler Air Flow (%)	**Natural Gas Flow (KSCFH)**	**Digester Medium Pressure Steam Flow (kpph)**	**Pulp Dryers (Each) Steam Flow (kpph)**
Controlled Variable	**Power produced by turbine – filtered (MW)**	A=0.96, B=0.033 Delay: 2 Min	A=0.66065, B=0.064825 Delay: 0 Min	A=0.88 B=-0.012 Delay: 0 Min	A=0.88 B=-0.012 Delay: 0 Min
Constraint Variables	**MP Steam Venting (%)**	MV forced down if venting AND V3 is maxed			
	LP Steam Venting (%)	MV forced down if venting			
	Feed Conveyor (Amps)	MV forced down if Amps low			
	HP to MP Valve Position (%)	MV forced down if V1 open too much			
	MP to LP Valve Position (%)	A=0.93 B=0.5 Delay: 5 Min	A=0.6607 B=0.286 Delay: 0 Min	A=0.639538 B=-0.131744 Delay: 0 Min	A=0.639538 B=-0.131744 Delay: 0 Min
	Condensing Valve Position (%)	A=0.93 B=1.0 Delay: 5 Min	A=0.6607 B=0.5721 Delay: 0 Min	A=0.639538 B=-0.263489 Delay: 0 Min	A=0.639538 B=-0.263489 Delay: 0 Min
	Power produced by turbine (MW)	A=0.96, B=0.033 Delay: 2 Min	A=0.66065, B=0.064825 Delay: 0 Min	A=0.88 B=-0.012 Delay: 0 Min	A=0.88 B=-0.012 Delay: 0 Min
	High Pressure Limit (psi)	A=0.0 B=5.082915 Delay: 1 Min			

The variables with models within the Bark Boiler Air Master will all influence the Bark Boiler Air Master output. We can approximate from the equation in equation 6 above that the deviation squared multiplied by the tuning weight (β) is how much that variable wants to move the Bark Boiler Air Master. This amount can be divided by the tuning weight for the Bark Boiler Air Master (α) to give the movement amount. This amount is compared with the maximum rate of change that has been set and is adjusted accordingly.

If the desired rate control for a variable is to be increased (there is a need to move the Bark Boiler Air Master more aggressively) the tuning weight for the variable (β) could be increased, provided the rate of change allowed for the Bark Boiler Air Master is not compromised. If the Bark Boiler Air Master were at the maximum rate of change permitted, that limit could be increased to allow for a greater response. Conversely, the Bark Boiler Air Master tuning weight (α) could be decreased (assuming again, that the rate is below the maximum rate for the Bark Boiler Air Master)

The projection models for three of the relationships are shown below. Figure 3.26 shows the response of the high pressure steam header pressure to an increase in the Bark Boiler Air Master set-point. It can be seen that the response is positive: an increase in hog fuel flow increases the header pressure.

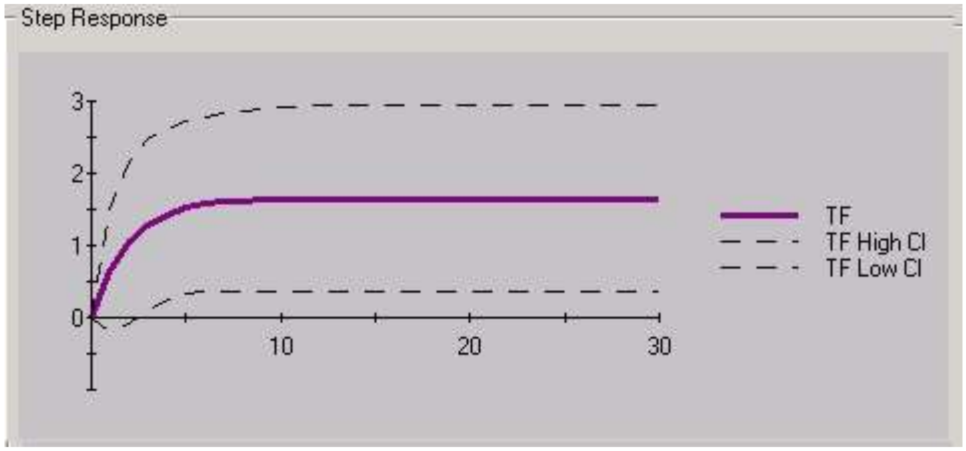

Figure 3.26 High Pressure Header Pressure Response to an increase in the Bark Boiler Air Master Set-point

Figure 3.27 shows the response of the low pressure to condensing stage valve rack to an increase in the steam flow to the digesters. It can be seen that the response is negative: an increase in steam flow decreases the valve rack position.

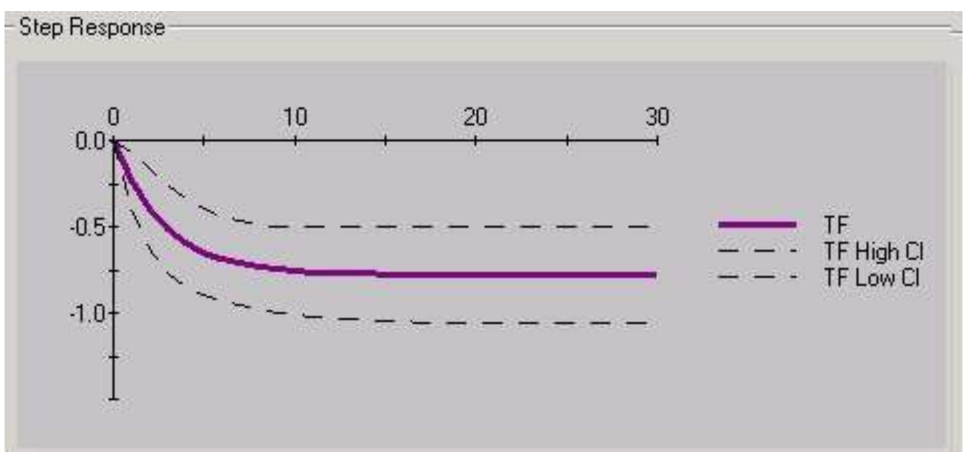

Figure 3.27 TG Condensing Valve Response to an increase in the Digester Steam Flow.

Figure 3.28 shows the response of the generator power production to an increase in the steam flow to the generator. It can be seen that the response is positive: an increase in the steam flow to the generator with other variables held constant increases the power generation. This response is much sharper and quicker than the previous curves.

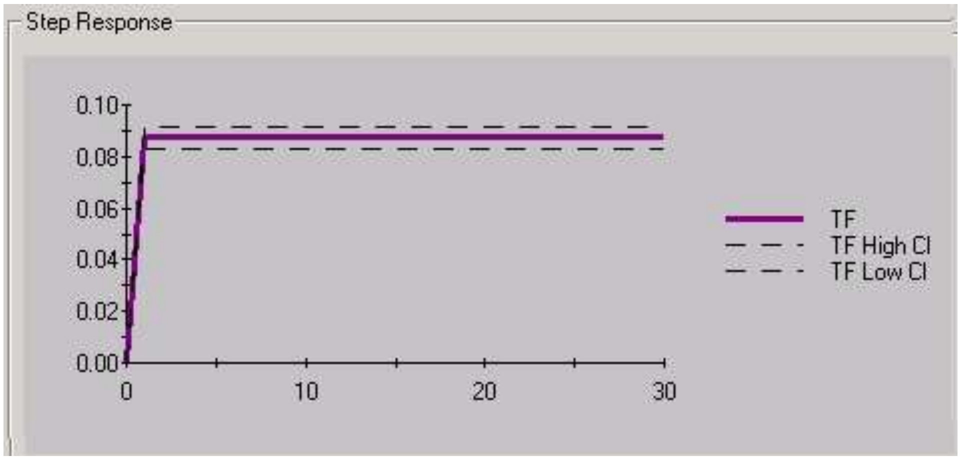

Figure 3.28 Power Generation Response to an increase in the Steam Flow

These curves were developed for the variables involved in the projection models and the control models for the boiler to ensure that the models take into account the response times of changes to the variables.

3.8 Experimental

An advanced controls server was added to the process LAN. Capstone's Multivariable Advanced Control System was chosen as the supervisory controls. It is connected via OPC to the DCS with two way data transfer. Once the process is modeled and the necessary constraints are established, the gains are determined and the process lags are established, the model is input into the server.

The DCS interface is shown in Figure 3.29 below. The system could be initiated by selecting the Bark Adv Controls button in the top right. The display is divided into three groups: the Manipulated Variable, the Controlled Variable, and the Constraint Variables.

MANIPULATED VARIABLES

VARIABLE	DESCRIPTION	MV LO	MV HI	SP	PROJ	OUT	WIND-UP	PV
1- 53PC098B	Bark Boiler Air Flow	39.0	70.0	885.0	59.5	60.0	OK	892.8

CONTROLLED VARIABLES

VARIABLE	DESCRIPTION	TARGET	PV	PROJ
1- S3_DWATT	S3 Power Produced	13.0	13.6	13.4

CONSTRAINT VARIABLES

VARIABLE	DESCRIPTION	LOWER	UPPER	PV
1- 50PC1603	150# Steam Vent Pos	------------	5.0	24.0
2- 50PC1604	50# Seam Vent Pos	------------	5.0	0.9
3- 53II3303	BB Feed Cnvr Amps	18.5	------------	21.0
4- S3_V1_POS	V1 Position	------------	98.0	78.0
5- S3_V2_POS	V2 Position	------------	92.0	93.0
6- S3_V3_POS	V3 Position	------------	88.0	89.0
7- 53TI639	Furnace Temp A	1000.0	------------	1286.0
8- 53TI638	Furnace Temp B	1000.0	------------	1276.3
9- 53II3140	ID Fan Amps	------------	310.0	234.4
10- S3_DWATT	S3 Power Produced	11.0	15.0	15.6
11- 50PC001	150# PRV Position	------------	5.0	0.0
12- 50PC002	50# PRV Position	------------	5.0	0.0
13- 53PC098B	Bark Boiler Master	850.0	900.0	892.8

MACS Advanced Controls are offline
Small Dig going to steam in 14 min

Figure 3.29 Multivariable Advanced Control DCS Interface

The manipulated variable is the variable that the advanced control will manipulate. In this case it is the Bark Boiler Air Flow for the hog fuel boiler. There are a number of fields shown on the graphic above (Figure 3.29). MV LO is the lowest value for the set-point that the control will set. MV HI is the highest value for the set-point that the control sets. SP indicates the current set-point. PROJ is the projected final set-point (in ten minutes). WIND-UP is the wind up state of the control loop accepting the set-point, and finally PV is the current value for the Bark Boiler Air Flow.

The controlled variable is the power generated on the condensing turbine. The TARGET is entered by the operator to set the amount of power to produce. PV is the current value and PROJ is the projection at the end of the prediction horizon (two hours into the future). The power produced is controlled by adjusting the Bark Boiler Air Flow output. The power produced has an α of 0.96 and a β of 0.04 (25 minute time constant). If α (the tuning weight) is increased, the controller more aggressively attempts to keep the power production on target. When the controller is on, the Bark Boiler Air Flow output adjusts the hog fuel flow according to the air/bark curve. An increase in the output increases the power produced as well as the positions of the medium to low pressure and low pressure to condenser valve trains in the turbo generator.

The constraint variables are the variables with high and/or low limits. LOWER and UPPER indicates the lower and upper limits for the constraint variables respectively. PV represents the current value of the respective constraints. PROJ is the projected value at the end of the prediction horizon (two hours into the future).

Both the low pressure steam vent valve and the medium pressure steam vent valve have upper constraints (typically 5%). The Bark Boiler Air Flow steps down (0.3% per minute) to keep the vent valve below the constraint.

The Boiler Feed Conveyor Amperage has a low limit (two amps below the last twelve hour running average current). This would be an indicator of a lack of fuel flow to the boiler. The controller steps down the Bark Boiler Air Flow (5% per minute) when this condition is met.

The turbo generator valve positions all have upper constraints. The feed to the turbo generator has an upper constraint of 98%, the medium to low pressure valve position has an upper constraint of 92%, and the low pressure to condenser valve has an upper constraint of 88%. When the upper limits are exceeded, the controller steps down 0.4% per minute.

The furnace lower temperatures have a low limit. A cooler lower furnace may be an indication of poor hog fuel burning. When the limit is violated it is dropped by 0.4%

per minute. The ID Fan Amperage has an upper limit. When the limit is exceeded, the controller will step down 0.4% per minute. This is typically associated with high moisture in the hog fuel.

The instantaneous power and high pressure header have both an upper and lower limit. The Bark Boiler Air Master would be adjusted to compensate at 0.4% per minute. The high pressure steam also sets the wind-up bit for the Bark Boiler Air Master when the pressure is above 900 psi. Also, if the pressure is above 905 psi, the Bark Boiler Air Master output is dropped by 3.5%.

Both the medium and low pressure vents have an upper constraint typically at 5%. If either of these constraints are violated the Bark Boiler Air Master will be reduced by 0.4% per minute.

There are also feedforward variables that have models built relating the variable and the manipulated variable. These include the Natural Gas Flow Master which will increase the power production if there is not a corresponding decrease in the hog fuel flow. As well, the medium pressure steam users: the batch digesters and the pulp dryers would have an impact on power production. As the users draw more steam, there will be a corresponding decrease in power production without a corresponding increase in the hog fuel flow. The tuning parameters for control are highlighted in Table 3.8 below.

Table 3.8 Tuning Parameters for the Multivariable Advanced Controller

Manipulated Variable	Min	Max	Rate Limit	Tuning Weight
Bark Boiler Air Master	39	70	0.4	1000

Controlled Variable	Target	Tuning Weight
Condensing Turbine Power	13	0.8

Constraint Variables	High Limit	Low Limit	Tuning Weight	Ramp Factor
Medium Pressure Vent Valve Position	5%		1	0.30%
Low Pressure Vent Valve Position	5%		1	0.30%
Bark Feed Conveyor Amperage		12 hr avg -2A	1	5%
Turbo generator Steam Inlet Valve Position	98%		1	0.40%
Med to Low Press TG Valve Position	92%		200	
Low Press to Condenser TG Valve Position	88%		30	
Lower Furnace Temperatures		1000	1	0.40%
Hog Fuel Boiler ID Fan Amperage	310 A		1	0.40%
Power Production	15	11	5	
HP to Med Press PRV Valve Position	5%		1	0.40%
Med to Low Press PRV Valve Position	5%		1	0.40%
Hog Fuel Boiler Steam Pressure	900 psi	850 psi	20	
Hog Fuel Boiler Steam Pressure	900 psi		1	0
Hog Fuel Boiler Steam Pressure	905 psi		1	3.50%

Initially, when the controls were turned on, there was a tremendous focus on monitoring the performance of the system, ensuring that the system was making the appropriate adjustments at the appropriate time and in the appropriate way.

For the first two months, the multivariable advanced controller was only run when it was being monitored by an engineer familiar with the system as the tuning weightings were optimized to give the appropriate responses. It was necessary to ensure that the controller was able to respond appropriately to the majority of process conditions and that it would disengage appropriately when conditions warranted.

3.9 Advanced Controller and Distributed Control Interface

The Distributed Control System (DCS) is connected to an OPC server that allows for two way communication. The Open Platform Communication (OPC) server is connected to the Multivariable Advanced Control Server (MACS) as an OPC Client as can be seen in Figure 3.30 below.

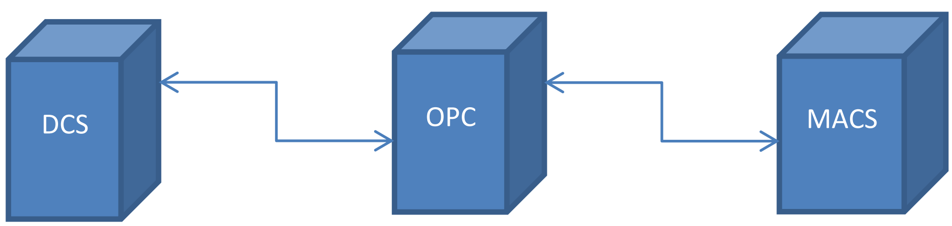

Figure 3.30 Communications from the DCS through to the Advanced Controller

The DCS provides the information necessary for the Advanced Controller to perform the required calculations. It passes the critical information, such as pressures, temperatures, and valve positions to the DCSs OPC server. The MACS is a client to the OPC server and reads the provided data, performs the calculations, and passes the information back through the OPC server to the DCS.

Chapter 4

Results

The focus of this thesis is to create models of the steam and power systems of a kraft pulp mill, to evaluate the models, and to develop a control system based on those models.

PCA and PLS methods were used to determine the relationships between the variables and develop control strategies to maximize power generation and minimize losses. After the initial optimization phase, the advanced controller was operated and compared to a baseline where the controller was off. Figure 4.1 shows the comparison for the power production. This represents an estimated 2.221 MWh increase (21.95%) with a P value of 0.000 with 95% confidence. Figure 4.2 shows that in addition to increasing the power generation, the valve position for the steam step down for the high to medium pressure reducing station is reduced by an estimate of 1.998% (P value is 0.000). The same can be said for the valve position for the steam step down for the medium to low pressure reducing station shown in Figure 4.3. The valve is an estimated 3.418% further closed (P values is 0.000). Figures 4.4 and 4.5 show the same results for the medium and low pressure steam vents respectively. Although the valves are only 0.2446% more closed the P values of 0.002 and 0.001 respectively indicate they are statistically significant. The results indicate that the process steam demands can be met, header venting can be minimized, and the controls can be operated in a manner to maximize power generation on hog fuel.

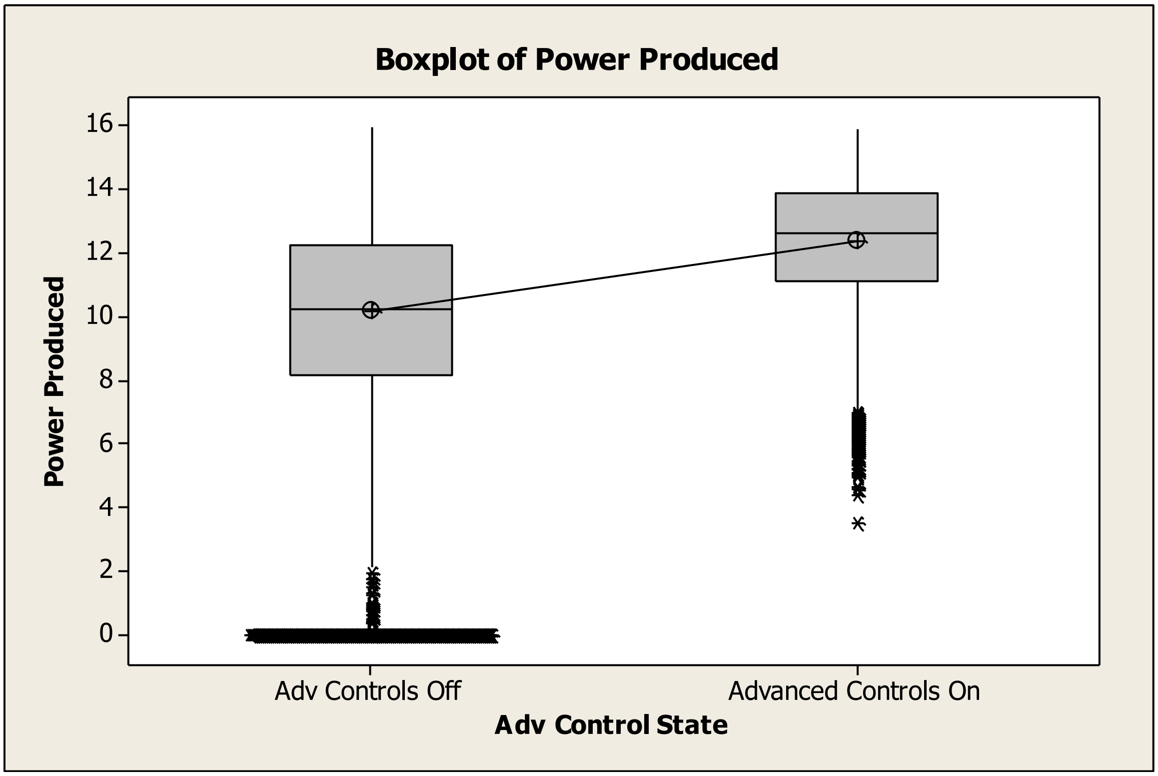

Figure 4.1 Power Production Comparison of when the system is Controlled by the Advanced Controls versus the Conventional Controls

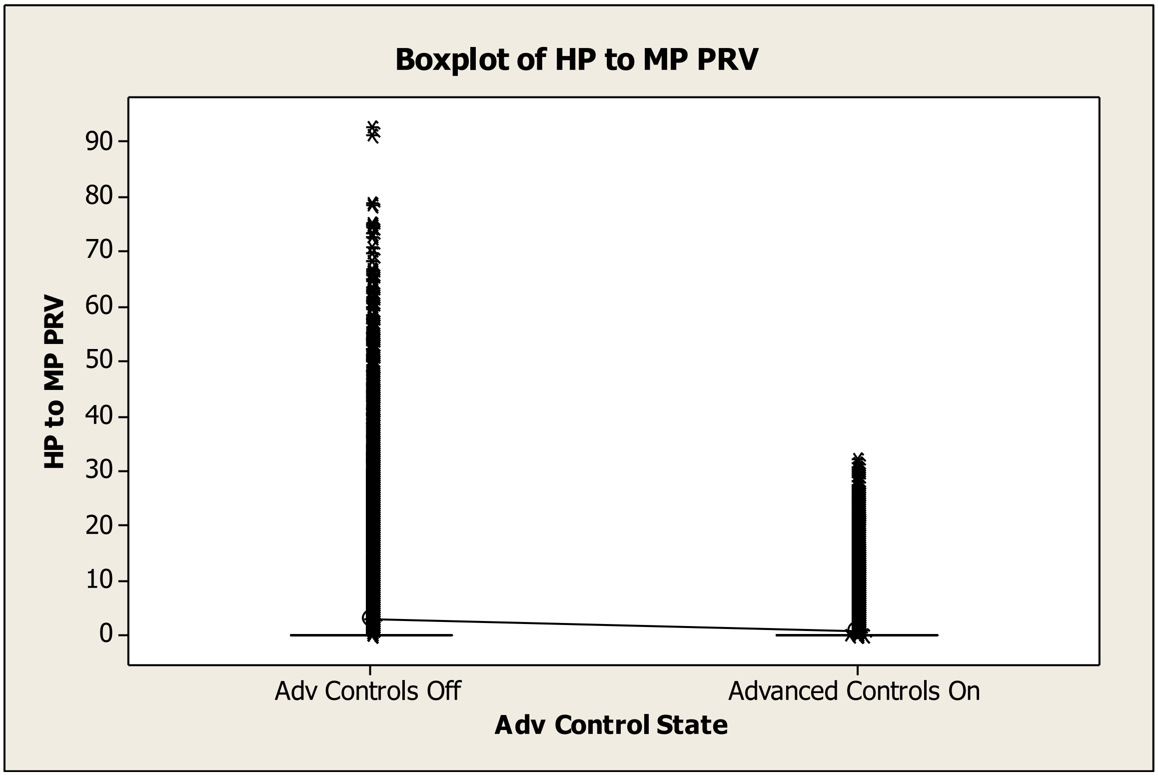

Figure 4.2 High to Medium Pressure Reducing Station Valve Position Comparison of when the system is Controlled by the Advanced Controls versus the Conventional Controls

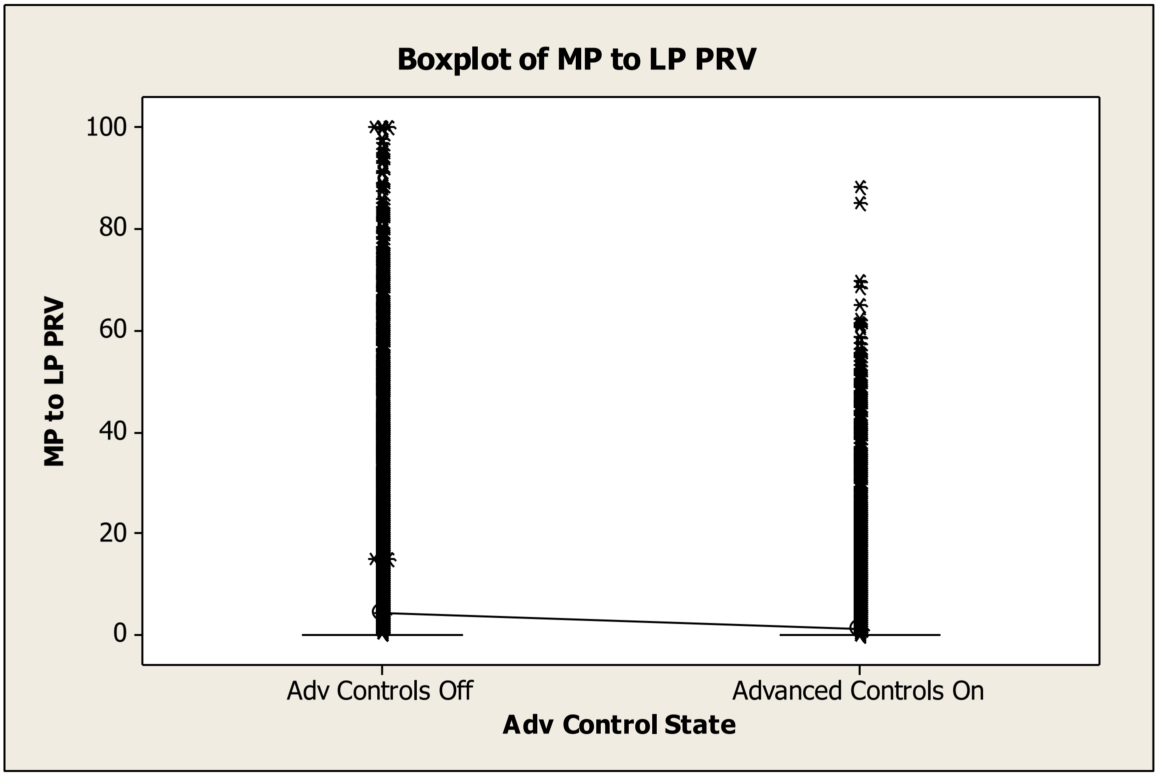

Figure 4.3 Medium to Low Pressure Reducing Station Valve Position Comparison of when the system is Controlled by the Advanced Controls versus the Conventional Controls

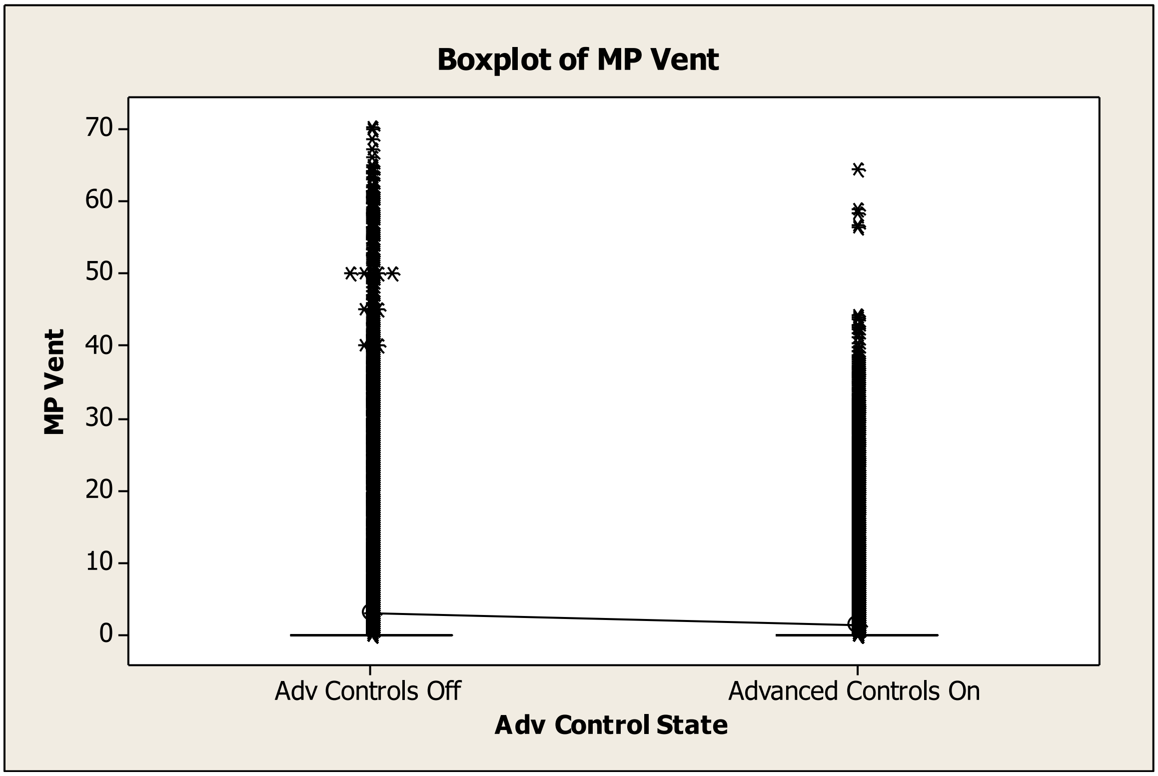

Figure 4.4 Medium Pressure Steam Vent Valve Position Comparison of when the system is Controlled by the Advanced Controls versus the Conventional Controls

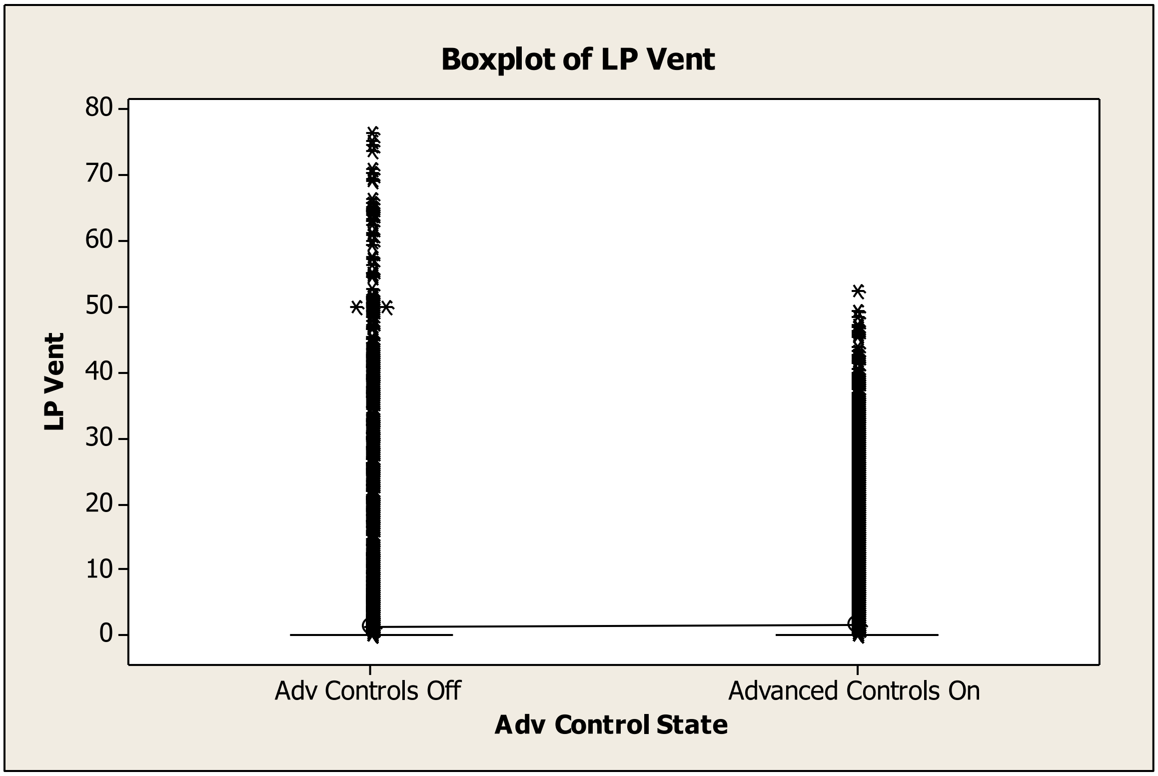

Figure 4.5 Low Pressure Steam Vent Valve Position Comparison of when the system is Controlled by the Advanced Controls versus the Conventional Controls

When the operators are solely focused on maximizing power production, providing steam to the process, minimizing venting, and maximizing hog fuel burning and have a complete understanding of the process interactions they can match and, at times (due to their knowledge of parameters that are not detailed in the models or of events that will occur) can outperform the advanced controls. However, this cannot be maintained as they are required to monitor many other process parameters as well.

Chapter 5

Conclusion

The predictive and control models performed well and facilitated the implementation of the advanced controls. The analysis techniques provided not only the relationships between the key variables and the predictions for power generation, but also encompassed the delays associated with those interactions. The objectives of this work were to provide models and provide controls sufficient to maximize hog fuel burning, minimize venting, provide sufficient process steam, and to optimize the turbo generator settings (optimize power production). These objectives were satisfied resulting in an increase of 2.2 MWh of hog fueled power produced, no interruption of process steam users, and statistically significant reductions in steam venting.

The PCA analysis provided information on the interrelationships between the key process parameters. The PLS model provided a prediction of the power generation. Bump tests were performed on the key variables to provide the response curves. Individual process constraints were also validated and limits were established. The models were coupled with the time responses and the process constraints to develop a multivariable advanced controller that did meet the project goals. Not only did this process make the advanced controls possible, but the process improved the understanding of the operators and others associated with this process area.

The results demonstrated that the PCA and PLS models when coupled with the process data from a complex pulp mill steam system that has many swings in demands, and feeds can be positively impacted by the implementation of a multivariable advanced controls system.

In commodity manufacturing operations, where the selling price is set externally, it is optimization and process improvement that drives financial success. This improvement in the energy efficiency of this mill helps to ensure that this mill is competitive into the future.

5.1 Recommendations

The complex pulp mill process environment is continuously being updated and optimized. Process steps are added or changed to improve efficiency, meet new regulations, or reduce costs. It is important to ensure that the models are periodically validated and updated as appropriate to ensure that the maximum benefit is being realized at all times. Small changes to the system may each be considered to have a negligible effect; however, when combined, these changes may have an impact on the model. In this case an increased use of steam for intermittent blow off or heating may not as a single user cause issues with the controls; however, if there were multiple applications that were not coordinated well, this could require an adjustment to the controls to maintain efficiency. Similarly a change from batch to continuous cooking would require a significant update to the models as this would have a huge impact on the medium pressure users.

It is clear this type of modelling technique has many applications in the mill environments and should be evaluated for implementation for systems that require heavy monitoring and adjustments to remain optimized and for systems that the interactions are not straight forward, that is complex systems with many variables. Examples include lime kiln and causticizing operations, bleach plant chemical dosing, and evaporator controls.

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GLOSSARY OF TERMS

Performance Index: Measure of the error associated with the variables in the system

Prediction Horizon: Time into the future that the system will predict the output variable

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