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Model Predictive Control for Temperature Dependent Systems

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MODEL PREDICTIVE CONTROL FOR

TEMPERATURE DEPENDENT SYSTEMS

by

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ABSTRACT

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Manipulating and monitoring the variables of temperature dependent systems can be a very complex task for most industrial facilities since they require either the close attention of experienced engineers or highly expensive control programs. These systems are often poorly operated, which increases the cost of production and affects the overall performance of the process. This paper aims at proposing a solution to this problem using adaptable Model Predictive Control (MPC) algorithms for temperature dependent systems and computational methods to optimize their performance, while maintaining a stable temperature within the process. This research investigates and evaluates MPC and compares its performance to manual procedures for controlling temperature dependent systems. The method being investigated approximates future output process values like chemical concentrations in order to determine accurate set point changes to input variables that keep them at their desired targets. In addition, the algorithms in this program match predetermined temperature patterns that indicate if the input variables of the system are correctly balanced for operating at the desired production rate. Balance is achieved by using PID closed-loop control procedures on the output variables, as well as data storage algorithms to help reduce the error of future set point computation.

ACKNOWLEDGMENTS

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Special thanks also to Alejandro Otero and Trygve Lund who collaborated doing some of the chemical testing which allowed me to calibrate and debug this steady state predictive controller. Alejandro showed me how engineers and technicians who are capable of combining concepts of Chemistry and Computer Science are destined for success.

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INTRODUCTION

Problem Statement

Nowadays, the economy of several developed and semi-developed countries depends on industry. Since the demand of production is every day larger, companies are always looking for new ways to maximize the efficiency and therefore the profit of their industrial facilities. Instruments such as control valves and pumps, as well as, different types of sensors make it possible to control the process and to monitor the performance of each area of an industrial plant. Through set point changes like those shown in Figure 1, control systems allow operators to control the production rate and all other outputs of the system.

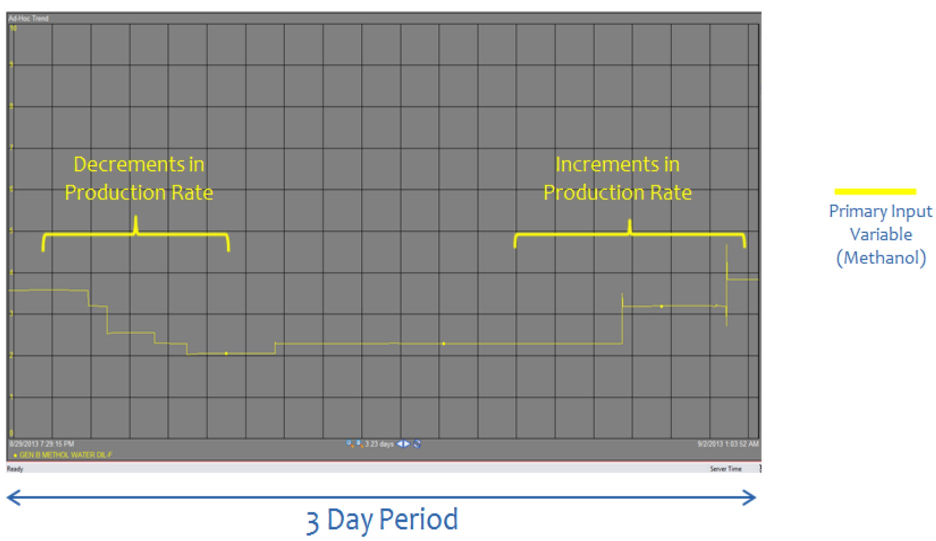

Figure 1. Set Point Changes Made to a Primary Output Variable to Control the Production Rate**.** This image shows set point increments and decrements made during a 3-day period to control the production rate of the system to supply the demand.

In order for operators to effectively maximize the efficiency of a system, they need to make accurate set point changes since these changes must maintain the balance of all variables after every change of production. However, as companies acquire more and more equipment, as well as more complex methods of monitoring the process, operators are often overtaken by the large number of processes they need to monitor. Here is where the first problem presents itself because operators often have too many processes to monitor and therefore they cannot pay close attention to all of them. This large time lapse without process monitoring disrupts the balance of all variables, drastically reducing the efficiency of the system and increasing the costs of production.

Another problem arises when set point changes made are inaccurate. This happens because controlling temperature dependent systems requires the close attention of experienced personnel who know how to effectively maintain the ratios of all variables. The most common method for performing set point changes is by feel, where operators choose arbitrary values for the new set points which often cause radical changes on the temperature of process. This arbitrary set point changes are rarely effective, which is one of the reasons why temperature dependent systems almost never come to a steady state. An example of these two problems is shown in Figure 2. Here, one can observe that there are periods of up to 5 hours, where no changes were made. This image also shows that inaccurate set point changes are very common when controlling this type of systems.

As a result of the system being unbalanced for several hours and also because of constant inaccurate set point changes, temperature dependent systems run at unbalanced conditions for most of the time they are manually operated. As it was mentioned before, these unbalanced conditions affect the efficiency of the system. However, this is not the only problem because these conditions also increase the danger in the work place since they cause unstable temperatures that can reach dangerous limits, decreasing the reliability of the equipment. Figure 3, shows the result of these problems and one can observe that for all this period of time, the system is clearly unbalanced. There are a few computational methods that attempt to solve these problems; however, they are developed and maintained by third parties at extremely high prices making them often unaffordable to small industrial facilities.

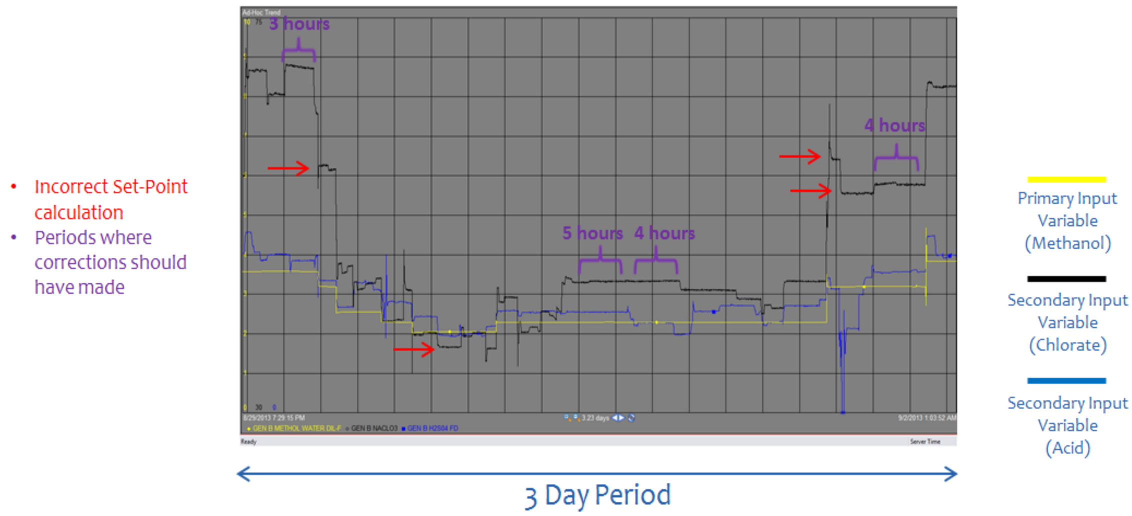

Figure 2. Inaccurate Set Point Changes and Manual Operation Periods without Monitoring. This image shows how manual operation often results in inaccurate set point changes for a particular production rate and long periods of time without monitoring.

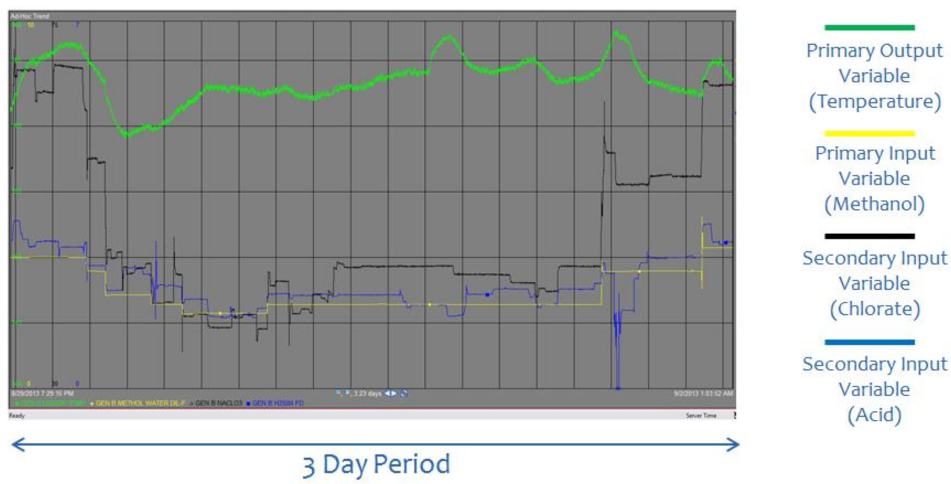

Figure 3. Resulting Unsteady Temperature from Improper Operation.
This image illustrates the resulting temperature due to the lack of constant and proper monitoring.

Previous Works

Bleach Plant PID and APCS Control by Guy Dumont, Juan Martin-Sanchez, and Christos Zervos (1989)

This paper describes a hybrid control system developed at the University of British Columbia that incorporates an auto-tuned PID regulator and an adaptive predictive control system (APCS) in order to take advantage of their particular features and get rid of their individual limitations. The creators of this program performed a study of each type of control system and they realized that the results for each were very much case dependent. From this study, they developed a methodology consisting of three steps to tune the constants needed for the particular chlorine dioxide generator. They first make a set point change using a Pseudo-Random-Binary-Signal (PRBS) that allows them to obtain the sizes of the response knowing settling time. After this, they use Laguerre computations of the closed loop system to determine the error of the response. Finally, with this process they are able to determine the tuning constants for the system.

Similarly to the steady state predictive controller that is being investigated in this thesis, this control system uses PID and predictive algorithms with the main objective of minimizing chemical consumption while maintaining high quality standards of all products. In addition, this software solution also aims at making the output equal to a desired value at some instant in the future by computing a sequence of control signals for the particular production rate. However, instead of using chemical stoichiometry and mass balance equations to determine the size of the set point changes, they use Laguerre functions to approximate future responses. The creators of this control system tested their program with a fiber line process. The results they obtained are shown in Figure 4 and these results demonstrate that the program effectively manipulated the output to its desired set point, but it is clear that the oxidation reduction potential ORP was far from steady.

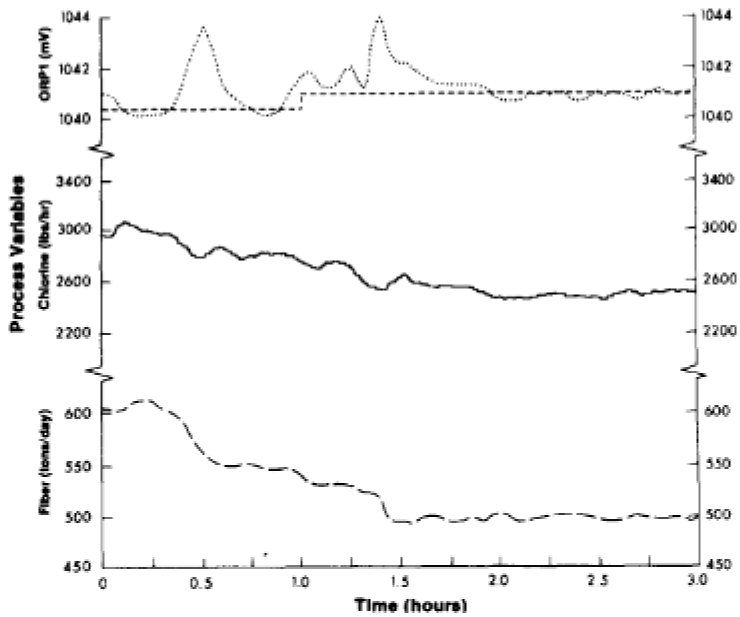

Figure 4. Set Point and Load Changes with Dumont, Martin-Sanchez, and Zervos' PID-APCS Control.

Advanced Predictive Adaptive Control of After Tower pH Control at Androscoggin Mill by Bill Gough, Sava Kovac, and Adam Webster (1995)

This thesis describes the application of an advanced predictive-adaptive process controller on after tower pH control. The creators of this control system had the task of improving the performance of a system that was being controlled manually and by an advanced controller. The control performance was poor in both cases. Similarly to the research done for this thesis, they performed laboratory sampling in order to determine the optimum bleach gain for a specific pH level. They had major difficulties with the dead times five times longer than a time constant, but they did demonstrate the advantages that paper makers can achieve by implementing regulatory process control in their processes.

Gough, Kovac, and Webster (1995) started the development of this model-based predictive adaptive controller by using Dumont and Zervos' research on mathematical representation of process response. They used a series of approximation techniques based on Laguerre polynomials and they efficiently modeled the dead time in the process response. These calculations allowed the process to reach the desired set point as rapidly as possible with little or no overshoot. In addition in the event of a fault the controller will automatically fall back to the original control. The following graph shows the performance of the process before and after Gough, Kovac, and Webster's APC control.

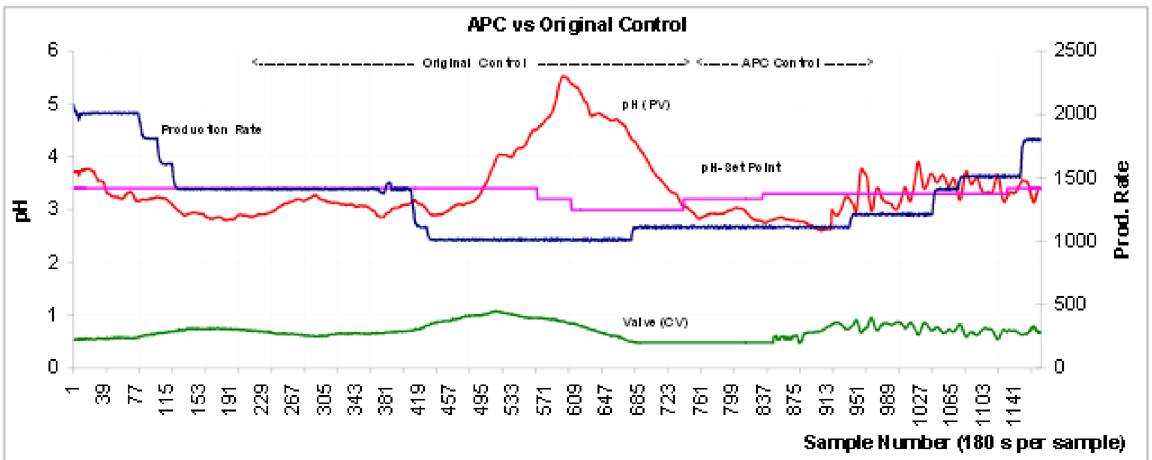

Figure 5. Performance Comparison Before and After Gough, Kovac, and Webster's APC Control.

Chlorine Dioxide Model Predictive Control Application By Rockwell Automation Solutions (2012)

Rockwell Automation is one of largest providers of power, control, and automation solutions in the world. One of their software and service packages offered by Rockwell Software is a Chlorine Dioxide Model Predictive Control Application. This predictive solution has the main purpose of maximizing the efficiency, yield, and stability of a chlorine dioxide generator while reducing operator oversight. Thanks to decades of research, this predictive solution offers several advantages such as management of solids, better management of concentrations, an many other features that can improve the performance of a chlorine dioxide generator.

The developers of this predictive control describe this program as a multivariable application that controls the interactions between all inputs that impact the generator reaction and the process limits that must be met in order to run the generator steadily. The program does this by manipulating the generator chemical feed rates as the bleach plant demand fluctuates to maintain the inventory at target. After their research they determined that it is much more cost-efficient to run the generator at a production rate that would meet the demand, instead of running it at a high production rate to fill up storage tanks and then turning the system off. The following graph shows how this program successfully controls the sodium chlorate concentration to the desired set point.

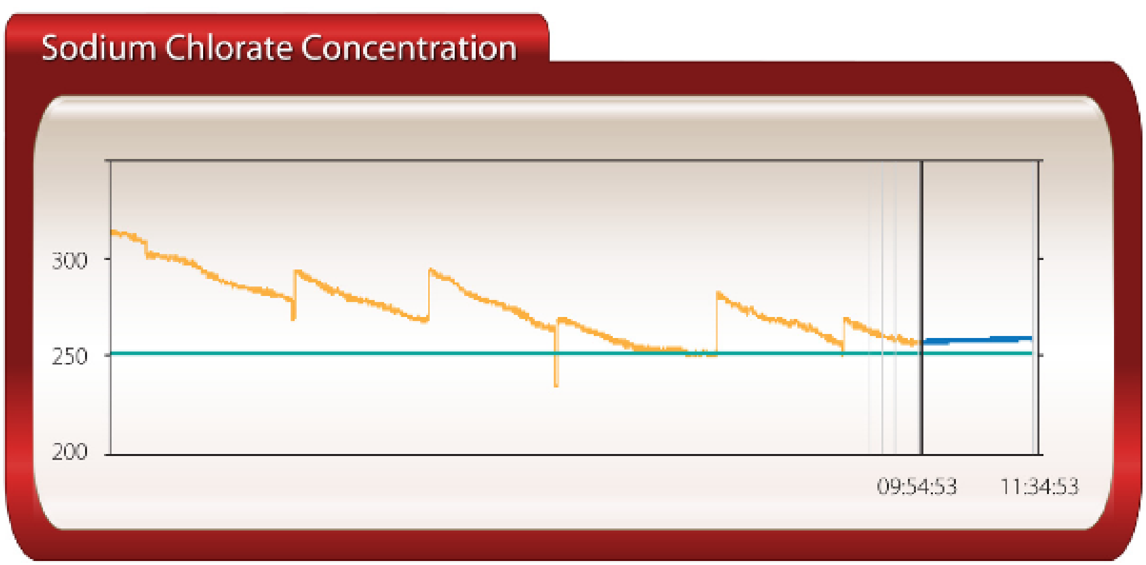

Figure 6. Sodium Chlorate Concentration Correction of Rockwell's Chlorine Dioxide MPC Application.

Significance of the Study

The study of model predictive controls for temperature dependent systems can provide several advantages. One being that current MPC technology has several limitations; therefore, investigating and evaluating current methods for controlling this type of systems could represent a significant improvement to the field. This research attempts to do this by aiming at proposing a new approach of adaptable algorithms that will guarantee a better performance of the system. This research embraces all industrial facilities, specially manufacturing industries, since they have several processes most of which are dependent on temperature.

Another advantage of the steady state predictive controls that are being investigated is that these algorithms and methods can be adapted to fit any industrial temperature dependent system. Of course these adaptations to the algorithms require a thorough study of the system in order to understand and be able to implement the equations for the reactions between all the variables of the system. Given the right tools, a solution like the one proposed in this paper can reap major benefits with very few obstacles. The primary benefits cited most often are cost reduction, productivity, availability, reliability, and performance (Cameron, n.d.).

1. Cost Reduction: By maximizing chemical and steam usage since the variables will always be kept at the most efficient ratios for the desired production rate.
2. Productivity: By allowing engineers to run the process safely at a higher production rates since a steady temperature allows operating the system at much higher production rates.

3. Availability: By offering safety features to run the process at the values recommended by the manufacturers which decreases the down-time of the equipment.
4. Reliability: By knowing when to use theoretical and practical computations which provides the confidence that fast and accurate set point changes are being made for all the variables.
5. Performance: All these benefits add up to a better overall performance of the system.

Thesis Organization

This thesis starts by introducing a common problem that affects most industrial facilities having temperature dependent systems. Since controlling this type of processes is very complex, industrial facilities have significant economic losses in these areas. These economic loses are caused either by the improper operation of these systems or by the expensive, but still unreliable technology that is available. A few publications are examined to provide a base for comparison with the results from this research. Additionally, the advantages of implementing this computational solution will be mentioned in order to show the value of this research.

Furthermore, a definition of model predictive control for temperature dependent systems will be given in order to analyze their particular characteristics as well as the limitations of the current technology. The input – output representation of variables will be introduced in order to provide a much better understanding of the parameters that will be controlled by this predictive solution. Finally, a list of the industrial systems that could have a great improvement from this research will be presented. From all these possible applications, three temperature dependent systems from different industries will be chosen in order to show that the algorithms that are being investigated can be adapted to fit any temperature dependent system performing at unstable conditions.

In order to provide a detailed report of the computational methods that are being investigated in this thesis, the writer has carefully separated the methodology used for developing this program. The first section of the chapter will show the characteristics and features of the implemented process model. Another section will describe the dynamics of the predictive controls that are used in order to be able to perform the algorithms and computational methods shown in future sections. Additionally, this chapter will provide a description of the analysis done to the behavior of temperature trends in order to match them with predetermined temperature patterns, as well as the theory and reason behind the set point computations for every production rate. Finally, a detailed explanation is provided for the procedures of how the temperature of the system is effectively stabilized and how the predictions of the output behavior are used to push the outputs to their desired targets. The results obtained from testing these MPC algorithms and methods will be analyzed to demonstrate how this solution can in fact represent a great improvement for any temperature dependent system. These results will be compared to manual methods of operation as well as to the results presented in previous works.

CHAPTER II

ANALYSIS OF TEMPERATURE DEPENDENT SYSTEMS

Model Predictive Control

Model Predictive Control (MPC) is a class of computer control algorithms that uses an explicit process model to predict the future response of a plant (Qin & Badgwell, 2002). It was originally developed for power plants and petroleum refineries, but this technology can now be found in several industrial fields such as chemicals, automotive, pulp and paper, food processing, and many others. MPC algorithms attempt to optimize future plant behavior at each control interval or cycle by computing a sequence of future input variable adjustments. A corrected or verified optimal future set point is then sent into the plant and the entire calculation is repeated at subsequent control integrals. This technology has progressed steadily for the last five decades and shows a significant penetration into DCS platforms since it has shown to be an effective method for operating processes for all industrial fields. The following are the process models that have been developed over the years. Most of them have similar methods that use predictions of future process values to effectively control outputs to their desired targets.

Linear Quadratic Gaussian (LQG)

This was the first model considered to be predictive and it provided a reference point for future predictive process models (Kalman, 1960a, 1960b). This process uses vectors to represent process states and to obtain an optimal state estimate for the objective function. These states of the system being operated are detectable through quadratic criterion; and process inputs are computed to optimize future plant behavior over a time interval known as the predictive horizon. This process model had little impact on the industrial control technology of that time because: it had too many constraints to follow, it was not effective versus process nonlinearities and uncertainties, it was not robust, it did not consider differences of performance of different systems, and it had a very steep learning curve for operators and engineers (Garcia, Prett, & Morari, 1989; Richalet, Rault, Testud, & Papon, 1976).

Identification and Command (IDCOM)

The first IDCOM predictive solution was presented by Richalet in 1978 which described a model of predictive heuristic control (Richalet, 1978). This approach used impulse responses to control future plant output behavior specified by a reference trajectory. In this process model inputs and outputs are included to formulate heuristic iterative algorithms which are experience based techniques for problem solving, learning and discovery (Qin & Badgwell, 2002). He chose an input-output representation where manipulated variables are the process inputs that directly influence the controlled variables which are the process outputs. In addition, Richalet made an important point about the hierarchy of a plant control functions that was used in later generations of this process model. This hierarchy describes four levels of control as shown in Figure 7 and it also used in the next generation of this process model which is IDCOM-M. At the highest level of this control structure is the Plant-Wide Optimization, which schedules the programs of the area and the production rate of each system. At the next level, the Local Optimizer minimizes costs and ensures quality and quantity of production. After this, the dynamic multivariable predictive controller uses future process values to control the outputs to their targets. Finally, at the lowest level the DCS sends commands and retrieves information from flow, pressure, temperature, and level controllers.

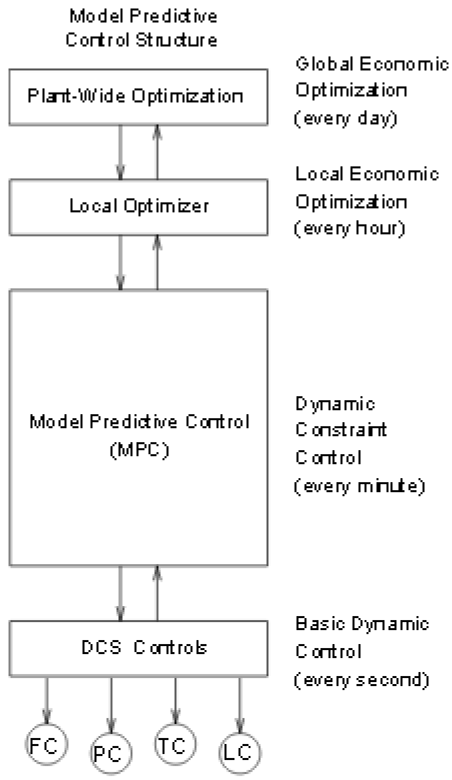

Figure 7. MPC structure or hierarchy describing the four levels of control.

Dynamic Matrix Control (DMC)

Dynamic Matrix Control technology was first introduced by Cutler and Remaker from Shell Oil in 1979, where they used this process model to control a fluid catalytic cracking reactor. In this process model, multiple outputs were handled by superposition; and by using a step response model one can write predicted future output changes as linear combinations of future input moves. A matrix ties this moves together and that is why it is called dynamic matrix. From this matrix, only the first row needs to be stored because only the first move needs to be computed, which represent the optimal solution to a least squares problem (Cutler & Remaker, 1979). This method was the first that included feed forward response to record temperature changes in the system.

Quadratic Dynamic Matrix Control (QDMC)

The previous process models introduced provided a solid control for unconstrained multivariable processes. For this reason, engineers at Shell Oil improved this process model by proposing a new approach for this algorithm as a quadratic program where input and output constraints appear explicitly. Some of the key features of this algorithm include (Qin & Badgwell, 2002):

- linear step response model for the plant;
- quadratic performance objective over a finite prediction horizon;
- future plant output behavior specified by trying to follow the set points as closely as possible;
- optimal inputs computed as the solution to a quadratic program.

Identification and Command for Multiple Process Outputs (IDCOM-M)

Using dynamic matrix approaches was a widely accepted process model of MPC technology. However, hardware disturbances such as signal nonlinearities, valve saturation, or direct operator intervention often created infeasible solutions for the objective function. In addition, it also became more and more difficult to translate control requirements into a single output objective. For this reason, with the purpose of overcoming these issues, engineers at Adersa, Setpoint Inc., and Shell created a new algorithm called IDCOM-M. This algorithm focuses on separate process outputs which add an extra degree of freedom for the inputs. Some of the features of this process model are the following:

- linear impulse response model of plant;
- monitoring of ill-conditioned data sets;
- Optimization of multiple process outputs;

- controls a subset of future points in time for each output;
- Single move is computed for each input;
- constraints can be hard or soft, with hard constraints ranked in order of priority.

Because of the features companies such as Setpoint continued to improve this technology and combined their identification, simulation, and control products into a single program called Setpoint Multivariable Control Architechture (SMCA). Meanwhile engineers at Shell Research developed a similar package called Shell Multivariable Optimizing Controller (SMOC) which also was implemented using this process model (Marquis & Broustail, 1998).

Robust MPC Technology (RMPCT)

As several industrial vendors have merged, this has produced several improvements to MPC technology. For instance, Honeywell's RMPC algorithm was merged with the Profimatics PCT controller which created their current offering called RMPCT. In addition another example is the merge of SMCA and DMC technologies which created Aspen's DMC-plus (Qin & Badgwell, 2002). These are some of the latest model predictive controllers and there is very few information about the methods and the algorithms they use since these have exclusive rights in order to sell this predictive solution as a service package. Some of the features of this process model include:

- Windows-based graphical user interfaces;
- multiple optimization levels and prioritized control objectives;
- additional flexibility in the steady state target optimization;
- direct consideration of uncertainties.

Limitations of Existing Technology

As mentioned throughout this section, every process model has its particular strengths and limitations. In addition to this, it is not possible to make detailed analysis of the performance of some of the latest exclusive predictive controls because there is not enough information published about their computational methods and algorithms. Having mentioned this, according to the Qin and Badgwell's (2002) survey about MPC technology the following are the limitations of the existing technology:

- lack of stability during operation;
- limited choices;
- very few use methods for detecting errors in procedures;
- inefficient dynamic optimization of equations;
- very few are adaptive to other systems.

Temperature Dependent Systems

A Temperature Dependent System is any industrial or chemical system whose behavior and performance depends significantly on the temperature of the process. Any industrial facility that manufactures any type of products or that processes chemical or any other type of compounds has several systems whose performances depend highly on the temperature of the process. For this type of systems, having all the variables correctly balanced is very important because it provides the following benefits: a safer workplace, an increment in the reliability of the equipment, and the main benefit is that it lowers the cost of production.

Input – Output Representation

Input Variables

Input variables can be controlled by either the operator or through a control system that directly controls the output variables. All Temperature Dependent Systems have primary and secondary input variables. Primary input variables are those independent from any other parameter. This means that their set points are not calculated from other variables and therefore, they do not depend on any other input or output variable. On the other hand, secondary input variables are those that do depend on other input variables as well as on the output variables of the process. They are initially calculated from the primary input variables using theoretical equations to determine their set points. After this, the output variables are analyzed and compared to their desired values to provide a feedback to the control system. This allows the program to determine the size of the adjustments that need to be made to the secondary input variables that will correct the outputs to the desired values.

Output Variables

Output variables provide information about the performance of the system, meaning that they reflect how well the input variables are being balanced and corrected for every time cycle. There are some aspects of the output behavior that are more important than others; this is why the output variables are also divided into primary and secondary. Primary output variables are the main aspects for evaluating a process. This means that when they are not at the desired set point, operators know they have to make changes to the input variables to try to reach these set points. However, sometimes more information is needed to understand what caused a particular unsteady behavior on the primary output variables and how this behavior can be corrected and prevented. In order to assist during this type of situations, secondary output variables provide additional information about a particular behavior of the primary output variables. For instance, the Acidity (secondary output variable) in a Chlorine Dioxide Generator helps operators understand why the temperature (primary output variable) of the solution keeps increasing even though the flow ratios of the input variables are kept the same.

Applications in Industry

As mentioned before, industrial facilities that manufacture products or that process compounds often have Distributed Control Systems controlling one or more processes whose efficiencies depend on temperature. Table 1 shows all the systems where an MPC solution could be implemented; these applications were separated by the different vendors from Qin and Badgwell's survey of MPC technology. From all these industrial applications, three examples of temperature dependent systems will be introduced, where this steady state predictive controller could greatly improve the overall performance of the process. These three industrial applications are shown in Table 2 and the chlorine dioxide generator application was the system used for testing this computational methods and predictive algorithms.

Table 1

Model-Predictive-Control Vendor Applications by Areas

Area	*Aspen Technology*	*Honeywell Hi-Spec*	*Adersa*	*Invensys*	*SGS*	*Total*
1. Refining	1200	480	280	25	-	1985
2. Petrochemicals	450	80	-	20	-	550

Table 1 (continued).

Area	*Aspen Technology*	*Honeywell Hi-Spec*	*Adersa*	*Invensys*	*SGS*	*Total*
3. Chemicals	100	20	3	21	-	144
4. Pulp and Paper	18	50	-	-	-	68
5. Air and Gas	-	10	-	-	-	10
6. Utility	-	10	-	4	-	14
7. Mining/Metallurgy	8	6	7	16	-	37
8. Food Processing	-	-	43	10	-	51
9. Polymer	17	-	-	-	-	17
10. Furnaces	-	-	42	3	-	45
11. Aerospace Defense	-	-	13	-	-	13
12. Automotive	-	-	7	-	-	7
13. Unclassified	60	40	1045	26	450	1601
Total	1833	696	1438	125	450	4542

Table 2

Examples of Industrial Temperature Dependent Systems

Industry	*Systems*
1. Pulp, Paper, and Water Treatment	Chlorine Dioxide Generators

Table 2 (continued).

Industry	*Systems*
2. Polymers and Steam Generators	Deaerators Systems
3. Crude Oil and Chemical Plants	Distillation Towers

Deaerator Systems

A deaerator system is a system designed to remove oxygen and other dissolved gases from a solution. It is used in industries that manufacture plastics and polymers, as well as in steam-generating boilers. They are very important pieces of equipment for any industrial facility because the presence of dissolved oxygen in a liquid causes corrosion in tubes and piping (Malki, 2013). Another gas that affects the processes of manufacturing plastics and generating steam is carbon dioxide since it lowers the pH levels of a solution and produces carbonic acid.

The process of deaeration is possible because gas solubility in a solution decreases as the partial pressure above the solution decreases. This means that there is a direct relationship between gas solution and temperature; that is why this is a Temperature Dependent System. In other words, gas solubility in a solution decreases as the temperature of the solution rises and approaches saturation temperature. A deaerator uses these principles to remove dissolved oxygen, carbon dioxide, and other non-condensable gases. Figure 8 illustrates this process and how the non-condensable gases are removed from the solution.

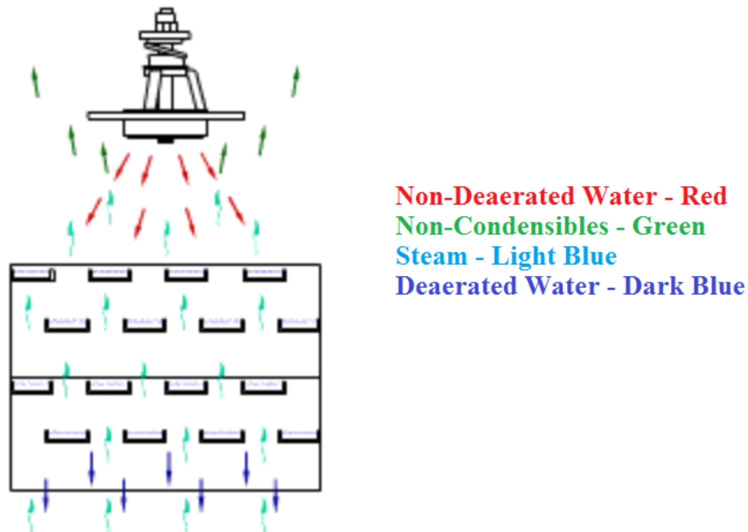

Figure 8. The Deaerator Principle for removing gas particles from a substance.

Like every temperature dependent system, a deaerator system has input and output variables. Figure 9 illustrates a complete diagram of a deaerator system and how the steam is introduced into the container to then proceed with the deaeration process and Table 3 lists all its variables.

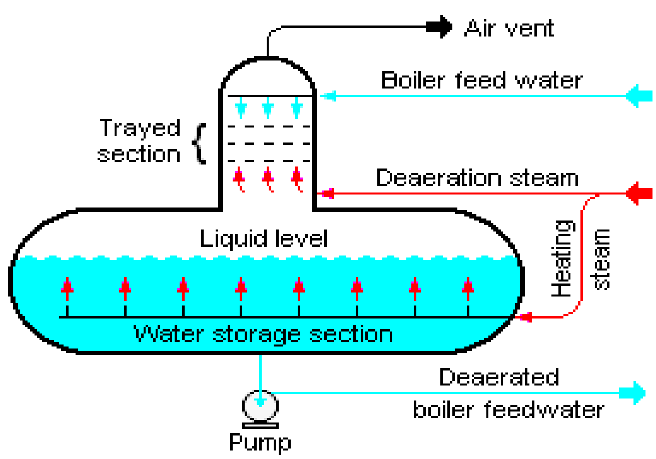

Figure 9. Diagram of a deaerator system showing input and output variables.

Table 3

Input and Output Variables of a Deaerator System

Variable	*Type*
1. Boiler Feed Water	Primary Input Variable
2. Deaeration Steam	Secondary Input Variable
3. Heating Steam	Secondary Input Variable
4. Temperature	Primary Output Variable
5. Dearated Boiler Water	Primary Output Variable
6. Air Ventilated	Secondary Output Variable
7. Liquid Level	Secondary Output Variable

Distillation Towers

A distillation tower is an industrial piece of equipment used to separate chemical compounds by their boiling points. This is done by heating the compounds to a particular temperature at which one or more fractions of the solution will vaporize separating them from the heavier compounds. Inside of the towers there are trays which enhance the separation of the components. After vaporizing the lighter components, they are condensed and accumulated to then continue with the process (Tham, 1997). On the other hand, the heavier compounds are then pumped to a reboiler which is a heat-exchanger that uses large amounts of energy to bring this liquid again to its boiling point. This process makes sure that all the particles of the lighter component have been separated.

This system requires a careful manipulation of its variables since it not only has two different temperatures, but also two different pressures at the top and bottom to allow the separation to be possible. An illustration of a distillation tower is shown in Figure 10 and a list of all the variables that are present in a distillation tower is shown in Table 4. This type of temperature dependent system is commonly used for crude oil distillation units. It distills the incoming crude oil into various fractions of different boiling ranges, each of which is then processed further in other refinery processing units (Jukic, n.d.). In addition, according to Professor Tham the best way to reduce operating costs is to improve the efficiency of the system through process control optimization. These statements show that implementing a process control program in temperature dependent systems such as this one could optimize the cost and the efficiency of the entire process.

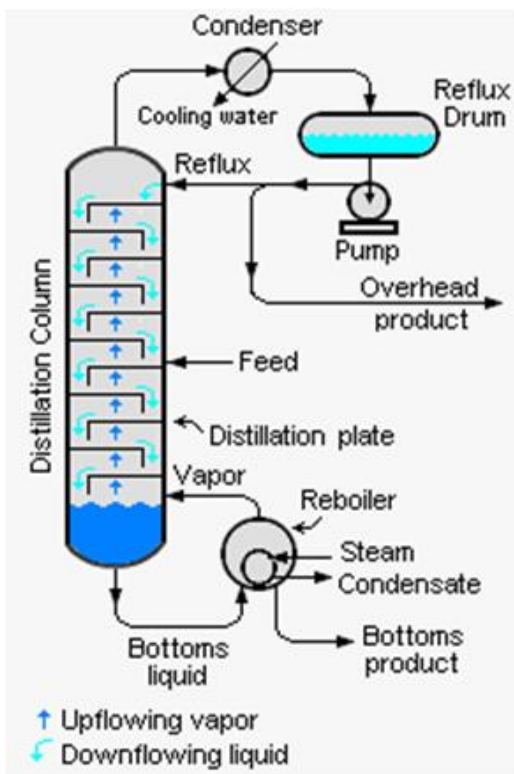

Figure 10. Diagram of a Distillation Tower showing input and output variables.

Table 4

Input and Output Variables of a Distillation Tower

Variable	*Type*
1. Boiler Feed Flow	Primary Input Variable
2. Steam Flow	Secondary Input Variable
3. Lower Pressure	Secondary Input Variable
4. Upper Pressure	Secondary Input Variable
5. Lower Temperature	Primary Output Variable
6. Upper Temperature	Primary Output Variable
7. Lighter Component Flow	Primary Output Variable
8. Heavier Component Flow	Primary Output Variable

Chlorine Dioxide Generators

A chlorine dioxide generator is a temperature dependent system that generates chlorine dioxide gas, which is an expensive and potent disinfectant and oxidizing agent used for water treatment, as well as for pulp bleaching. For water treatment applications, this type of system is very effective since it removes iron and manganese from the water. However pulp bleaching is a much more profitable field, where this particular process represents one of the most expensive parts in the making of paper and other related products. Since this gas deteriorates very quickly and since it is explosive, it cannot be transported at any concentration and therefore industrial facilities produce it on the site. A generic diagram of a chlorine dioxide generator is shown in Figure 11.

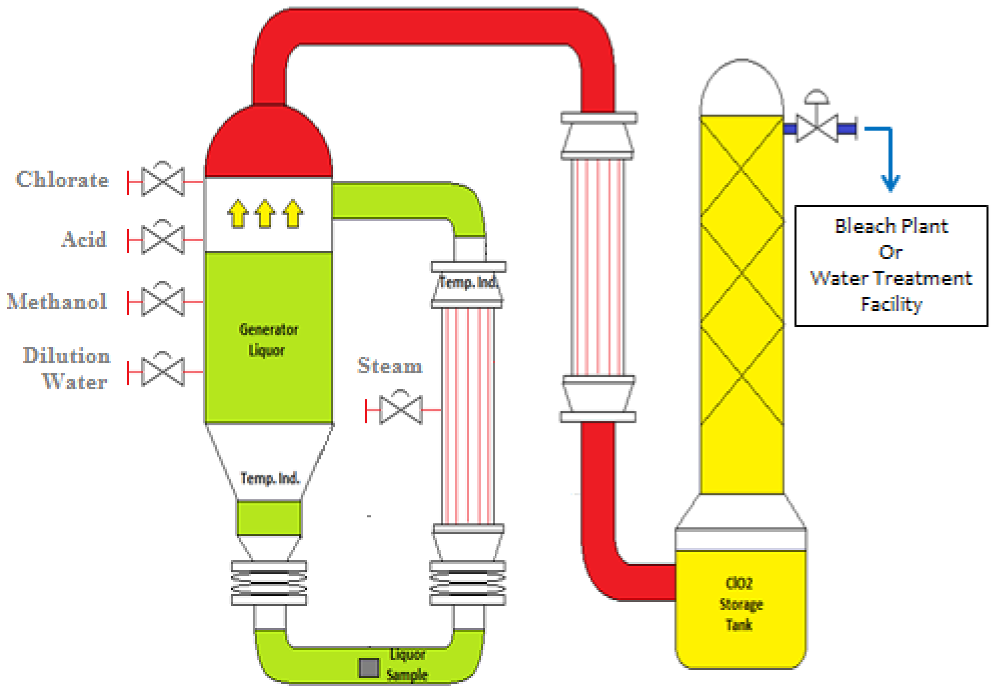

Figure 11. Diagram of a Chlorine Dioxide Generator.

The method for creating chlorine dioxide gas was discovered in the year of 1814 by Humphrey Davy. He discovered that by adding the following components into a tank, the reaction generates a gas with bleaching capabilities, as well as by products of this reaction ("Chlorine Dioxide as a Disinfectant," 1998). This process is described by the following formula.

Chlorate	+	Acid	+	Reducing Agent	=	Chlorine Dioxide	+	By-Products
↑		↑		↑		↑		↑
Sodium Chlorate		Sulfuric Acid		Methanol		Bleaching Gas		Crystals

The operation of this process requires a solid knowledge of stoichiometry reactions and mass balance equations, which increases the complexity of its operation. Operators often have difficulties balancing the variables of the system, which disrupts the steadiness of the temperature of the process. This problem increases the cost of production since the amount of chemicals and steam that is used in the process is greater than at stable conditions. A publication for Pulp and Paper Canada magazine states that unsteady conditions may cause problems like the degradation of the product; and that because of this, enabling alternative approaches to run the process without human intervention could represent significant advantages (Kammer, Allison, Laurendeau, & Kopat, 2006). With this in mind, one can say that the predictive control solution that is being investigated would not only be faster and more accurate than the manual methods of operation, but it could also be the most convenient solution to improve the overall performance of a generator working at unstable conditions. Table 4 lists all the variables of this type of temperature dependent system.

Table 5

Input and Output Variables of a Chlorine Dioxide Generator

Variable	*Type*
1. Methanol Flow	Primary Input Variable
2. Acid Flow	Secondary Input Variable
3. Chlorate Flow	Secondary Input Variable
4. Steam Flow	Secondary Input Variable
5. Water Dilution Flow	Secondary Input Variable
6. Liquor Temperature	Primary Output Variable

Table 5 (continued).

Variable	*Type*
7. Chlorate Concentration	Primary Output Variable
8. Acid Normality	Secondary Output Variable

CHAPTER III

METHODOLOGY

Dynamics of Predictive Controls

The purpose of this thesis is to propose adaptable predictive algorithms to control temperature dependent systems for an overall better performance. Therefore, first it is necessary to introduce the environment where these algorithms will operate. A distributed control system (DCS) is a type of control system that is usually from a manufacturing process, or any kind of dynamic system. In a DCS, the controller elements are never all at a central in location, since they are distributed throughout an area. Each system or sub-system of the area is controlled by one or more controllers (Shome, 2011). This type of control system executes all the programs of an area; and for this reason, programs are often scheduled to operate once every minute.

A distributed control system uses sensors, control valves, pumps, and other instruments. For this predictive control, control valves and pumps are used to control the flow of the input variables and the temperature sensors are used to determine the temperature of the system. However, after analyzing temperature trends of this system, it was determined that the signal to noise ratio was of about 60 decibels meaning that one measurement would not provide an accurate feedback on the current behavior of the temperature. For this reason, it was crucial to find a method that would eliminate these fluctuations and that would allow the program to know if the temperature is in fact increasing or decreasing regardless of this noise. It was determined that the best method for doing this would be to record a temperature measurement every time the program iterates; and after every 10 cycles it would obtain the average of all these measurements. For this application, a cycle is a parameter determined by the engineer in charge of the process. It represents the time lapse when all temperature measurements are averaged, in order to know if corrective procedures need to be performed to the system. This average is then stored and compared to the average of the next cycle, which provides a real idea of the behavior of the temperature. The following graph provides an illustration of how a DCS operates and how this predictive control determines the temperature change for every 10-minute cycle.

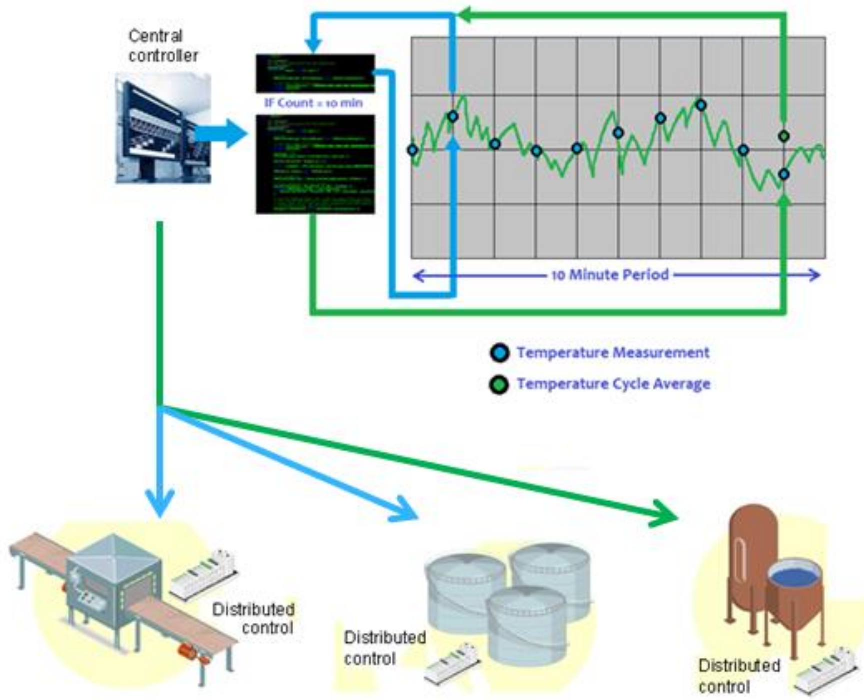

Figure 12. Dynamics of the Predictive Controls in a DCS Environment.
This image illustrates a DCS controlling several systems of an area and how it runs once per minute, executing procedures every 10 minutes.

Implemented Process Model

IDCOM-M is the process model implemented for developing the steady state predictive controller described in this paper. It uses an algorithm called MPHC that uses iterative heuristic techniques to drive the predicted future output trajectory as close as possible to the reference trajectory. This means that it uses a set of future points in time to bring each output to its target; and it does so using a linear impulse model response.

Moreover, the steady state optimization objective that this predictive solution uses is referred as multiple-sequential-objective since the algorithms first attempt to stabilize the temperature of the system, before using the predictions to control the output to its target. The steady state optimization constraints have output hard maximum and minimum values. This implies that temperature and the concentration need to be at all times within a specific range and the rate of change of the temperature cannot be higher than 0.8 degrees Fahrenheit for each 10 minute cycle. Finally, input manipulation is done through multiple moves since it was determined through careful study of the process that this is the most efficient way for maintaining a stable temperature in the system.

Determining Temperature Patterns

For all temperature dependent systems the correct matching of temperature patterns will be the most important aspect for bringing a system to a steady state since temperature directly affects the overall performance of the process. In order to determine the temperature patterns of a system, it is necessary to perform a careful study and analysis of past trends. For the chlorine dioxide generator used for this research, it was determined that there were six temperature patterns; and after a further examination, the parameters for their classification were documented. These patterns were then hard coded to the program to allow future pattern matching and they are introduced in this section.

Stable-Temperature Pattern

This is the optimal behavior of the temperature since it indicates that all the input variables are perfectly balanced for the desired production rate. For this particular system, a temperature is considered stable if the difference between the current average and the average from two cycles earlier does not exceed 0.2 degrees Fahrenheit. By looking at the following temperature trend, one can see that the difference between the current cycle average and the cycle average from two cycles earlier is 0.03 degrees Fahrenheit. Therefore the temperature is considered stable for that cycle average.

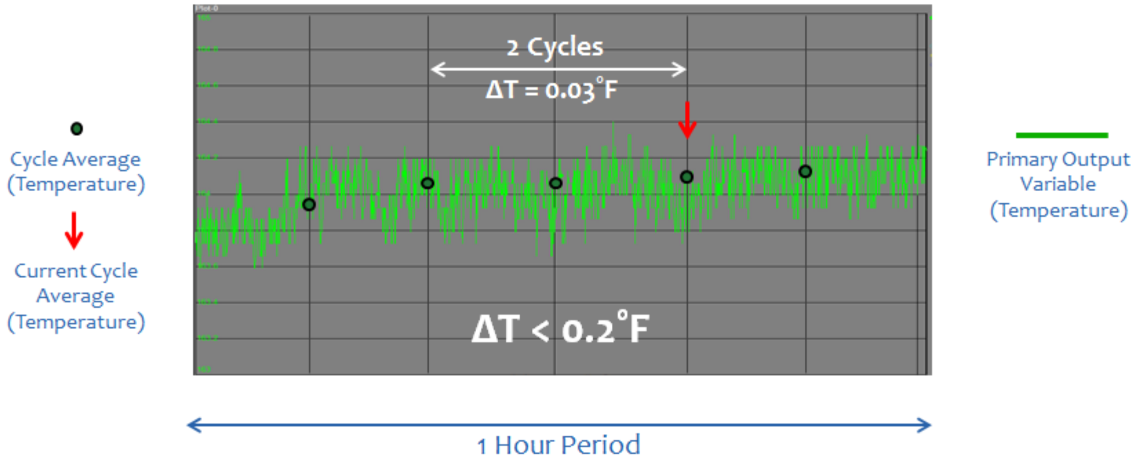

Figure 13. Stable-Temperature Pattern for a Chlorine Dioxide Generator.
This temperature trend shows an example of a Stable-Temperature Pattern since the average temperature difference was less than 0.2˚F.

Unstable-Temperature-Over-1-Cycle Pattern

This is the most common unbalanced behavior of the temperature. This pattern indicates that the input variables are not correctly balanced for the current production rate which is causing an increment or a decrement in the temperature. For this particular system, a temperature is considered unstable over 1 cycle if the difference between the current average and the average of the last cycle exceeds 0.2 degrees Fahrenheit. By looking at the following temperature trend, it is possible to determine that the difference between the current cycle average and the previous cycle average is 0.25 degrees Fahrenheit. Therefore, the temperature is considered unstable for that cycle average.

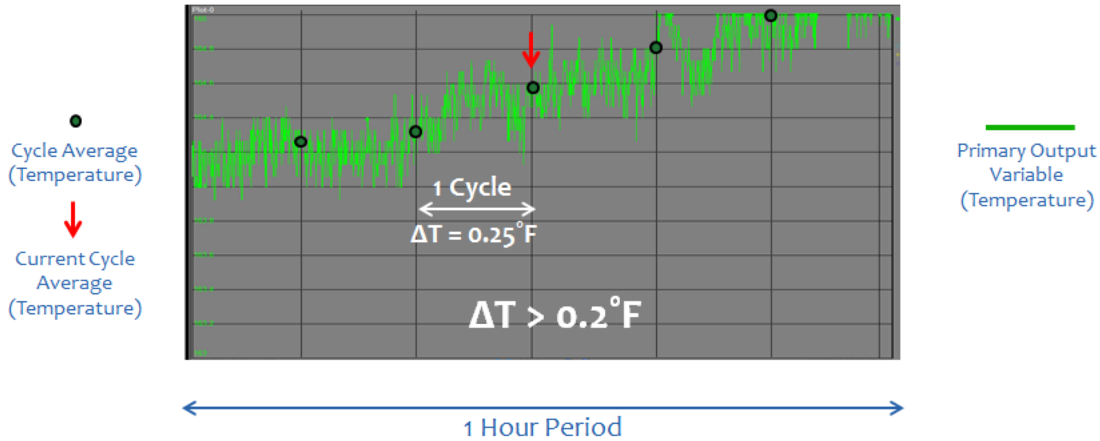

Figure 14. Unstable-Temperature-Over-1-Cycle Pattern.
This temperature trend shows an example of an Unstable-Temperature-Over-1-Cycle Pattern since the average temperature difference was greater than 0.2˚F.

Unstable-Temperature-Over-2-Cycles Pattern

This pattern represents a very slight temperature increment or decrement that because of its small rate of change, it would not be matched by the previous pattern. However, this increment would still show that the variables of the system are not balanced correctly. For this reason, in order to detect this pattern it is necessary to store temperature averages from two cycles earlier than the current cycle since only then the program will be able to determine if the temperature is in fact slowly increasing or decreasing. For this particular system, a temperature is considered unstable over 2 cycles if the difference between the current average and the average from two cycles earlier exceeds 0.2 degrees Fahrenheit. By looking at the following temperature trend, one can see that the difference between the current cycle average and the average from two cycles earlier is 0.24 degrees Fahrenheit and therefore the temperature is slowly increasing. Therefore it is also considered unstable for that cycle average.

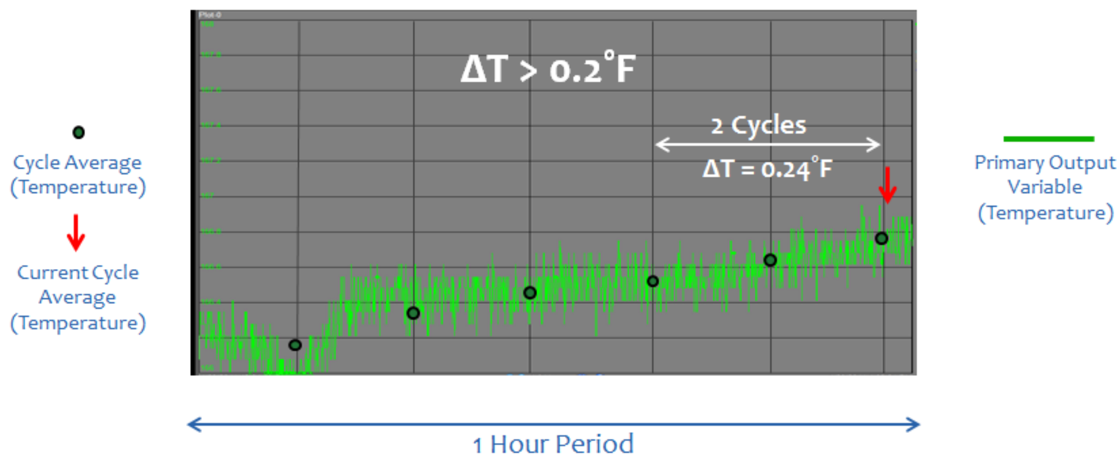

Figure 15. Unstable-Temperature-Over-2-Cycles Pattern for a Chlorine Dioxide Generator. This temperature trend shows an example of an Unstable-Temperature-Over-2-Cycles Pattern since the average temperature difference was greater than 0.2˚F.

Riskily-Unstable-Temperature Pattern

Even after doing a careful study of previous temperature behaviors, sometimes there are other factors that could cause the temperature to change at dangerous rates. This type of behavior means more than just an unstable temperature and thus when it is detected it will turn on a flag in the program to stop making changes to the acid flow since this changes would be erroneous and they could really upset the process. In situation, the program will use an alarm to alert the operator in charge of the system, so that he or she can monitor the variables and determine what caused this sudden change of temperature. For this particular system, a temperature is considered riskily unstable if the difference between the current average and the previous average exceeds 0.8 degrees Fahrenheit. By analyzing the following temperature trend, it is possible to determine that there was an unusual behavior in the temperature since the difference between the current cycle average and the previous cycle average was 0.85 degrees Fahrenheit. Therefore, the temperature was riskily unstable for that cycle.

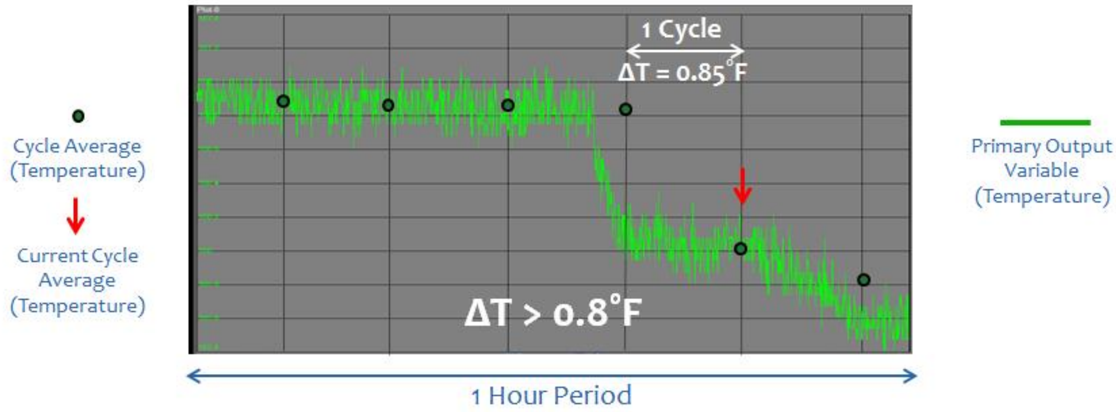

Figure 16. Riskily-Unstable-Temperature Pattern for a Chlorine Dioxide Generator. This temperature trend shows an example of a Riskily-Unstable-Temperature Pattern since the average temperature difference was greater than 0.8˚F.

Temperature-Above/Below-Recommended-Limits Pattern

For any equipment there are recommended parameters to follow. For this reason, it is essential to have a method for detecting when a system is operating outside its recommended limits. For the particular system used for this research, the recommended temperatures were between 162 degrees Fahrenheit and 168 degrees Fahrenheit because problems like Puffs can occur. Puffs is a degradation of the product that happens when a generator's temperature gets too high and problems like low chlorate efficiency occur when the generator's temperature gets too low (Chlorine Dioxide Model Predictive Control Application, 2012). If the temperature is detected to be higher or lower than this limits, special procedures will be performed by the program to bring the temperature back to the recommended range. This special procedure will set the target temperature as 165 degrees Fahrenheit in order to bring the temperature within the recommended range. The PID algorithms of the temperature stabilization procedures will take care of bringing the temperature to a steady state with a gentle rate of change.

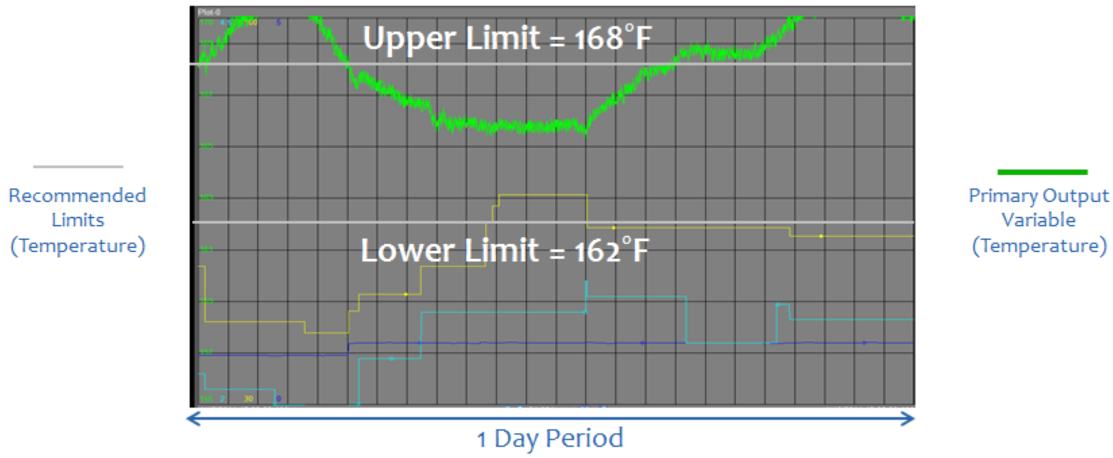

Figure 17. Temperature-Above/Below-Recommended-Limits Pattern for a Chlorine Dioxide Generator. This temperature trend shows an example of a temperature trend that is over the recommended limits since it exceeded the upper limit of 168˚F.

Error-in-Temperature-Data Pattern

This is the least common of all the temperature patterns and it detects sensor nonlinearities, meaning that for a very short period of time the sensor failed to send a voltage signal to the DCS. This malfunctioning could cause several problems to the procedures of the program since without this pattern, the trend would indicate that the temperature is riskily unstable. Nevertheless, when the temperature sensor continues to send voltage signals, it is possible to see that the temperature's behavior was not riskily unstable and that it was simply a malfunctioning of the sensor.

By performing a careful study of the standard deviations of past temperature trends, it was discovered that for all previous five temperature patterns the standard deviation never exceeded 1 degree Fahrenheit, except when there was a signal miscommunication. For this reason, a feature was added to this program to also calculate the standard deviation of the 10 temperature measurements after every cycle. This feature will check for any temperature average cycle where the standard deviation exceeded 1 degree Fahrenheit. Then, the program will know that this cycle's average provides a false temperature behavior. If this happens, it is said that there was an error in measuring the temperature for that period.

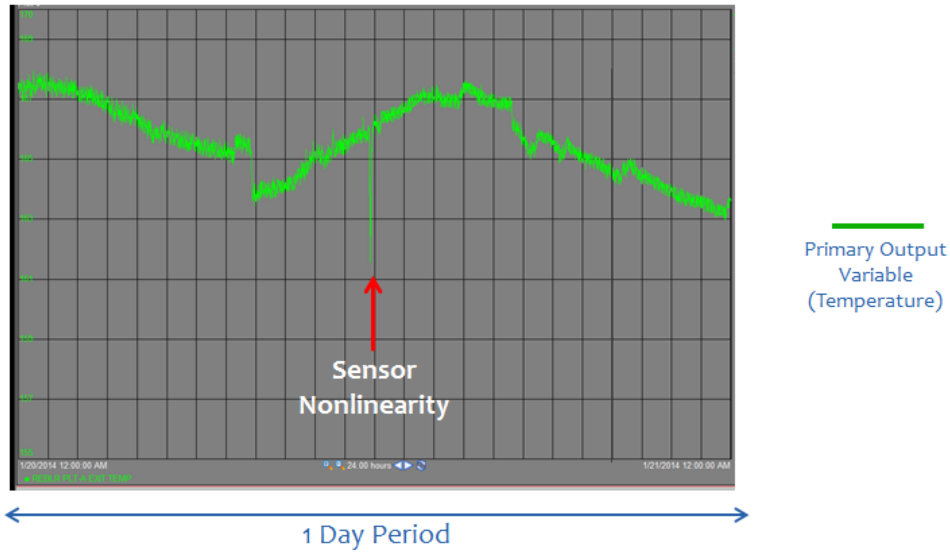

Figure 18. Sensor Nonlinearity of a Temperature Trend.
This image shows a sensor nonlinearity since it is clear that the temperature was increasing before and after it occurred and that this drastic change was caused because a sensor failed to send a voltage signal to the DCS.

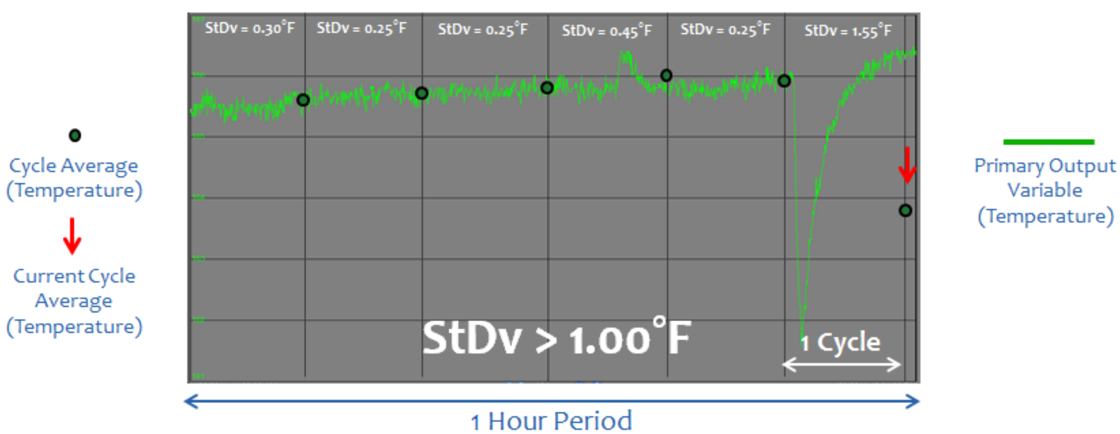

Figure 19. Error-in-Temperature-Data Pattern for a Chlorine Dioxide Generator.
This image shows the method for detecting errors on the temperature measurements. It is done through an analysis of the standard deviation of every cycle.

Set Point Computations

As it was mentioned in previous sections, the main cause for an unbalanced and inefficient process is inaccurate set point calculations during and after production rate changes. This task can be very difficult when a person tries to manually calculate these changes because there are complex equations, as well as theory that need to be taken into account in order to achieve an appropriate value. This characters were studied for the development of this predictive control and it was determined that set point changes for any temperature dependent system relied on whether the system is starting up or whether the system is already running.

Theoretical Set Point Changes for Process Start Up

When a system or a process starts it is very difficult to determine the external factors that will influence the process. For this reason, the initial set points for all the variables of the system are calculated using the theoretical values of the process. Since all temperature dependent systems use chemical reactions of different compounds, it is necessary to understand the stoichiometry reactions of the particular process. These concepts are very important because Stoichiometry is the section of chemistry that uses relationships between reactants and products in a chemical reaction to determine desired quantitative data (Nijmeh & Tye, 2008). This provides understanding of the relationships between products and reactants allowing the calculation of the reaction yield as well as the calculation of the limiting reagent ("Mass Relationships and Chemical Equations," n.d.). Reaction yield is the amount of product obtained in a chemical reaction and the limiting reagent is the compound that will be totally consumed indicating the production of the process.

Taking into consideration the theory behind the relationships of compounds in temperature dependent systems, the next step is to construct the formulas that will be the starting-point of all the variables which will bring the system to a theoretically balanced state. The following equations were created for the system that was used for this research and they reflect an example of how stoichiometry can be applied to calculate the set point changes. These formulas will differ for any other temperature depended system.

Generic Equation for Input Variables

$$Input_f\,[Gal/min] = Prod\ Rate\,[Tons/Day] * Ratio_{\frac{Input\,[GPM]}{Product\,[TPD]}}$$

Tailored Equations for an Chlorine Dioxide Generator

$$Methanol_f\,[Gal/min] = Prod\ Rate\,[Tons/Day] * Ratio_{\left(\frac{Methanol\,[Gal/min]}{ClO2\,[lbs/day]}\right)}$$

$$Dilution_f\,[Gal/min] = Prod\ Rate\,[Tons/Day] * Ratio_{\left(\frac{Methanol\,[Gal/min]}{ClO2\,[lbs/day]}\right)} * Ratio_{\left(\frac{H2O\,[Gal/min]}{Methanol\,[lbs/day]}\right)}$$

$$Acid_f\,[Gal/min] = Prod\ Rate\,[Tons/Day] * Ratio_{\left(\frac{Acid\,[Gal/min]}{ClO2}\right)}$$

$$Chlorate_f\,[lbs/min] = Prod\ Rate\,[Tons/Day] * \frac{Ratio_{\left(\frac{ClO3\,[lbs]}{ClO2\,[lbs]}\right)}}{\frac{ClO3_{efficiency}\,[\%]}{100}} * Ratio_{\left(\frac{ClO2\,[lbs]}{day\,[min]}\right)}$$

$$Steam_f\,[Klbs/hour] = Prod\ Rate\,[Tons/Day] * Ratio_{\left(\frac{H2O\,[lbs]}{ClO2\,[lbs]}\right)} * Ratio_{\left(\frac{H2O\,[Klbs]}{H2O\,[lbs]}\right)}$$

Practical Set Point Changes for Ongoing Process

Procedures and formulas for determining the starting points for all variables of the system were introduced above. However, temperature dependent systems are always subject to external factors such as a changing environment, aging, and other natural factors which affect a control process ("Control Systems," n.d.). These conditions affect the theoretical ratios of all the variables, meaning that they can make theoretical computation of set points not as effective. In order to overcome this problem a new approach was investigated, where instead of using theoretical equations the program would execute practical equations that use the modified ratios of all variables making changes in direct proportion to the new desired production rate. In addition, most large industrial facilities often find that it is more profitable to maintain a system running for as long as there is demand in the inventory ("Chlorine Dioxide Model Predictive Control Application," 2012). Therefore, most of the time set point calculations for production rate changes are performed using practical equations since they take into consideration changes to the theoretical equations due to external factors.

As said before, practical equations are based on the ratio of the desired production rate to the current production rate. They are much more effective than the theoretical equations because it is assumed that they have gone through error-correction procedures to attempt to bring the process to a steady state. For the chlorine dioxide generator which was the system used for this research, the first four variables where obtained from ratios of the desired production rate to the current production rate. However, because this system uses steam to control the level of the generator; mass balance equations had to be done in order to take into consideration the current quantity of each variable in the system. Mass balance equations are an application of the conservation of mass that accounts for material entering and leaving a system to determine mass flows which might have been difficult to measure without this technique (Honrath, 1995).

Generic Equation for Input Variables

$$Input_f\,[Gal/min] = \frac{Prod\ Rate_f\,[Tons/Day]}{Prod\ Rate_i\,[Tons/Day]}\,Input_i\,[Gal/min]$$

Tailored Equations for a Chlorine Dioxide Generator

$$Methanol_f\,[Gal/min] = \frac{Prod\ Rate_f\,[Tons/Day]}{Prod\ Rate_i\,[Tons/Day]}\,Methanol_i\,[Gal/min]$$

$$Dilution_f\,[Gal/min] = \frac{Prod\ Rate_f\,[Tons/Day]}{Prod\ Rate_i\,[Tons/Day]}\,Dilution_i\,[Gal/min]$$

$$Acid_f\,[Gal/min] = \frac{Prod\ Rate_f\,[Tons/Day]}{Prod\ Rate_i\,[Tons/Day]}\,Acid_i\,[Gal/min]$$

$$Chlorate_f\,[lbs/min] = \frac{Prod\ Rate_f\,[Tons/Day]}{Prod\ Rate_i\,[Tons/Day]}\,Chlorate_i\,[lbs/min]$$

$$Methanol_{Balance}\,[Gal/min] = \left(Methanol_f\,[Gal/min] - Methanol_i\,[Gal/min]\right) * 1.19$$

$$Dilution_{Balance}\,[Gal/min] = \left(Methanol_f\,[Gal/min] - Methanol_i\,[Gal/min]\right)$$

$$Acid_{Balance}\,[Gal/min] = \left(Methanol_f\,[Gal/min] - Methanol_i\,[Gal/min]\right) * 0.07$$

$$Chlorate_{Balance}\,[Gal/min] = 680/\left(Methanol_f\,[Gal/min] - Methanol_i\,[Gal/min] * 454 * 3.785\right)$$

$$Water_{Balance}\,[Gal/min] = Methanol_{Balance} + Dilution_{Balance} + Acid_{Balance} + Chlorate_{Balance}$$

$$Steam_f\,[Klbs/hour] = Steam_i\,[Klbs/hour]\,\frac{Water_{Balance}}{1.5}$$

Steady State Procedures

Variable Dominance on Temperature Behavior

In order to effectively develop algorithms with the purpose of stabilizing the temperature of a system, the first step is to determine what input variables have a larger effect in temperature variations of the process. For example, in a Chlorine Dioxide Generator the order of what input variables are more dominant is given by the acronym MASSD. Since Methanol is the reducing agent of this reaction, it is the component that drives the temperature (Deshwal & Lee, 2004). However, since this variable is also the primary input variable of the system; its set point will not be changed for controlling the temperature because these changes to the variable flow would decrease or increase the production rate. Therefore, in order to effectively control the temperature of the system one needs to manipulate the variable whose dominance precedes the methanol. This next variable is the acid. Thus, the temperature in the system will be controlled by constantly changing the flow of acid to prevent the temperature from becoming unstable.

Methanol
Acid
Sodium Chlorate
Steam
Dilution

Extensible Array for Storage of Temperature Measurements

As mentioned before, since the DCS operates several programs of an area at once it was determined that this program would run once per minute. For this reason, it was necessary to create a procedure that would store every temperature measurement of the process in the memory of the computer in order to be able to retrieve these values during the tenth iteration. This is not an easy task because industrial facilities often have temperature dependent systems that operate in parallel one to another in order to increase the availability and the production rate. Nevertheless, these systems in parallel are part of the same process; and therefore, they need to be controlled by the same program. In addition, for this program to be adaptable to any temperature dependent system it is very important to provide the flexibility of allowing changes to the time of execution. For example, a chlorine dioxide generator is a very large process that requires execution of procedures every 10 minutes. However, there are also industrial deaerators of volumes down to 35.31 cubic feet that would need a much higher frequency of execution of procedures. This feature of allowing flexibility in the frequency of execution of procedures increases even more the difficulty of this task.

For this reason, in order overcome this problem a very clever algorithm was created that would store the temperatures of all the systems in parallel in the same array, while allowing changes to the frequency of execution of procedures. This algorithm reduces the complexity of this task to three simple formulas. Once these three variables are calculated and after recording all the temperature measurements to complete the cycle time, the program is capable of computing the average temperature of the cycle for each one of the systems in parallel.

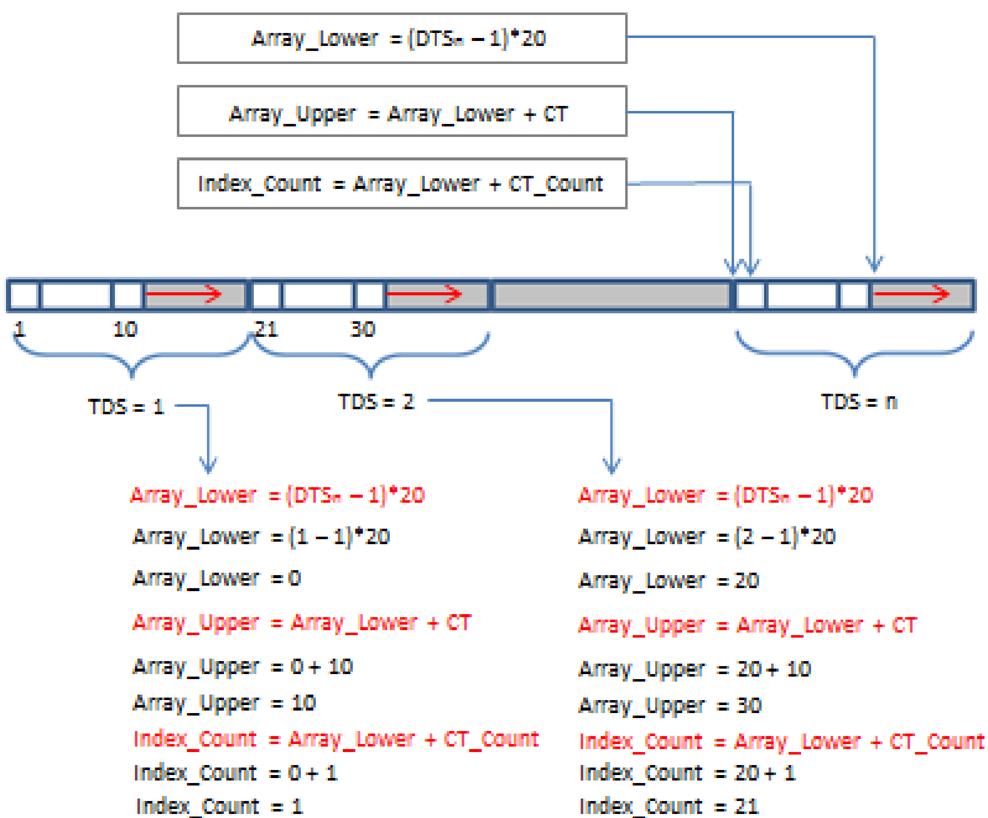

Figure 20. Diagram of the Extendable Array used for Storing Temperature Measurements. This image illustrates how these three formulas allow storing temperature measurements for any number of systems in parallel while providing flexibility in the frequency of execution of procedures.

Adapting PID Algorithm for Dominant Variable

In order to design an algorithm that will effectively stabilize the temperature of the system, it is necessary to understand the basic concepts of PID control. PID is a control loop feedback mechanism that computes the difference between an actual process variable and its desired set point using a proportional, integral, and derivative gain (Astrom & Murray, 2012). Therefore, this mechanism will be used to control how aggressive will be the set point changes of the dominant variable, in order to control the temperature of the system.

Since the purpose of the program is to stabilize the temperature, it cannot have a fixed target since different production rates will increase the temperature of the system. However, the temperature should always remain stable and within the recommended ranges. For this reason, an innovative idea was applied to this PID algorithm, where the program sets the previous temperature average cycle as a target and after every cycle it updates the target to the next temperature average. This feature will guarantee to stabilize the temperature of the system at a level in accordance to the production rate of the system.

For the temperature dependent system used in this research, it was determined that acid flow is the variable that will be manipulated in order to bring the temperature to a steady state. With this concept, it is possible to adapt the PID control formula with the desired gains that will regulate aggressiveness of the temperature changes (Messner & Tilbury, 2012). In this equations, DV represents the dominant variable which in the case of the system used for this research was the acid flow. This variable has an initial value that represents the current flow rate and a final value that represents the flow rate with a smaller error because of the PID error correction. The derivative gain K_D will be set to zero since the temperature trend has a slope that is constantly fluctuating. Having a derivative gain within this procedure would cause an inaccurate performance of the PID algorithm since the derivative gain is a value determined by the slope of the error over time (Cooper, 2008) .

$$u = K_P(e) + K_I \int e\,dt + K_D \frac{de}{dt}$$

$$DV = K_P(e) + K_I \int e\,dt + K_D \frac{de}{dt} \ \ , K_D = 0$$

$$DV_{Final} = DV_{initial} + K_P(e) + K_I \int e\,dt$$

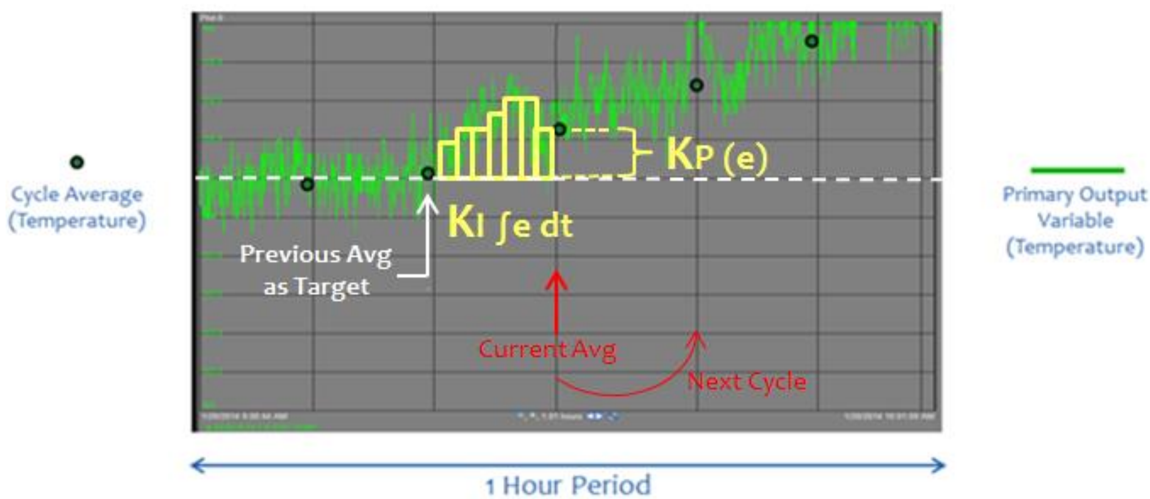

Figure 21. Adaptation of PID Algorithm for Predictive Controls of a Temperature Dependent System. This image illustrates the PID algorithm used for stabilizing the temperature of the system, where the target is the previous temperature average cycle and how this target is updated after every cycle.

Predictive Control of Outputs

Description of the Procedure

This is one of the most important aspects of the proposed solution since one of the easiest ways to reduce the costs of production is by maximizing the efficiency of the most expensive compound in the process. When an industrial vendor sells a system to an industrial facility, he or she always includes in the specifications the most efficient values at which to run the process. Achieving these output targets is definitely not an easy task because current methods for testing output variables of a system such as concentrations, involve labor intensive testing to determine whether the output is above or below target. Even with the information from the testing, this paper shown in previous sections that accurate set point computations depend on a solid understanding of the theory behind the process. Therefore, operators rarely succeed at controlling the outputs to their desired targets; and as a result, the outputs never stop fluctuating above and below this target.

In order to effectively control these outputs, this method of operation uses predictions of future process values that are computed using the current flow rates of all the input variables. These computer control algorithms attempt to optimize future plant behavior at each control cycle, by computing a sequence of future manipulations to the input variables (Qin & Badwell, 2002). A corrected or verified optimal future set point is then sent into the plant and the entire calculation is repeated at subsequent control intervals. This procedure becomes easier to understand by looking at Figure 22. One can observe that the output is far from its target, so future moves can be calculated to correct this output and bring it to its desired target.

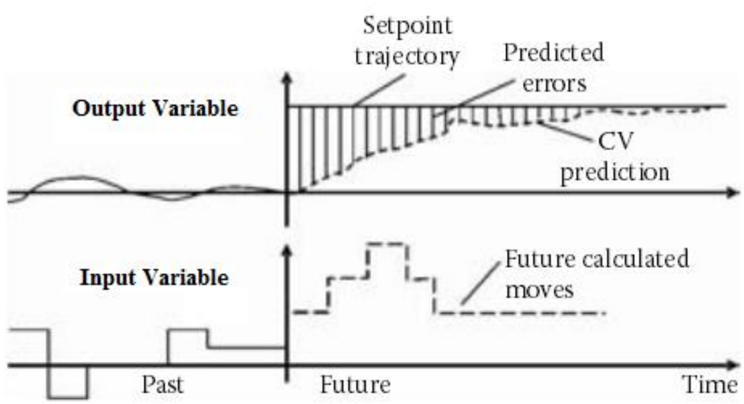

Figure 22. Future Input Manipulations for Control of Output Variable.
This image illustrates how an output variable that is far from its target can be controlled using calculations of future input variable moves.

Operation of the Procedure

The operation of this procedure will be explained using the chlorine dioxide generator as an example. In this example, the operation of the predictive procedures will be explain showing how the temperature is stabilized and the chlorate concentration (primary output variable) of the system is controlled to its desired target. The following are the five input variables that will be manipulated to maximize the production of chlorine dioxide.

- Methanol (Primary Input Variable): Used for controlling the production Rate of the system.
- Acid (Secondary Input Variable): Used for stabilizing the temperature of the process since it was chosen as the dominant variable.
- Chlorate (Secondary Input Variable): Since it is the most expensive chemical in this process it is used to control its concentration at the optimal target.
- Dilution Water: Used to dilute methanol since this chemical is flammable.
- Steam: Used to control the level of the generator.

This example starts when the generator is off and therefore the production rate is zero and the temperature of the system is below the recommended range. In addition no predictions are made because it is assumed that the predictive control is off.

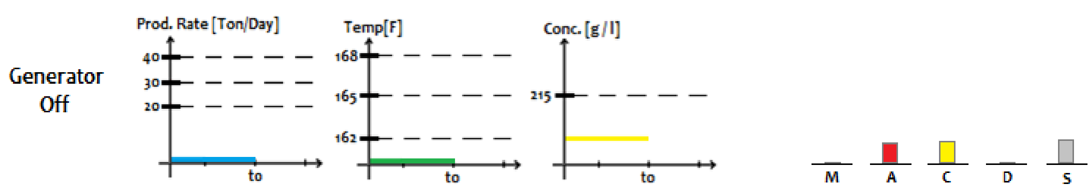

Figure 23. Predictive Control of Outputs: Generator Off.
This image shows the output and the input variables at their initial state on a chlorine dioxide generator for a predictive control of outputs procedure.

When the generator is then turned on, the new set points are calculated using theoretical computations and now the production rate is increased to a certain value. Therefore, the temperature starts to rise up and it is matched by the Unstable-Temperature-Over-1-Cycle Pattern, which indicates to the program that the flow of acid needs to be reduced. In addition, the predictive algorithms indicate that the concentration will still be below target if those flows are maintained so for the next iteration the flow of chlorate needs to be increased. As it was mentioned before, the dilution represents water where the methanol is diluted, so for this example it will grow in accordance to methanol flow.

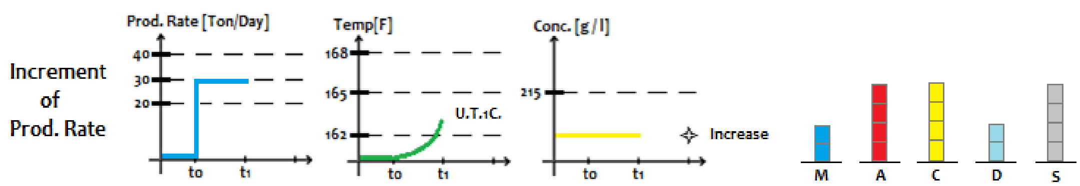

Figure 24. Predictive Control of Outputs: Increment of Production Rate.
This image shows the output and the input variables after an increment of production rate on a chlorine dioxide generator for a predictive control of outputs procedure.

For this new cycle, the chlorate has being increased which starts to raise the chlorate concentration. The temperature is increasing at a much slower rate, so it is now matched by the Unstable-Temperature-Over-2-Cycles Pattern. This means that the flow of acid still has to be reduced. In addition, a new prediction is made for the future chlorate concentration at the current flows and it is determined that it will still be below the desired set point. This means that flow of chlorate needs to be increased again for the next cycle.

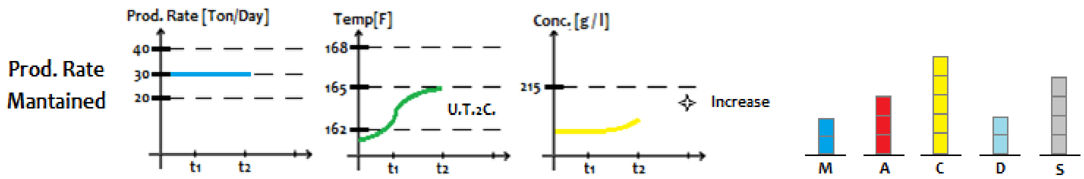

Figure 25. Predictive Control of Outputs: Production Maintained While Stabilizing Temperature. This image shows the output and the input variables when the production rate on a chlorine dioxide generator is maintained while the predictive control stabilizes the system.

For this new cycle, the chlorate has being increased which starts to raise the chlorate concentration. Since the production rate has been maintained and the temperature has been stabilized, the system is now stable. However, when a new prediction is calculated for the concentration, it is determined that at the current set points the concentration will be overshot from its target and therefore the chlorate flow needs to be decreased to a smaller flow rate

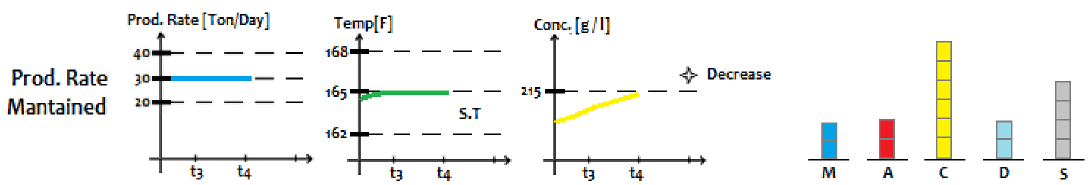

Figure 26. Predictive Control of Outputs: Production Maintained while Correcting Concentration. This image shows the output and the input variables when the production rate on a chlorine dioxide generator is maintained while the predictive control attempts to bring the concentration to its target.

At this new cycle, the chlorate was corrected to a lower flow rate. One can say that the system is operating at its optimal conditions for that particular production rate since the temperature is stable and since the predictions indicate that the concentration will remain at these targets.

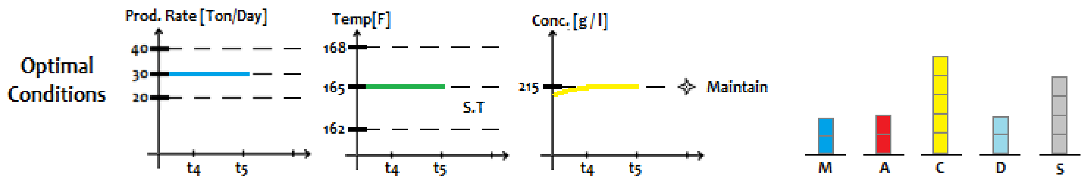

Figure 27. Predictive Control of Outputs: Generator at Optimal Conditions for a High Production Rate. This image shows the output and the input variables when the optimal conditions are reached for a high production rate; meaning that the temperature is stable and the primary output variable at the desired target.

This example then proceeds to indicate the operation after a production rate change. The new set points for all the input variables are calculated using practical computations of the optimal previous set points. One can see that the production rate was reduced causing a slightly unsteadiness of the temperature and it is again matched by the Unstable-Temperature-Over-1-Cycle Pattern. The predictive procedures indicate that at these set points the concentration will continue to decrease. Thus, for the next cycle the chlorate needs to be set at a higher flow rate.

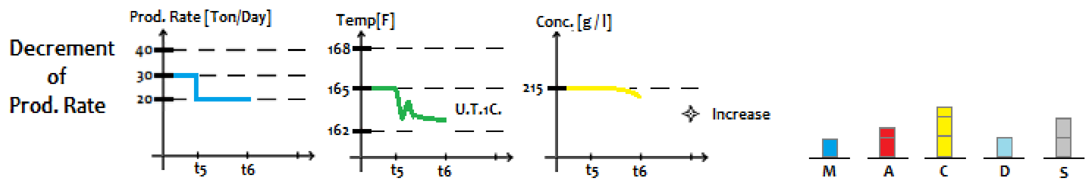

Figure 28. Predictive control of outputs: Decrement in production rate.
This image shows the output and the input variables after a decrement of production rate on a chlorine dioxide generator for a predictive control of outputs procedure.

At this final cycle the chlorate was corrected to a higher flow rate. The system is again operating at its optimal conditions for this lower production rate since the temperature is stable and since the predictions indicate that the concentration will remain at these targets.

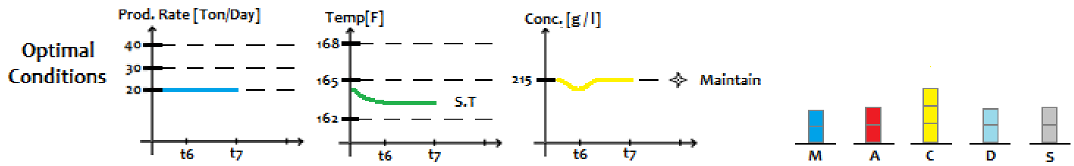

Figure 29. Predictive control of outputs: Generator at optimal conditions for a low production rate. This image shows the output and the input variables when the optimal conditions are reached for a low production rate; meaning that the temperature is stable and the primary output variable is at its desired target.

CHAPTER IV

DISCUSSION OF RESULTS

Phase 0: Analysis of Previous Operation

Start Up of the System

As it was mentioned in earlier sections of this paper, the set points for all the input variables are initially calculated using theoretical computations since these equations will create a balance between all the compounds. This maintains the temperature constant for that production rate. In the following image, one can see that when the generator is turned on and the production rate is increased to a certain value, there is a small fluctuation in the temperature of the system that lasts for about an hour. This fluctuation is perfectly normal since large amounts of methanol, acid, and chlorate were added to the system increasing the temperature of the process. However after this, the temperature of the system continues to increase for the following three hours, meaning that a certain amount of acid is being accumulated in the system because this variable is not at a correct ratio to the flow of methanol and chlorate. Because of this, a decrement is made to the flow of acid; however, now too much acid is being consumed in the reaction causing the temperature to start slowly dropping.

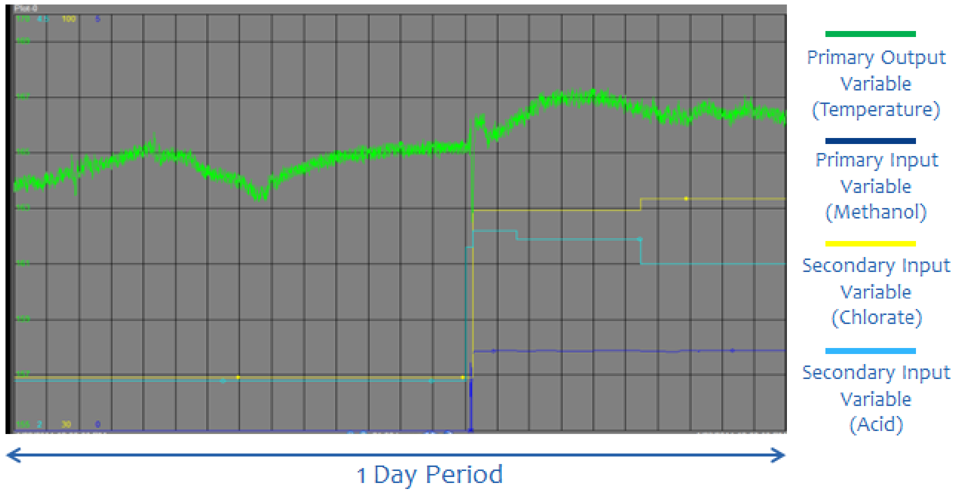

Figure 30. Start Up Operation of a Chlorine Dioxide Generator.
This image shows how the input variables are slightly unbalanced after startup which causes fluctuations in the temperature of the system.

Analysis of the Temperature of the System

As mentioned before, when generators are operated for long periods of time, production rate changes are performed using practical computations of the variables. The new set points for a production rate change are calculated from the current ratios of input variables, after the system has become stable. In Figure 31, one can observe that the system was clearly unstable since the temperature is above the recommended limits and since it continues to fluctuate even after several input manipulations. After performing a production rate change and a series of manual set point changes the system appears to slowly stabilize; however, when one of these set point changes is inaccurate it totally disrupts the balance of all input variables which causes a radical increment on temperature. This drastic increment in the temperature was caused because the flow of acid was increased at the same time as the flow of chlorate was decrease and therefore creating a high accumulation of acid in the system. After reducing the flow of acid the temperature again settles, but not for long since another erroneous set point change is made to the flow of acid making the temperature to exceed its recommended limits.

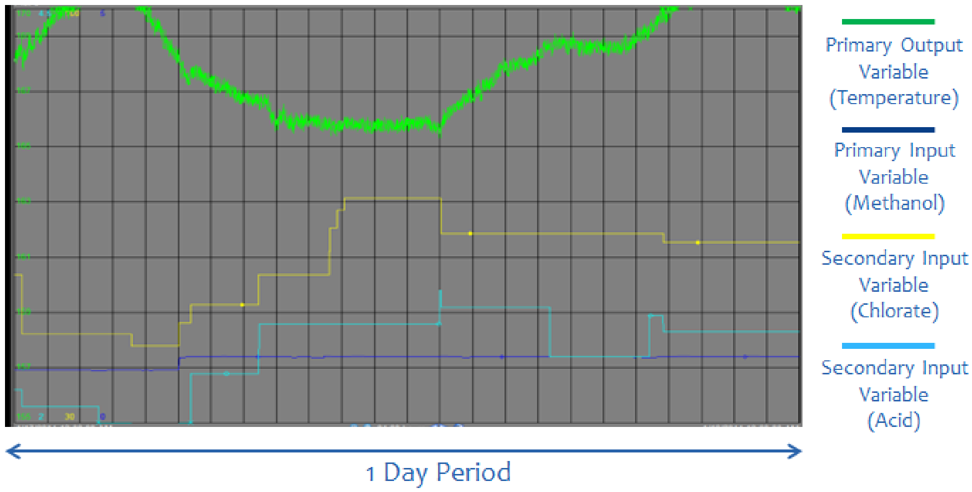

Figure 31. Trend Showing the Temperature of the System After Innacurate Set Point Changes. This image illustrates how a series of inaccurate set point changes causes the temperature of the system to keep increasing until falling out of the recommended limits of 162F to 168F.

Analysis of Output Variables of the System

Effectively controlling the chlorate concentration and the acidity of a chlorine dioxide generator is a complex task. As shown in the previous graph, inaccurate set point changes cause the temperature to fluctuate making the system unstable; however, this is not the only problem. The following image shows sample titrations of the generator liquor in order to determine the chlorate concentration and the acidity of the process. It is clear that the chlorate concentration never reaches its desired target and in fact it fluctuates up and down which increases the cost of production of the process. In addition, the acidity which is the output variable that indicates the efficiency of the chlorate, also continues to vary for this period time. This can be dangerous for the process since chlorine dioxide could start decomposing if the acidity gets too high.

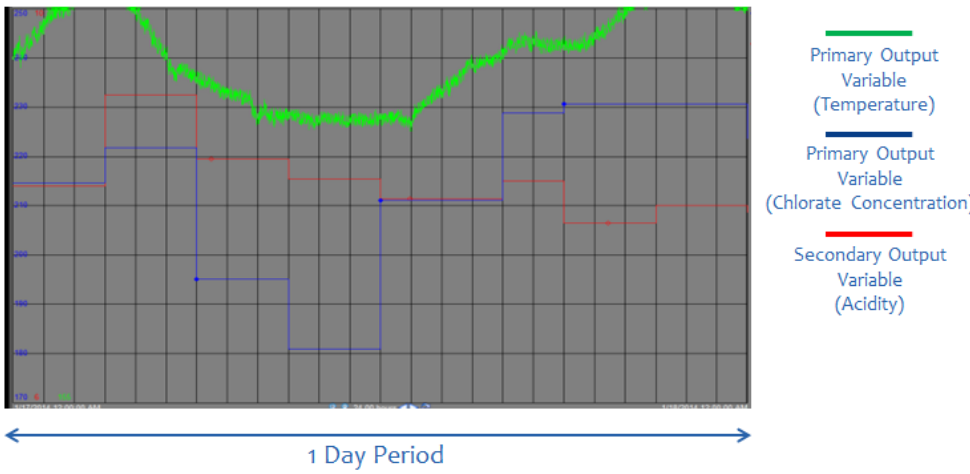

Figure 32. Output Variables for an Operation at Unstable Conditions.
This image illustrates the chlorate concentration fluctuating for the same production rate.

Phase 1: Testing Correctness of Set Point Computations

Determining the correctness of set point computations was the first step for verifying is that these equations would in fact improve the stability of the temperature. One can verify if these equations in fact improve the stability of the system by making a production rate change since this is when set point changes need to be the most accurate in order to maintain the balance of all variables. By analyzing Figure 34, it is clear that when the program was in control the temperature remained stable since the program effectively manipulated the flow of acid to control the temperature and bring it to a steady state. When comparing the temperature behavior of the system being operated by the predictive controls versus the system being manually operated as in Figure 33, one can observe that manual operation leaves flows at the same set point for long periods of time. This causes the temperature to slowly fluctuate which usually results on the variables becoming unbalanced. On the other hand, as shown in Figure 34 the predictive control program makes set point changes every 10 minutes, reducing fluctuations of the temperature to a minimum.

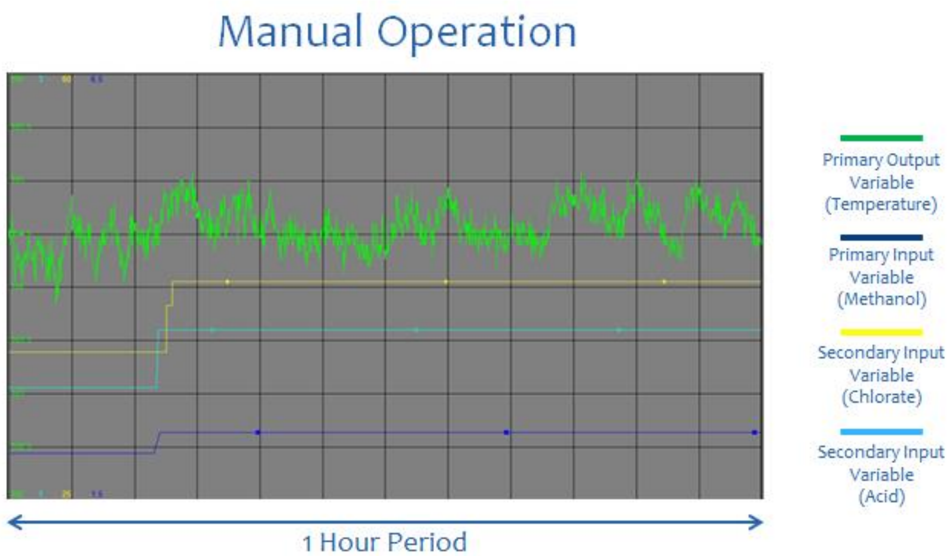

Figure 33. Temperature during Manual Operation after a Production Rate Change. This image shows that when input variables are left unattended after a production rate change, this causes the temperature of the system to fluctuate which usually results in the system becoming unbalanced.

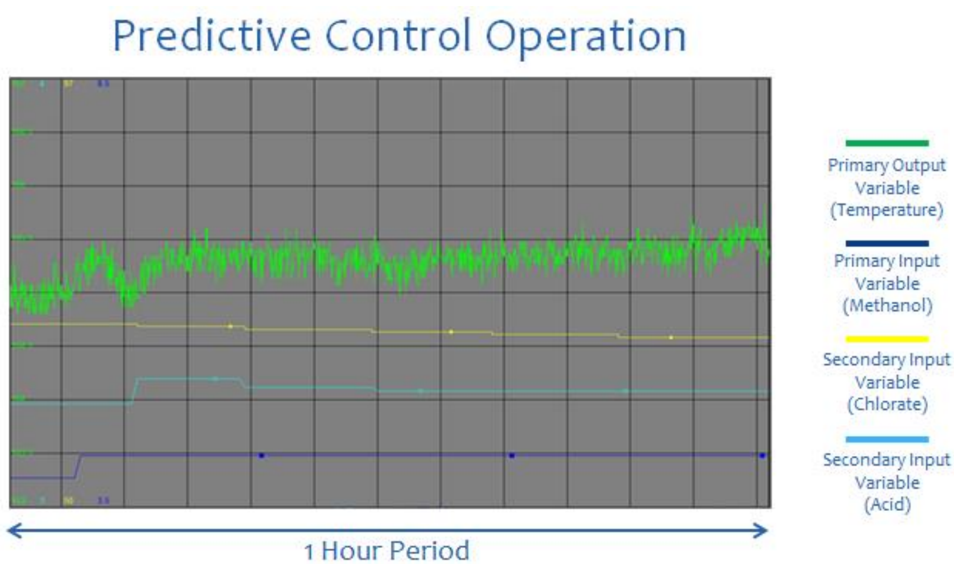

Figure 34. Temperature during Predictive Control Operation after a Production Rate Change. This image shows that set point changes made at a regular basis reduces temperature fluctuations to a minimum making the temperature of the system stable.

Phase 2: Testing of Steady State Procedures

The most efficient way to operate chlorine dioxide generators is to adjust its production rate in accordance to the demand in the inventory. This implies that these predictive controls would have to effectively operate the system for long periods of time.

For this reasons, this phase tests the predictive controls for a much longer period of time since this would provide a more realistic evaluation of its operation. One can observe in Figure 35 that for the day before the testing the system was very unstable, mainly because of inaccurate set point manipulations made after production rate changes. On the other hand, for the approximately six hours when the predictive control solution was running the process, the temperature of the system had an optimal behavior since the set point changes were successful at bringing and maintaining the temperature of the system at steady state. Another important observation of the temperature trend shown in Figure 36 is that once the testing of the program ended, operators immediately made a set point change. This set point change disrupted the stability of the system since the input variables became unbalanced. Further corrections were attempted, but they were unsuccessful making the temperature of the system even more unstable.

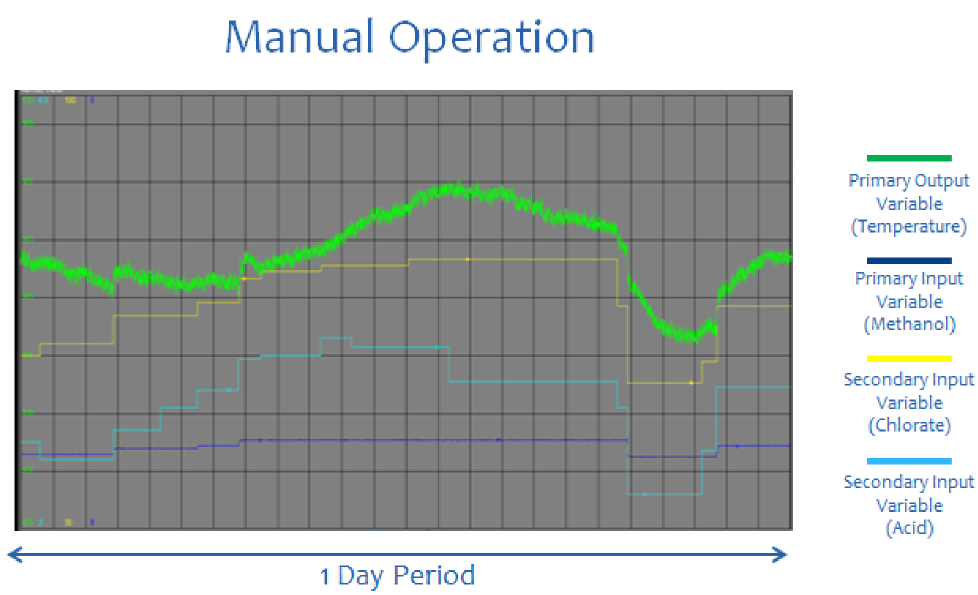

Figure 35. Temperature during Manual Operation of the day before testing for Phase 2. This image shows manual operation of the system the day before testing of stabilizing procedures.

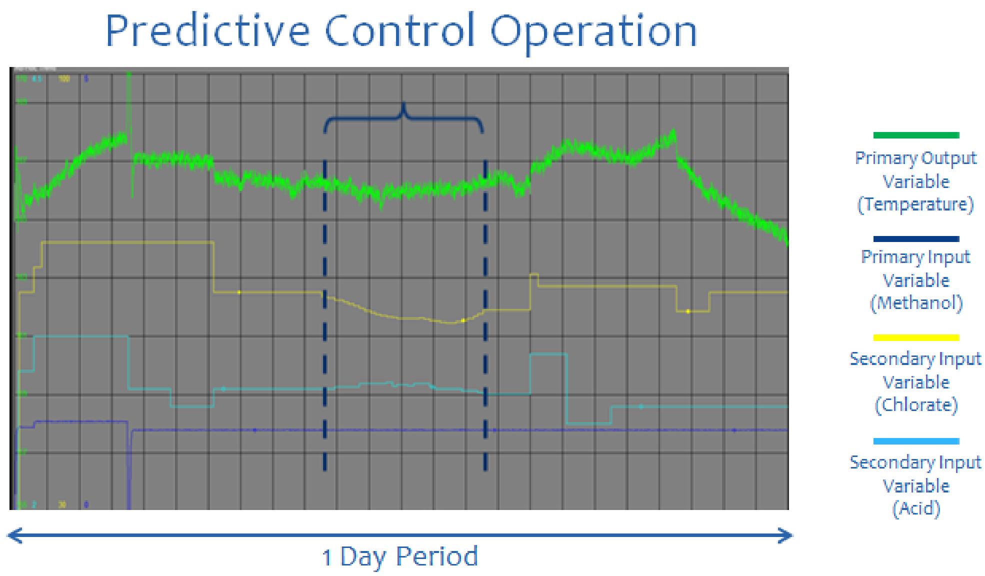

Figure 36. Temperature during Predictive Control Operation when testing for Phase 2. This image shows the predictive control solution operating the chlorine dioxide generator for a 6 hour period where it is clear that the temperature stayed at stable thanks to this method of operation.

Phase 3: Testing of Predictive Control of Outputs

The most common way to reduce costs of production is by maximizing the chemical usage of the system. In order to do this, concentrations need to be kept at the ideal values specified by the manufacturer of the system. Figure 37 shows the predictions of future chlorate concentrations for a period of approximately 8 hours. For this testing period, a sample of the generator liquor was taken in order to perform a laboratory titration that would provide an initial concentration for the program. Predictions of future concentrations were made from this point on and it was determined that the concentration was increasing. Thus, the program manipulated the flow of chlorate to attempt to bring this concentration to its ideal concentration.

A second sample was taken five hours later which shows that the predictions were within an acceptable range of accuracy. In addition, these predictions also show that the concentration seized to increase thanks to the actions taken by the program. However, the target was overshot meaning that calibrations needed to be done to the proportional and integral gains of the control since the corrective procedures were too aggressive. This was expected since calibrations need to be made for all predictive controls. However, it still gave an encouraging starting point since for this long period of time the predictions in fact reflected the future chlorate concentration of the system.

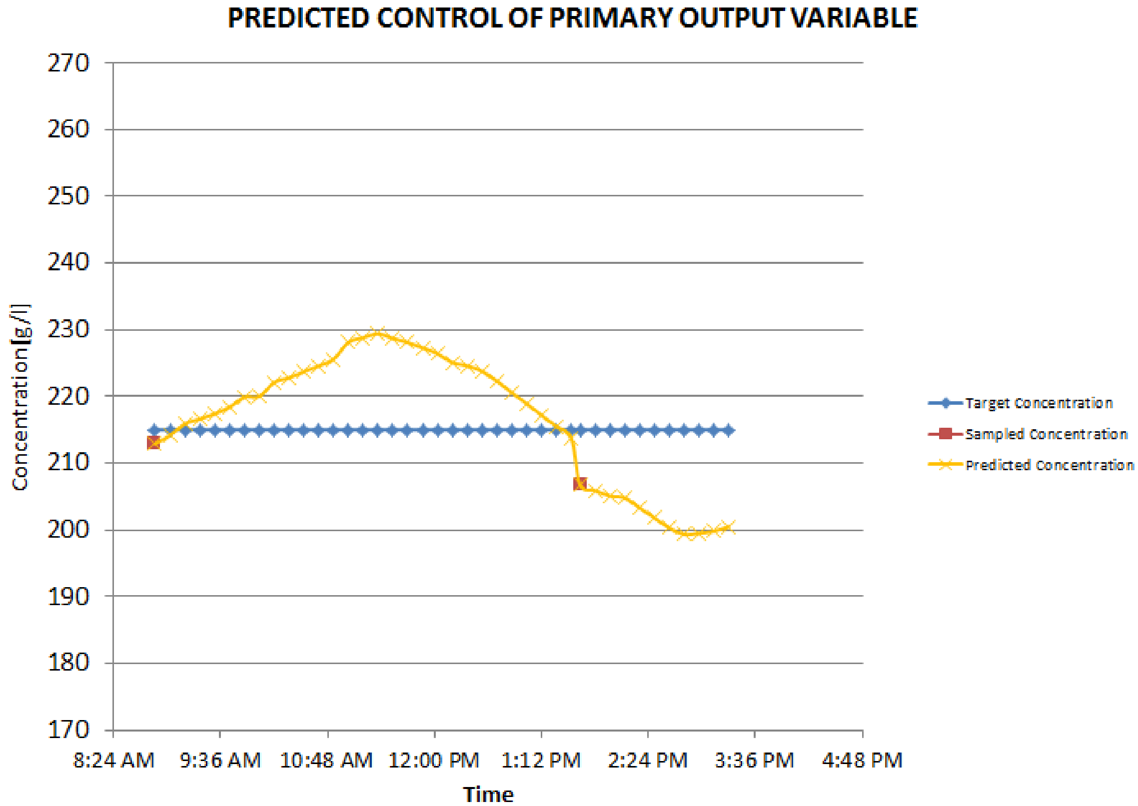

Figure 37. Predicted Concentration during Predictive Control Operation of the first test for Phase 3. This image shows the first testing of the predictions of future concentrations which allowed determining that the gains of the program were too aggressive since the target concentration was overshot.

Phase 4: Testing of Predictive Control with a Steady Temperature

This IDCOM-M predictive control system has two main objectives which are bringing the temperature of the system to a steady state and using predictions of future moves to control an output variable to its ideal process value. Figures 39, 40, 42, and 43 show the results obtained for testing periods of approximately 8 and 12 hours respectively, where the predictive control program effectively controlled both the temperature and the chlorate concentration system.

For the first test of this phase, the predictive controls had an excellent operation on the temperature. One can observe that before the program's operation shown in Figure 38 the system was clearly unstable and once it was turned on as shown in Figure 39, the accurate manipulations to acid flow stabilized the temperature completely for an 8 hour period. The analysis of Figure 40 shows the predictive control of the concentration for this testing period; and it allowed determining that the calibrations made to the gains of the program were still too aggressive since the target concentration was still overshot. However, this change provided a clear notion of the final calibration that needed to be done to obtain the desired outcome.

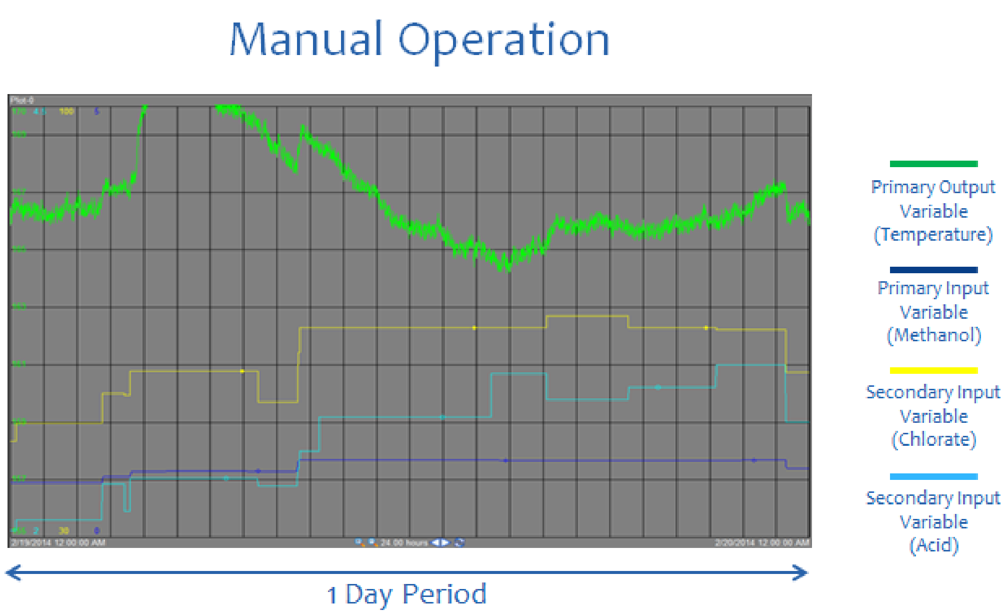

Figure 38. Temperature during Manual Operation of the day before the first test for Phase 4.

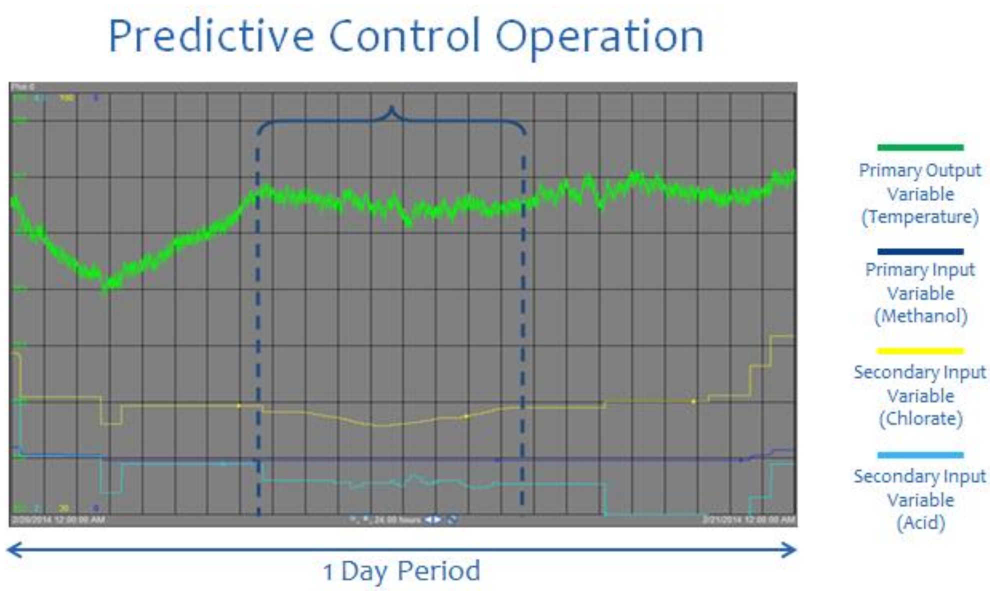

Figure 39. Temperature during Predictive Control Operation of the first test for Phase 4.

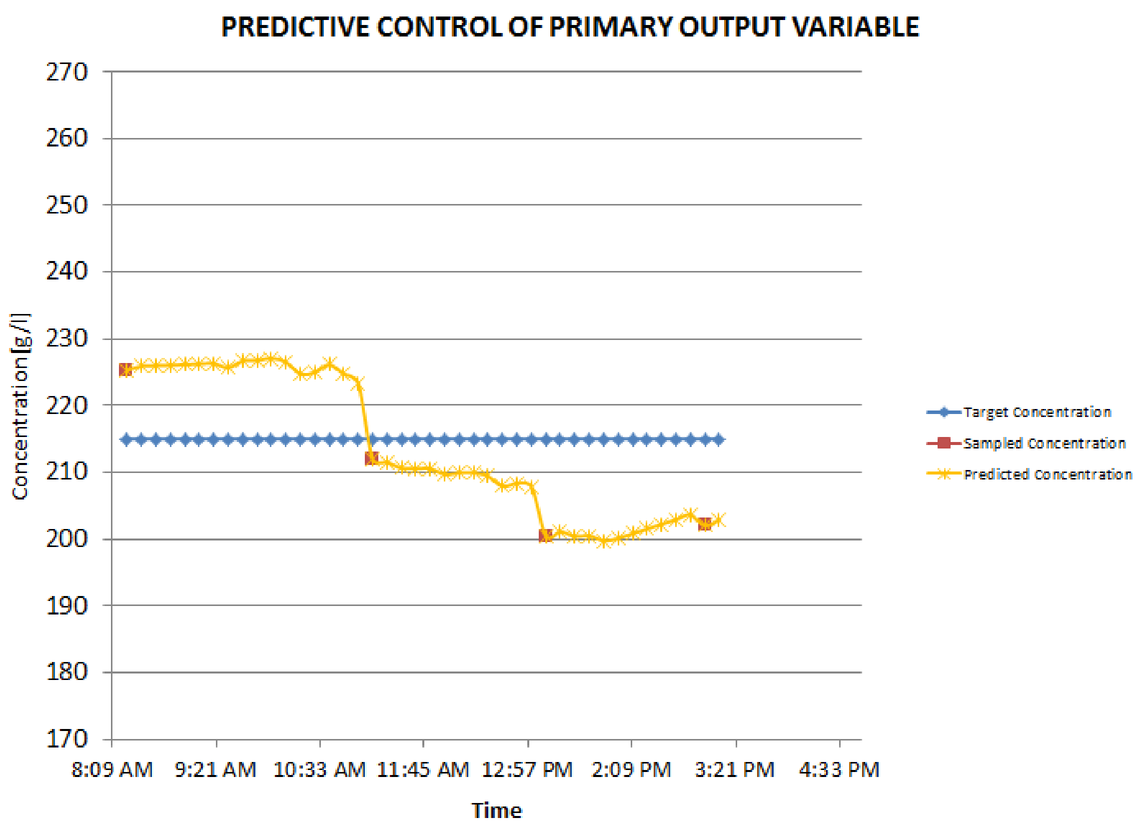

Figure 40. Predicted Concentration during Predictive Control Operation of the first test for Phase 4.

For the second test of this phase, the proportional and the integral gains were recalibrated one last time. This test was the most successful of all, for two reasons. The first reason is because the temperature of the system was extremely unstable the day before operation as shown in Figure 41. This provided an idea of how the predictive controls would behave when all the variables are very unbalanced in the system. On the other hand, Figure 42 illustrates the temperature trends during the testing period of approximately 12 hours. This image showed how the PID algorithms stabilized the increasing temperature and brought it to a steady state with very few fluctuations. The second reason why this testing provided excellent results is because after a second recalibration of the gains, the predictive controls effectively brought the concentration to its desired target without overshooting it. As shown in Figure 43, seven liquor samples where take from the generator and they confirmed that the concentration was effectively reaching its target. After approximately 12 hours, these samples indicated that the concentration had reached its target; and that it did so, while maintaining a steady temperature.

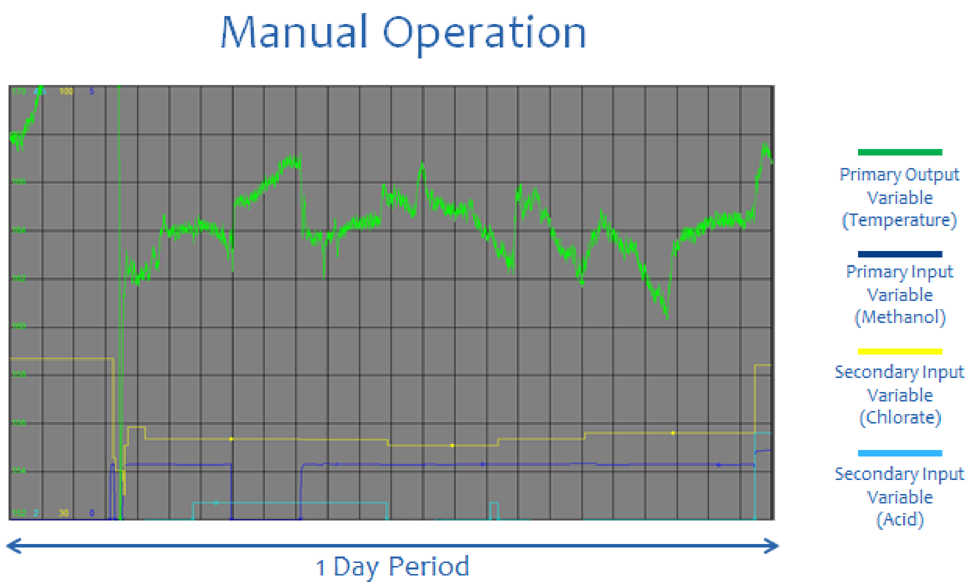

Figure 41. Temperature during Manual Operation of the day before the second test for Phase 4.

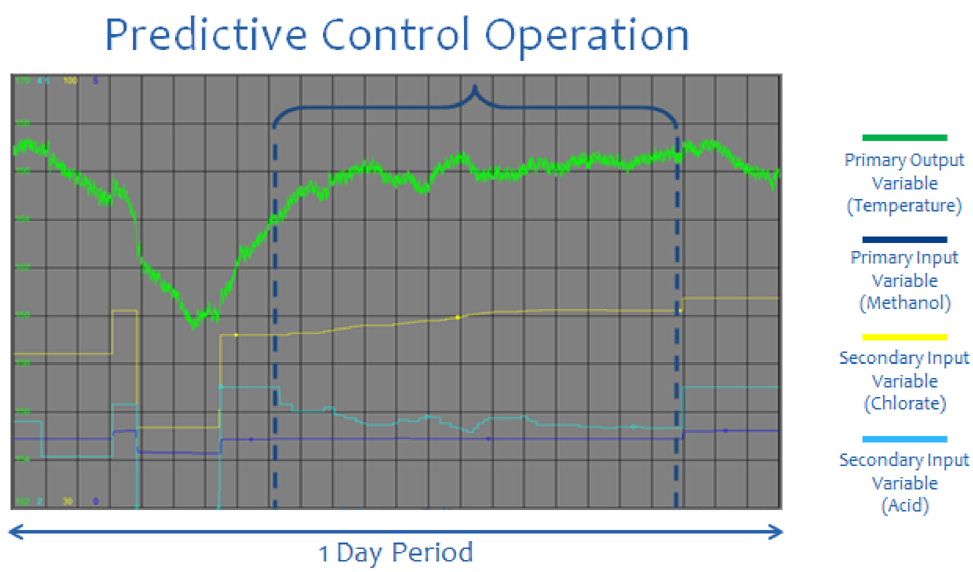

Figure 42. Temperature during Predictive Control Operation of the second test for Phase 4.

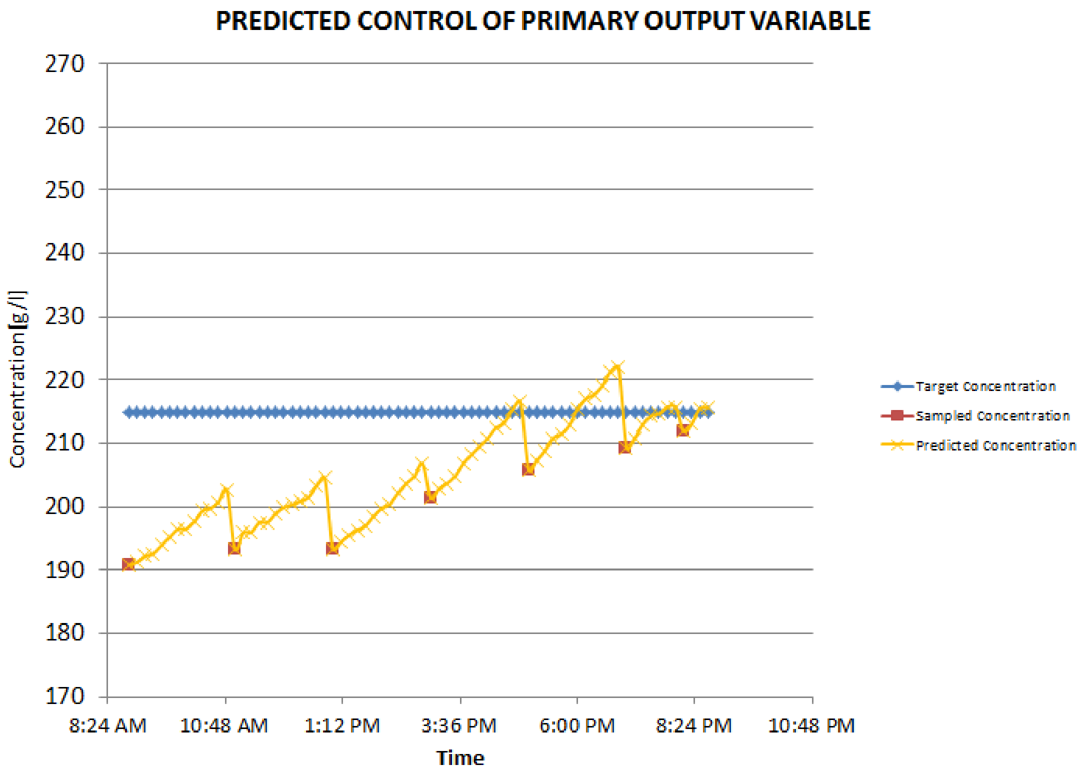

Figure 43. Predicted Concentration during Predictive Control Operation of the Second test for Phase 4.

CHAPTER V

SUMMARY

Conclusions

Temperature dependent systems are poorly operated in most industrial facilities increasing the costs of production and affecting overall performance of the process. These systems require either the close attention of experienced engineers or control programs that have exclusive rights and that are offered at extremely high prices. For this reason, through the investigation of Model Predictive Control technology, new methods and algorithms were proposed to provide solutions for several unnecessary limitations of the current operation of temperature dependent systems. Limitations such as the lack of stability during operation, failure to detect errors in procedures, and inefficient dynamic optimization of equations were addressed by this steady state predictive control.

A chlorine dioxide generator was the system used for testing these computational methods and algorithms. The results of this research demonstrate that the equations implemented after the study of the inputs and outputs of the system are an effective method for bringing the temperature of the system to a steady state; when used on a regular basis. In addition, it was also demonstrated that computing predictions of future process values in fact allows the effective control of these outputs to a desired target. This is a very valuable feature since operating a system at its ideal specifications maximizes the efficiency of the process. This steady state predictive control showed a significant improvement of the process when compared to manual operation. For this reason, these computational methods will continue to be investigated to expand this approach for other temperature dependent systems.

Future Work

Future investigation will be conducted for implementing these computational methods and algorithms for other temperature dependent systems. Since newer distributed control systems take advantage of the robustness of Windows' operating systems, it would be a great improvement expanding this steady state predictive approach to a Windows based DCS. This would allow not only the development of more user-friendly operator interfaces, but also it would facilitate the adaptation process of this predictive solution.

Another aspect of this research that could be expanded is the investigation of methods to safely push the efficiency of these stable systems to their limits. As it was mentioned throughout this paper, one of the main objectives of this steady state predictive controller is to improve the performance by stabilizing the temperature of the system. However, this is only the first step for the creation of significant economic benefit as shown in Figure 44 because with a stable system, engineers can focus on maximizing its production. They can do this while having the security that this stable process would always be under strict control and that the system constraints will be respected at all times thanks to this robust predictive operation.

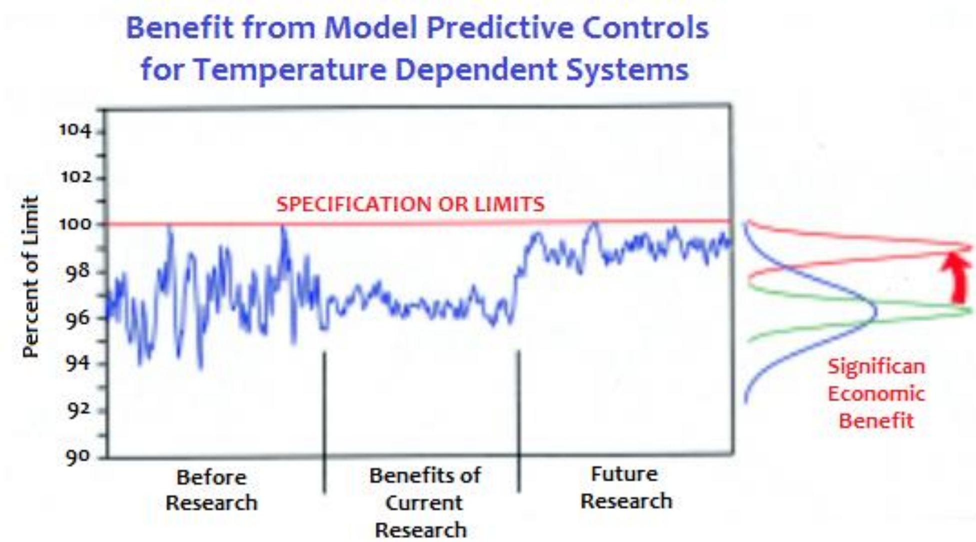

Figure 44. Future benefits of steady state predictive controller for temperature dependent systems. This image shows a theoretical representation of the unsteadiness of a system before the steady state predictive controller, the stable behavior of a system being operated by this predictive solution, and the future improvements consisting on safely pushing the operation of a stable system to its limits.

Research never really ends because learning is a cyclical process. A researcher is always observing, analyzing, designing, assessing, and adjusting. The cyclical nature of research provides professionals with ongoing opportunities to reflect on and refine their own practices (Beagle, Robey, & McCay, 2011).

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