Neural Network and Model-Predictive Control for Continuous Neutralization Reactor Operation

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Abstract. This paper outlines neural network non-linear models to predict moisture in real time as a virtual on line analyzer (VOA). The objective is to reduce the moisture variability in a continuous neutralization reactor by implementing a model-predictive control (MPC) to manipulate the water addition. The acid-base reaction takes place in right balance of raw materials. The moisture control is essential to the reaction yield and avoids downstream process constraints. The first modeling step was to define variables that have statistical correlation and high effect on the predictable one (moisture). Then, it was selected enough historical data that represents the plant operation in long term. Outliers like plant shutdowns, downtimes or non-usual events were removed from the database. The VOA model was built by training the digital control system neural block using those historical data. The MPC was implemented considering constraints and disturbances variables to establish the process control strategy. Constraints were configured to avoid damages in equipments. Disturbances were defined to cause feed forward action. The MPC receives the predictable moisture from VOA and anticipates the water addition control. This process is monitored via computer graphic displays. The project achieved a significant reduction in moisture variability and eliminated off-grade products.

Keywords. Model-predictive control, Neural networks, Virtual on-line analyzers, Moisture, Process variability.

1 Introduction

A neural network, also known as a parallel distributed processing network, is a [1]computing solution that is loosely modeled after cortical structures of the brain. It consists of interconnected processing elements called nodes or neurons that work together to produce an output function. The output of a neural network relies on the cooperation of the individual neurons within the network to operate. Processing of information by neural networks is characteristically done in parallel. Since it relies on its member neurons collectively to perform its function, a unique property of a

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neural network is that it can still perform its overall function even if some of the neurons are not functioning. It is robust to tolerate error or failure, as described by Mandic[1].

Neural network theory is sometimes used to refer to a branch of computational science that uses neural networks as models to simulate or analyze complex phenomena and/or study the principles of operation of neural networks analytically. It addresses problems similar to artificial intelligence (AI) except that AI uses traditional computational algorithms to solve problems whereas neural networks use software or hardware entities linked together as the computational architecture to solve problems, Saint-Donat[2]. Neural networks are trainable systems that can "learn" to solve complex problems from a set of exemplars and generalize the "acquired knowledge" to solve unforeseen problems as in stock market and environmental prediction. They are self-adaptive systems as shown in figure 1, according to Wikipedia[3].

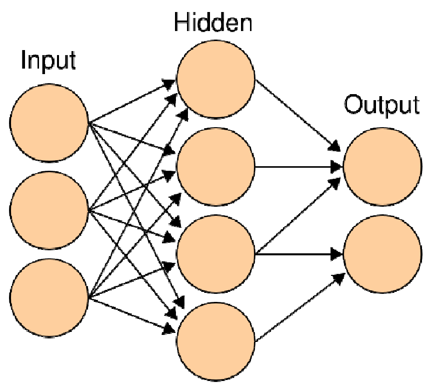

Figure 1. Neural network

Predictive process control involves the ability to monitor and control a continuous materials process in real time. This allows the conditions of the process to be adjusted quickly and responsively, and avoids the delay associated with only monitoring the final product. The potential of this technology sub-area is great, as it can improve the yields and productivity of a wide range of industrial processes. It can also contribute to the reduction in unwanted or polluting side processes.

Advancing the state of the art in predictive process control requires advances in sensor capability, in data communications and data processing, and in modeling. Improved interfaces with operators, usually via graphic displays, will also provide improved control system performance. The most important class of sensors for this sub-area is non-imaging sensors which can be used to measure a vast range of phenomenology such as temperature, pressure, humidity, radiation, voltage, current, or presence of a particular chemical or biological material. Specialized micro sensors can be used to detect particular chemical or biological agents. The information generated by the sensors must be combined and processed using data processing and models specific to the process being monitored.

The United States is a major player in all of the technologies which make up predictive process control. For example, historically Honeywell has had a major presence, having introduced the first distributed control system (the Honeywell TDC 2000) in 1975. Many other countries are also players in this area, however. In the UK, BNFL has developed advanced control system. In Germany, Siemens Industrial Automation has been leader in designing control systems with open architecture. The Japanese company, Yokogawa, is active in the International Fieldbus Consortium.

Model Predictive Control (MPC) is widely adopted in industry as an effective means to deal with large multivariable constrained control problems. The main idea of MPC is to choose the control action by repeatedly solving on line an optimal control problem. This aims at minimizing a performance criterion over a future horizon, possibly subject to constraints on the manipulated inputs and outputs, where the future behavior is computed according to a model of the plant, as showed in figure2. Issues arise for guaranteeing closed-loop stability, to handle model uncertainty, and to reduce on-line computations, according to Bemporad [4].

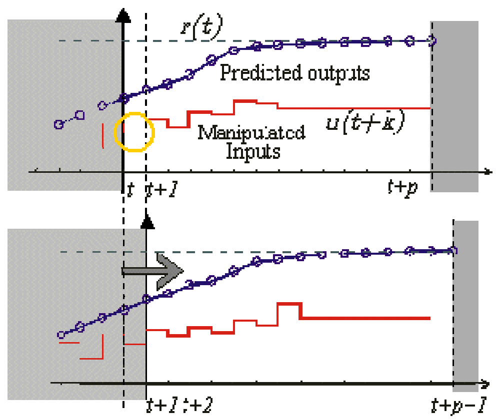

Figure 2. Model predictive control

MPC is an advanced method of process control that has also been in use in the process industries such as chemical plants and oil refineries since the 1980s. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification. The models are used to predict the behavior of dependent variables (outputs) of a dynamical system with respect to changes in the process independent variables (inputs). In chemical processes, independent variables are most often set points of regulatory controllers that govern valve movement (e.g. valve positioners with or without flow, temperature or pressure controller cascades), while dependent variables are most often constraints in the process (e.g., product purity, equipment safe operating limits). The model predictive controller uses the models and current plant measurements to calculate future moves in the independent variables that will result in operation that honors all independent and dependent variable constraints. The MPC then sends this set of independent variable moves to the corresponding regulatory controller set points to be implemented in the process, Patwardhan[5].

Despite the fact that most real processes are approximately linear within only a limited operating window, linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the plant. In model predictive controllers that consist only of linear models, the superposition principle of linear algebra enables the effect of changes in multiple independent variables to be added together to predict the response of the dependent variables. This simplifies the control problem to a series of direct matrix algebra calculations that are fast and robust, according to Garcia [6].

2 Baseline Process

Monsanto has implemented a manufacturing unit in Sao Jose dos Campos city using as concept a continuous process to make a specific salt through a continuous acid-base reaction. The basic process consists in a continuous addition of an acid to be stoichiometrically neutralized with a base, in presence of water according to figure 3. Since the start-up of the plant several operating constraints were observed regarding the high variability in moisture control. Moisture is an important parameter to ensure that the acid-base reaction takes place properly. The control is done by feeding water into the continuous reactor, creating product dough. It is done automatically via a closed-loop configured in the Distributed Control System (DCS). The set-point for water feed rate is determined by the operators through a previews visual analysis of the product in the reactor outlet pipeline.

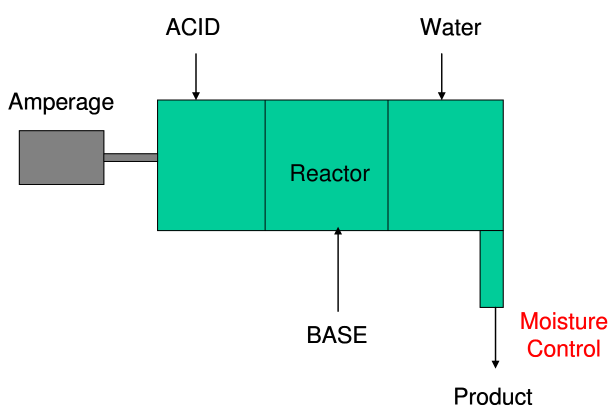

Figure 3. Continuous neutralization reactor

The ideal moisture operating range is within 4 – 6%. Working off the range many plant shutdowns is observed due to pluggages in the equipments located in the downstream process. It can also impact the product quality once the higher moisture causes lump formation and lower moisture creates dust in the further process steps.

In order to establish the process baseline many six sigma statistical tools were applied to the historical data of the manufacturing unit. MINITAB® software was used for calculating the indexes and supports the technical evaluation. According to Hayashi[7], the capability tool was applied and the result showed a process cpk of 0.29 for moisture control. This value is much lower than 1.32 that is the reasonable number for a capable process, see figure 4.

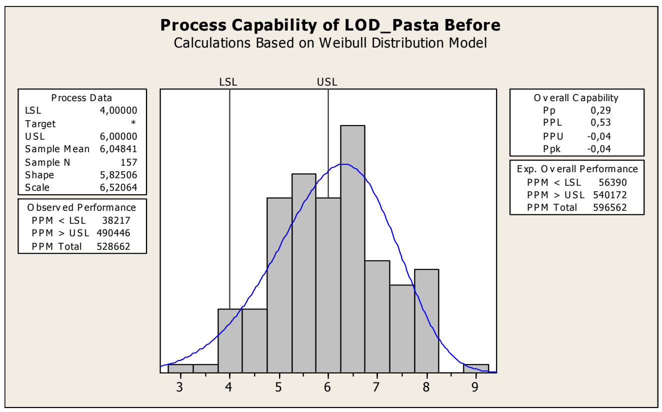

Figure 4. Baseline process capability analysis

Prior to implement advanced process control concepts, it was configured in the DCS a linear modeling created by MINITAB®**.** The main objective was to correlate the water feed rate as a function of the reactor amperage, acid feed rate and acid moisture. The linear regression equation, as described below, did not work properly due to a cyclical variation in the closed control loop, causing many plant upsets.

$$Water\_feed\_rate = \frac{Reactor\_amp + 310 + Acid\_rate*0.023 + Moisture*31}{(248 + Moisture*21)}$$

3 Project Implementation

In order to implement a more reliable system this project outlines neural network models to predict the moisture in the continuous reactor in real time as a virtual on-line analyzer. The project considered also a model-predictive control to manipulate the water feed rate based on the predicted moisture in the continuous reactor.

A benchmarking was done to find out potential softwares to be used for implementing the VOA and MPC applications. The marketing search considered the restrictions of the current plant DCS. A versatile software was defined to be the platform to run the neural network and MPC applications, Emerson [8].

The neural network was trained using 6-month period of historical data with the objective to establish a control block system in order to replace the linear regression equation, previously used in the DCS. The amount of data used represented the plant operation for long term, excluding the outliers that in fact, are non-usual events, plant shutdowns, downtimes or experiments. The model is expected to predict the moisture in the continuous process.

The first step of modeling was to calculate the correlation between chosen variables and select those ones which statistically had the main effects with predictable variable (moisture). Based on the engineering flow diagram, the reactor temperature, amperage and raw material feed rates, assays and moistures were selected as potential variables to obtain the model correlation. The selected variables were the acid feed rate, acid assay and the water feed rate which have demonstrated correlations higher than 0.80. Virtual on-line analyzer was obtained by training the digital control system neural block through historical data of the unit, as showed in figure 5.

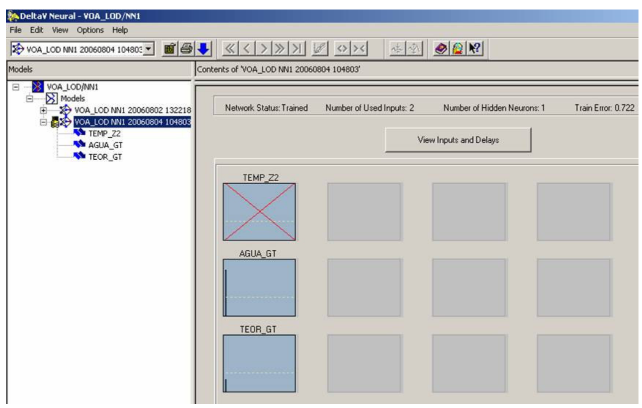

Figure 5. Neural network model

The predictive model gains were obtained by providing steps in the process, collecting and treating the data through the software. In figure 6 is shown the software template. To establish the process control strategy for MPC it was considered the following variables:

- Constraint variable: Reactor amperage that can not exceed a certain value to avoid damages in the reactor mechanical structure.
- Disturbance variables: Acid feed rate and acid assay have a direct correlation to the reactor moisture and influenciate the predictable parameter by the VOA.
- Controlled variable: Moisture predicted by the VOA. The operators insert the moisture set point in the DCS and based on that the MPC manipulates the water feed rate set point.
- Manipulated variable: Water feed rate, is the variable adjusted by MPC automatically in remote operation mode.

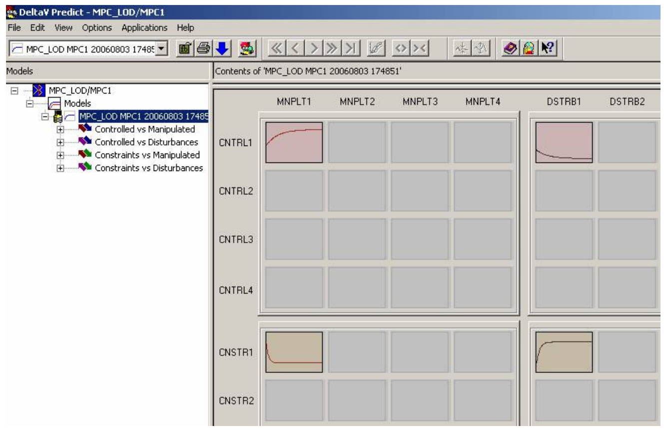

Figure 6. Model-Predictive Control

4 Results and Discussion

The process constraints were minimized by reducing the moisture variability throughout better water feed rate control. The achieved process capability (cpk) is 2.22, as demonstrated in figure 7. The related off-grade product was eliminated and the continuous reactor operation became more reliable. No plant downtimes occurred, increasing the plant productivity.

The most important part of the modeling process is to get reliable historical data as well as planning the plant trials and parameters adjustments. Besides the software tools, the process control strategy should be evaluated by an expert technical group prior its implementation to avoid future problems.

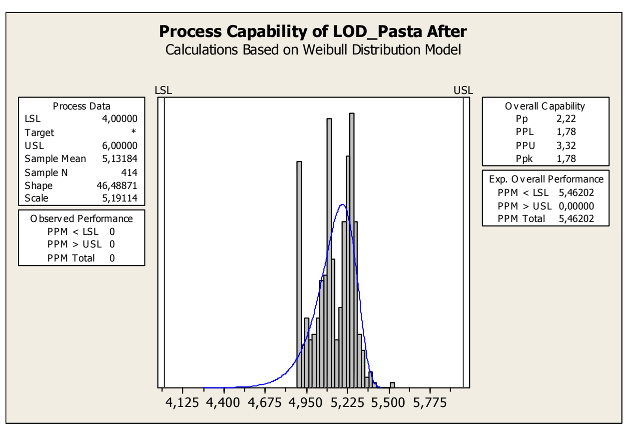

Figure 7. MPC capability analysis

5 Conclusions

The project was implemented accomplishing the goals and was recognized as a breakthrough solution. Technology innovation and business strategies were focused on this project by searching modern ways for manufacturing process control and management. Smart tools, new control strategies, process modeling and teamwork were the key to achieve success in this implementation. The engineering approach in this work allowed the process to be anticipated avoiding waste of resources in the manufacturing organization and working in a proactive vision. The technology innovation provided a friendly user tool for the operators and knowledge exchange among the team. Being so, by applying intelligent control, it was possible to increase overall productivity of the manufacturing unit. The collaboration among all the individuals involved from different areas of knowledge was essential to get the results in an integrated manner. The overall results lead the company to a sustainable business strategy due to the large potential to increase the instantaneous plant capacity. This project opens also new opportunities to reduce costs in the manufacturing units by applying smart control system.

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