NEURAL NETWORK AND MODEL-PREDICTIVE CONTROL FOR A CONTINUOUS NEUTRALIZATION REACTOR OPERATION

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Abstract. *This project outlines neural network non-linear models to predict the moisture in the continuous reactor in real time as a virtual on line analyzer (VOA) and a Model-predictive control (MPC). This work presents the development and implementation of an automation solution in order to obtain lower variability in moisture control for a continuous neutralization reactor. In this process an acid-base reaction is expected to take place within 30 seconds in a continuous feed rate of raw materials. The paste moisture in the reactor is the most important variable to get a proper neutralization reaction. This control is also essential to get the desired yield and avoid some constraints in the downstream process. Plant downtimes and off-grade products are going to be eliminated by reducing the moisture control variability in the reactor paste through a flat material balance. The first step of modeling is to calculate the correlation between chosen variables and select those ones which statistically have the main effects with predictable variable (in this case moisture). The second step is to select an enough amount of data which can represent the plant operation for long term, and also excluding the outliers, that in fact, are non-usual events like plant shutdowns, downtimes or tests. VOA is obtained by training the digital control system neural block through historical data of the unit, considering the previous steps. MPC is based on constraints, disturbances, controlled and manipulated variables to establish the process control strategy. Constraints variables must be configured to avoid damages in equipments considering safety and reliability issues. Disturbances variables have a direct gain associated to the controlled one (moisture). The manipulated variable (water feed rate) is adjusted according to the process control strategy defined previously to keep as stable as possible the controlled variable. The MPC receives the prediction from VOA and anticipates the calculation of the set point for the water feed rate control loop. Operators on line monitor the moisture via computer graphic displays. The project was successfully implemented achieving the goals by reducing the moisture variability, eliminating off-grade products and getting a more reliable operation with no plant downtimes.*

Keywords: *Model-predictive control. Neural networks. Virtual on-line analyzers. Process variability*

1. INTRODUCTION

A neural network, also known as a parallel distributed processing network, is a 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 rather than in series (or sequentially) as in earlier binary computers or Von Neumann machines. Since it relies on its member neurons collectively to perform its function, a unique property of a neural network is that it can still perform its overall function even if some of the neurons are not functioning. In other words 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 either 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 'networks of agents' (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, according to figure 1.

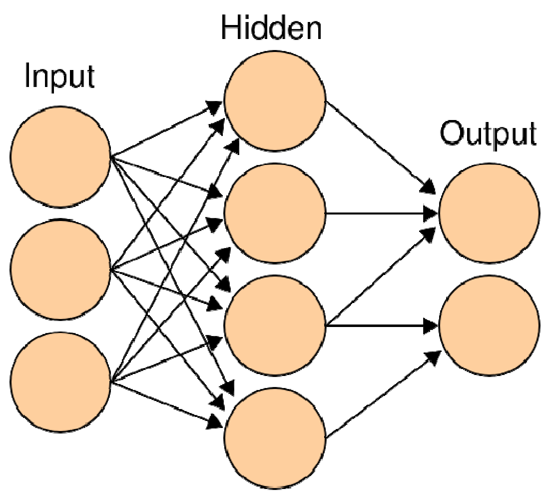

Figure 1. Neural network.

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, see example in figure2. Issues arise for guaranteeing closed-loop stability, to handle model uncertainty, and to reduce on-line computations, according to Bemporad [3].

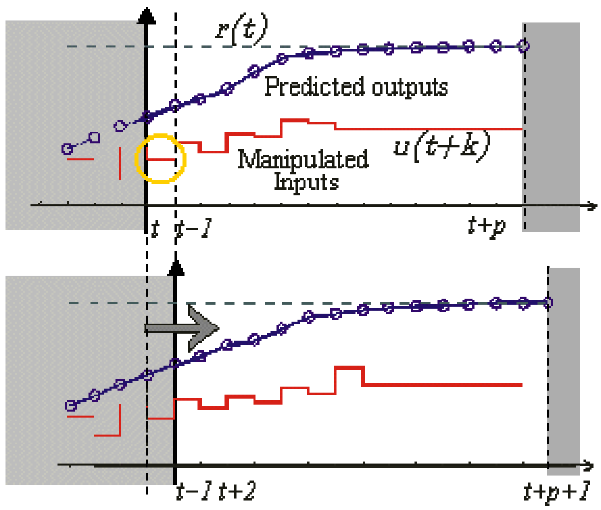

Figure 2. Model predictive control.

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[4].

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 [5].

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. Its control is done by feeding water into the continuous reactor, creating a product paste. It is done automatically via a closed-loop configured in the Distributed Control System (DCS). The water feed rate set-point is determined by the operators through a previews visual analysis of the product in the reactor outlet pipeline.

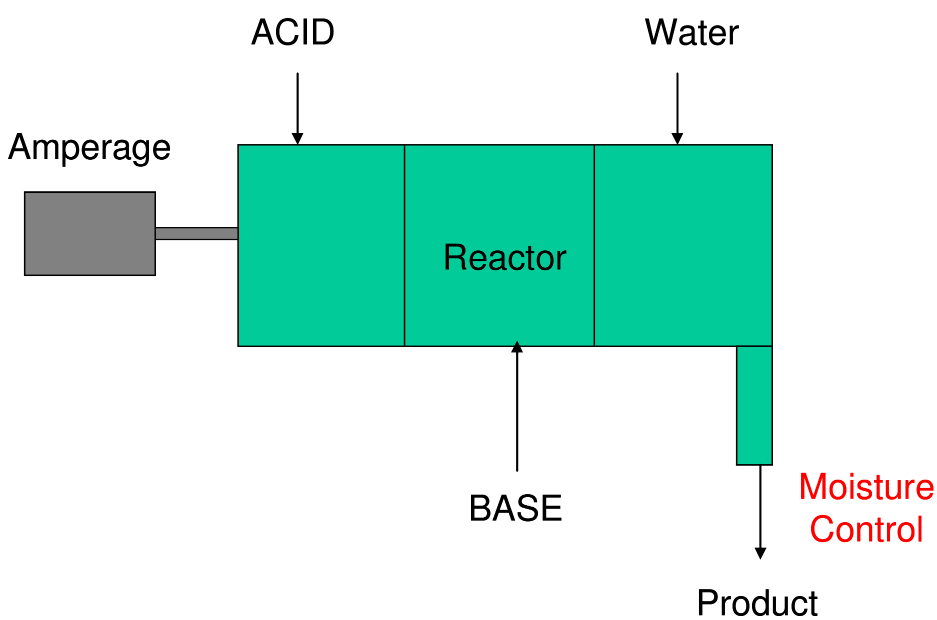

Figure 3. Continuous neutralization reactor.

The ideal moisture operating range is between 4 – 6%. Working off the range many plant shutdowns is observed due to pluggages in the equipments located in the process downstream. 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 create a process baseline many six sigma statistical tools were applied to the available historical data of the manufacturing unit. MINITAB software was used for calculating the indexes and helps the analysis. The available historical data for moisture was statistically normal due to the p-value of 0.540 is higher than 0.05, according to figure 4. Then all statistical tools used were based on the normal set of data, according to Hayashi[6].

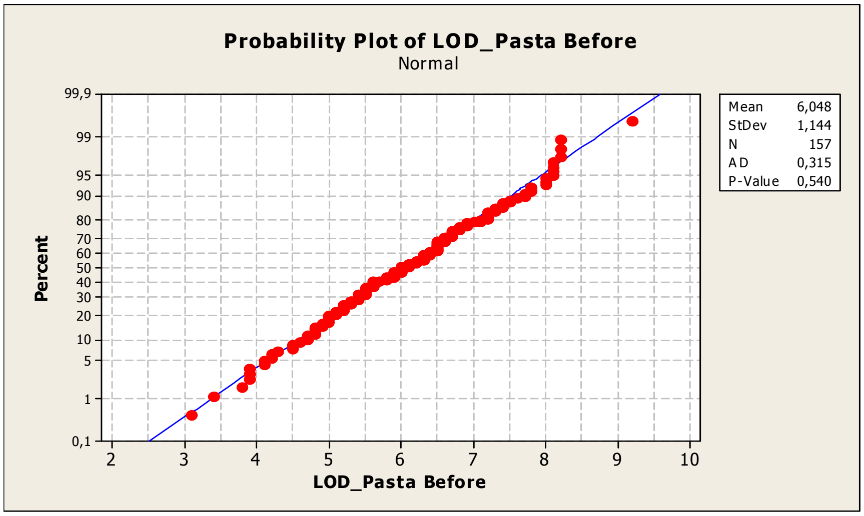

Figure 4. Normality test of the moisture historical data.

When it was applied the capability analysis tool, the results shown a cpk of 0.29, much less than 1.32 that is the reasonable number for a capable process, according to figure 5. Then, the work proposal was to develop and implement an automation solution in order to obtain lower variability in moisture control for the continuous neutralization reactor.

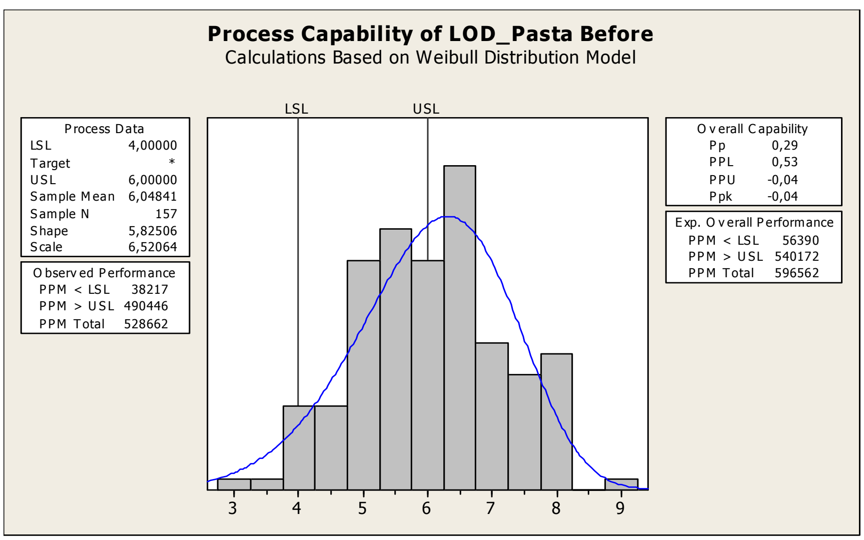

Figure 5. Baseline process capability analysis

First, it was used a linear modeling, as presented below, for correlating the water feed rate with the reactor amperage, acid feed rate and moisture.

Water_feed_rate = Reactor_amperage +310 +Acid_feed_rate*0.023 +Moisture*31
(248 + Moisture*21)

The linear regression did not work properly due to the cyclical variation between the amperage and water feed rate. When the reactor amperage goes up the water feed rate goes up as well, causing a not suitable process control for the water feed rate as shown in figure 6.

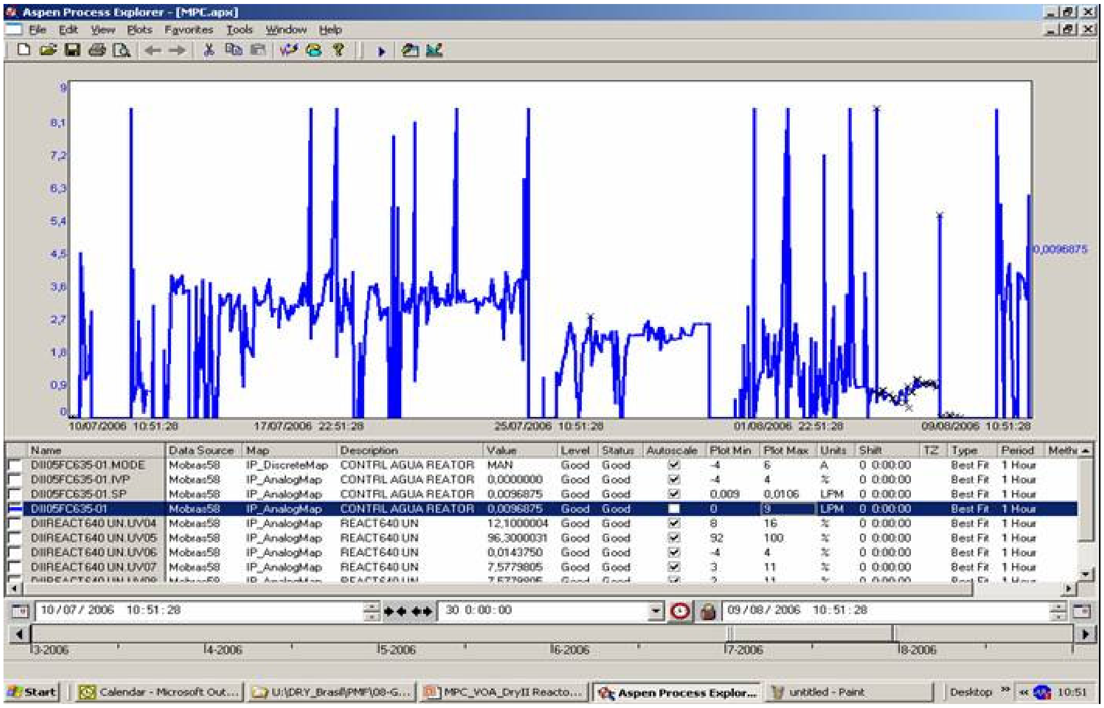

Figure 6. Water feed rate variation.

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 VOA. And also a non-linear MPC was considered to control the water feed rate based on the moisture prediction.

A search was done in the market to find out software to implement the VOA and MPC modules, considering the constraints of current DCS installed in the plant. A versatile software was defined to be the platform to run the neural network and MPC applications, Emerson Co[7].

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 represents the plant operation for long term, excluding the outliers that in fact, are non-usual events like plant shutdowns, downtimes or tests. 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 have the main effects with predictable variable (in this case moisture). Based on the engineering flow diagram, the rector 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 presents correlation higher than 0.80. VOA was obtained by training the digital control system neural block through historical data of the unit, as showed in figure 7.

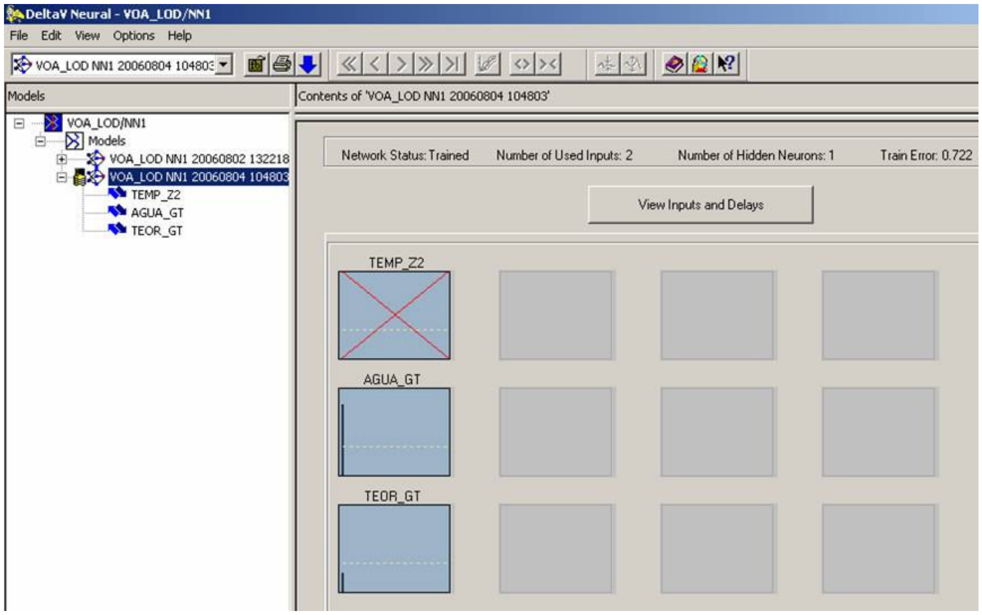

Figure 7. Neural network model.

The predictive models gains were obtained according to figure 8. To establish the process control strategy for MPC it was used the following variables:

- Constraint variable: Reactor amperage that can not exceed a certain value to avoid damages in the reactor structure.
- Disturbance variables: Acid feed rate and assay, which have a direct correlation to the reactor moisture and are taken in consideration to the VOA.
- Controlled variable: Moisture predicted by the VOA. The operators insert the moisture set point and based on that the MPC manipulates the water feed rate set point.
- Manipulated variable: Water feed rate, is the variable adjusted by MPC.

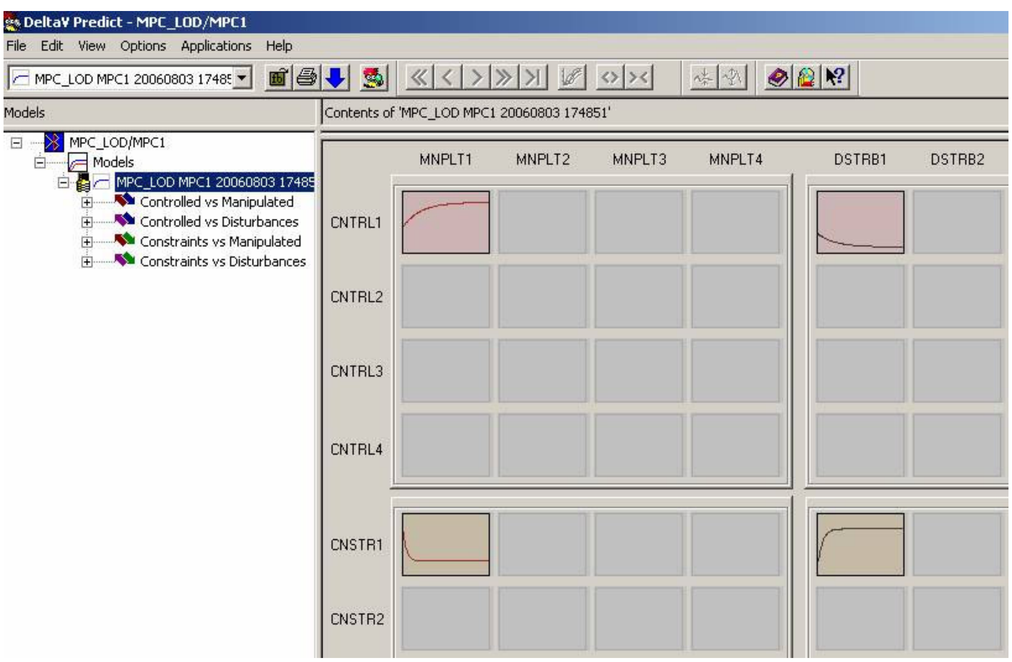

Figure 8. Model-Predictive Control.

4. RESULTS

The process capability was achieved (cpk = 2.22) as demonstrated in figure 9. The process constraints were minimized by reducing the moisture variability through a better water feed rate control, as it is shown in figure 10. The related off-grade product was eliminated and the continuous reactor operation became more reliable. No plant downtimes and shutdowns occurred, increasing the plant productivity.

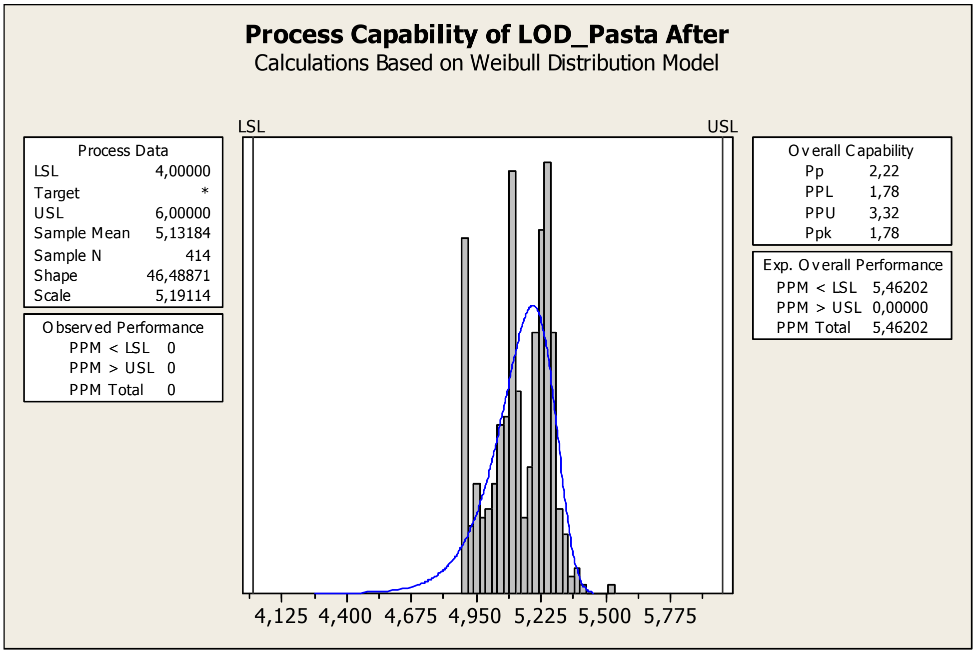

Figure 9. MPC capability analysis

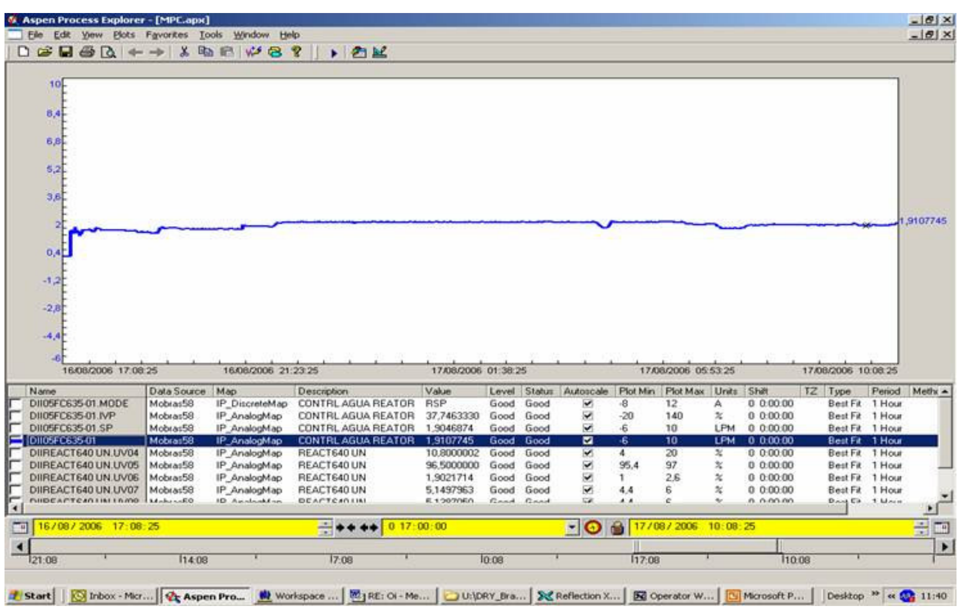

Figure 10. New water feed rate variation

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 instantaneuos plant capacity. This project opens also new opportunities to reduce costs in the manufacturing units by applying smart control system.

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