Neuro-Fuzzy Model of the Detergent Leavings Kinetics' Removal in a Clean in Place System

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***Abstract*— This paper has focused on the Neuro-Fuzzy model of the detergent leavings kinetics' removal of a CIP System, which has been evaluated based on the pH measured. The plant dynamics has been identified for different operational conditions. Flow rates above 10,5 L.min^{-1} has no contribution for the rinsing process time decreasing; it allows to state that is possible to optimize the process reducing energy, water and steam consumption as well as the time of unused machinery, with consequent productivity gains. The obtained models, based on Neuro-Fuzzy systems, allowed the prediction of the system dynamics behavior. The results of the obtained models were validated when compared with the experimental data. Three triangular membership functions for the input data modeled accordingly the pH dynamics with an error of 0.011 when comparing the validation data and the obtained model.**

***Index Terms*— CIP System, Neuro-fuzzy, Optimization**

I. INTRODUCTION

The contact of food with poorly sanitized surfaces may increase the incidence of microorganisms affecting its quality. The presence of leavings also cause operational issues on the equipments, since it causes yields decreasing in thermal exchange performance and increases the system pressure drop. These factors justifies the value of a correct cleaning procedures of the inputs used in food processing. Usually the cleaning procedures are performed poorly by companies because it requires breaks in production.

The Clean in Place – CIP process is the most common cleaning procedure used in industry to ensure that the pipes/equipments are free of organic and inorganic contaminants. Thus, its study and optimization is fundamental, through the establishment of the residual kinetic removal in each step of the process [1].

Issues related with the production machinery, including the heat exchangers, are common in dairy industry. Nowadays, the process equipment involved with the milk and other dairy industry products manipulation must be completely stopped for a long time during the cleaning procedures. Such cleaning procedure involves the cleaning of the equipment with caustic detergent promoting the reduction of the residue (fat, lactose, proteins and minerals). After this step, the equipment must be rinsed to remove the sanitizing compound.

The aim of this paper is the dynamic behavior identification of the residual concentration of sanitizing agent in the effluent rinse water of the equipment using Neuro-Fuzzy systems; this identification will be performed in function of the operating flow [2]. Models using the ANFIS (Adaptative Network-based Fuzzy Inference System) system were obtained which allows predicting the system's dynamic behavior.

II. THEORETICAL FRAMEWORK

Cleaning the equipment properly may bring economical benefits for industry. According with [3], costs are related with production breaks for maintenance and equipment repairs, production losses, the excessive water usage and energy losses.

The knowledge and consequent optimization of a cleaning process allows its cost reduction [4]. The understandings on how residues are generated, as well as the temporal behavior of its removal, are necessary to optimize a cleaning procedure.

The residues kinetic removal knowledge may contribute to optimize the heat exchangers cleaning operations resulting, most of the times, in operational costs reduction of those equipments on the order of at least 50% [5]. The kinetic removal establishment is obtained by the mathematical model of the system, and one of the techniques is the Neuro-Fuzzy modeling.

An adaptative neural network is characterized by a network formed by nodes and connections, where each node consists of a process unit associated with a function, and the connections represents inputs and outputs of each node. Each connection of the network indicates a relationship between the connected nodes. The group of nodes may be divided in two subgroups [6].

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1) Adaptative nodes, where the outputs depends not only on the inputs, but also on modifiable parameters within the model.
2) And the other case, nodes, which function depends only on the inputs, called non-adaptative.

One of the approaches that use hybrid methods is the Adaptative Network-based Fuzzy Inference System (ANFIS) proposed by [7]. The ANFIS model works equivalently to the fuzzy inference systems, and its adaptative capabilities makes it applicable into a wide range of areas of study, for instance, in data classification and, in the case of this study, feature extraction from response curves. One of the properties of the ANFIS model is that the group of parameters may be decomposed to be used in a more efficient hybrid learning rule than the traditional techniques found in publication [8].

The ANFIS model is available in MATLAB® tool which supports only orders zero or one Takagi-Sugeno systems. The tool allows multiple input variables, but is limited to one output variable; in other words, for MISO (Multiple Input Single Output) studies [8].

III. Material And Methods

A. Experimental system

The executed experiments to obtain the data used for the mathematical modeling of the residue kinetic removal of the heat exchanger used in this study were proceeded using the system showed in the Fig. 1 [9].

The system works as described in the sequence (referring to the Fig. 1). The product flows through the heat exchanger piped, by a positive displacement pump (1), making it possible for the process fluid to pass into the heat exchanger tubes (4 tubes pass). The centrifugal pump (2) is responsible for the heating agent movement through the heat exchanger shell. The heating agent temperature control is proceeded by the control valve (3), which is responsible to adjust the quantity of steam.

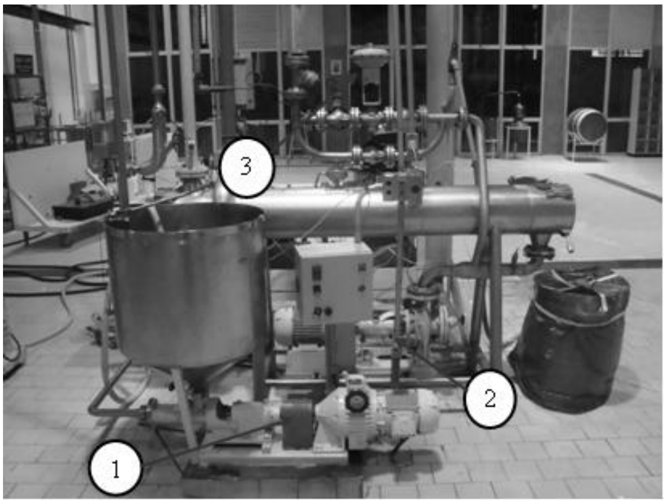

Fig. 1. Shell and tube heat exchanger for the studied system.

A simplified general diagram of the studied system is presented in Fig. 2, where:

1) TT1 represents the temperature measurement of the process fluid on the heat exchanger output.
2) TT2 the temperature of the heating agent output.
3) TT3 the temperature of the process fluid on the heat exchanger input.
4) TT4 the temperature of the heating agent input.
5) FT the process fluid flow on the heat exchanger input.
6) TC the heating agent temperature control.

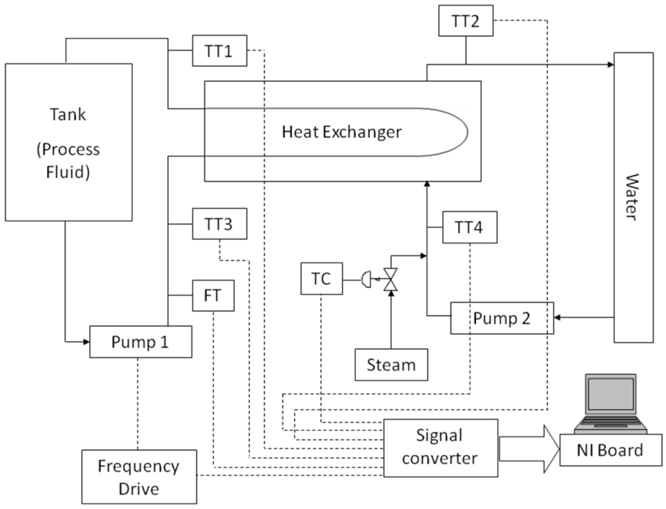

Fig. 2. Instrumentation flowchart for the studied system.

The electronic system used to collect data is basically composed of a microcomputer, a National Instruments® data acquisition board (model: NI PCI-6259) and the Labview® tool used to monitor, acquire data and control the process in real time.

Also, it has been developed an application using Labview® dedicated to collect data acquired in the proceeded experiments, from which the model of the studied system has been developed.

B. Sediment build up and clean up stage with detergent

Initially, milk at 85 °C and 9.0 $L.min^{-1}$ was circulated during 90 minutes inside the tubes of the tube bundle of the heat exchanger to promote the desired deposits formation, for subsequent chemical cleaning stage. After the end of the heat exchanger incrustation stage, the milk was drained. Afterwards, such milk protein deposits was kept to rest for nearly one hour considering the consolidation of the deposit process on the inner walls of the heat exchanger tubes.

Following the previous stage, the cleaning stage with detergent solution (sodium hydroxide, 0.5 % w/w) on the inner tubes of the heat exchanger has been started. Firstly, the solution was put in circulation in the inner tubes of the heat exchanger, with temperature and flow controlled respectively at 50 ºC and 9.0 $L.min^{-1}$ for one hour, returning the output product to the tank of hot detergent. The monitored process variables were the values of pH, temperature, and flow of the solution and heating agent versus time.

C. Rising process

Once the cleaning stage with detergent solution was

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finished, the rinsing process starts with potable water to remove residual detergent attached to the inner tube walls, used in the previous stage. The equipment is placed in steady state operation, feeding the inlet nozzle of the exchanger with water, pre-heated at nearly 50 ºC, keeping the temperature controlled at 50 ºC and flow at 9.0 $L.min^{-1}$, and directing the output of the process fluid to a small intermediate tank, used for the measurement of pH without turbulence.

The experimental procedure mentioned in the previous paragraphs was repeated for temperature of 50 °C and different values of flow of rinse water (4.0 $L.min^{-1}$, 6.0 $L.min^{-1}$, 7.5 $L.min^{-1}$, 9.0 $L.min^{-1}$, 10.5 $L.min^{-1}$, 12$L.min^{-1}$, 14 $L.min^{-1}$ and 16 $L.min^{-1}$). The flow was disturbed considering step changes imposed on the set–point of the flow controller, keeping the temperature controller operating in automatic mode.

D. Behavior of pH in function of the flow fluctuation

Based on the procedure described on the item C, flow disturbances has been applied during the rinsing process, keeping the process fluid temperature constant and equals to 50 ºC. In this test, as already mentioned, steps from 0 $L.min^{-1}$ to 4.0 $L.min^{-1}$, 6.0 $L.min^{-1}$, 7.5 $L.min^{-1}$, 9.0 $L.min^{-1}$, 10.5 $L.min^{-1}$, 12 $L.min^{-1}$, 14 $L.min^{-1}$ and 16 $L.min^{-1}$ has been applied.

Analyzing the obtained response curves, it has been concluded that the cleaning time decreases while the flow increases, but not linearly.

A flowrate value of 10.5 $L.min^{-1}$ (Re=2,071) has been proved to be effective in order to provide the minimum required rinse water volume to execute the rinse stage of the CIP system and flow rates higher than 12 L/min (Re=2,367) has been proved to not contribute in a significant way to improve the removal process [9].

E. Modeling using the Adaptative Network-based Fuzzy Inference System (ANFIS)

From the obtained values during the tests, the modeling of the pH behavior relative to the sodium hydroxide solution concentration present on the rinse water in the heat exchanger output over time has been performed with the Simulink/MATLAB® tool, using the ANFIS inference system. For that, it was used the "Fuzzy Logic" toolbox of the MATLAB® (performed using the Sugeno inference system).

For the neural network training, it has been used the pH responses for steps from 0 $L.min^{-1}$ to 4.0 $L.min^{-1}$, 6.0$L.min^{-1}$, 9.0 $L.min^{-1}$, 10.5 $L.min^{-1}$, 12 $L.min^{-1}$, 14 $L.min^{-1}$ and 16 $L.min^{-1}$.

As described in [6] the data for the neural network training were sequentially inserted. It has been used 3 triangular membership functions for the fuzzy inference system generation: the current flow, F[k], and the pH delayed one sample, pH[k-1], as the inputs and the current pH, pH[k], as the output, with a selected tolerance for the error of 0.01 and 10 epochs of iteration. The "Grid Partition" algorithm has been used for the membership functions generated. For the neural network training, a 0.0099 average error has been achieved in 4 epochs (generated by MATLAB®).

The membership function obtained for the flow (F[k]) and the pH[k-1] inputs are shown in the Fig. 3 and Fig. 4, respectively.

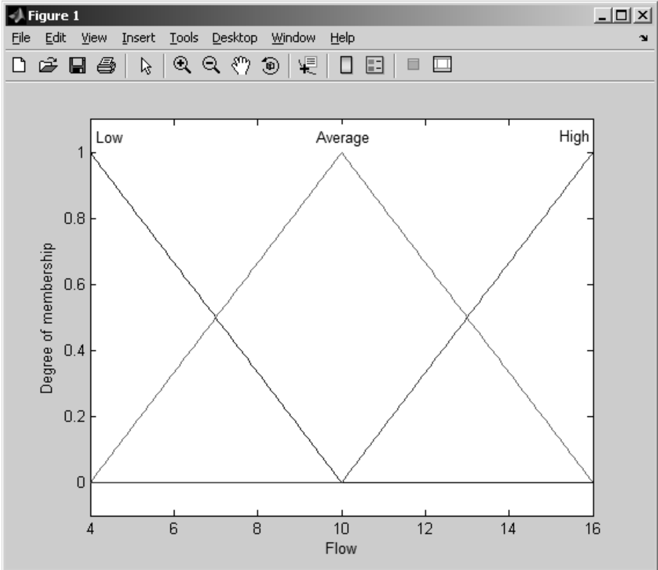

Fig. 3. Flow (F[k]) input for the neural network training.

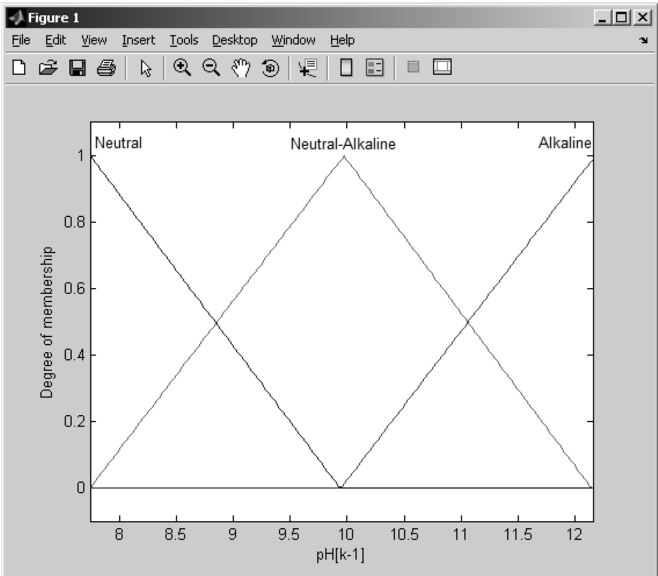

Fig. 4. pH delayed 1 sample (pH[k-1]) input for the neural network training.

The response surface obtained is presented in the Fig. 5.

It has been obtained 9 rules (listed below). The linguistic terms used in the membership functions for the pH[k-1] input and the pH[k] output were *Neutral*, *Neutral-Alkaline* and *Alkaline*; and the linguist terms for the flow (F[k]) input were *Low*, *Average* and *High*.

The obtained rules are:

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1) *If (pH[k-1] is Neutral) and (Flow is Low) then (pH is Neutral)*
2) *If (pH[k-1] is Neutral) and (Flow is Average) then (pH is Neutral-Alkaline)*
3) *If (pH[k-1] is Neutral) and (Flow is High) then (pH is Alkaline)*
4) *If (pH[k-1] is Neutral-Alkaline) and (Flow is Low) then (pH is Neutral)*
5) *If (pH[k-1] is Neutral-Alkaline) and (Flow is Average) then (pH is Neutral-Alkaline)*
6) *If (pH[k-1] is Neutral-Alkaline) and (Flow is High) then (pH is Alkaline)*
7) *If (pH[k-1] is Alkaline) and (Flow is Low) then (pH is Neutral)*
8) *If (pH[k-1] is Alkaline) and (Flow is Average) then (pH is Neutral-Alkaline)*
9) *If (pH[k-1] is Alkaline) and (Flow is High) then (pH is Alkaline)*

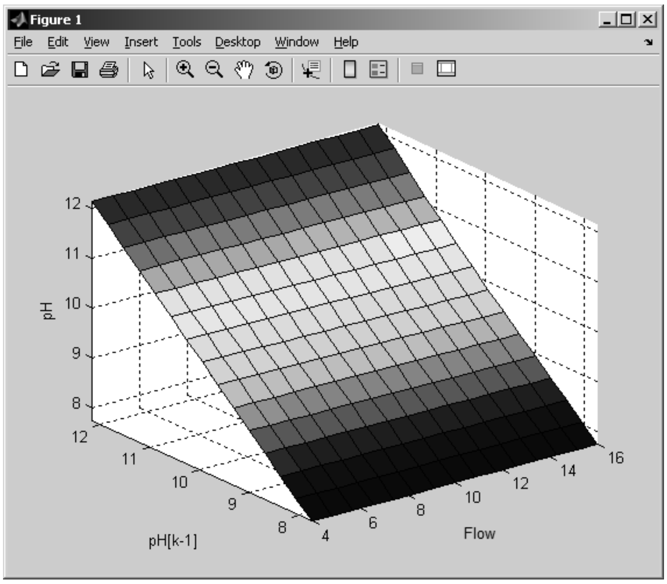

Fig. 5. Surface response of the model with 2 inputs and 1 output.

For the model validation it has been used the pH response for a step from 0 $L.min^{-1}$ to 7.5 $L.min^{-1}$; the average error between the model and the validation data was 0.011. The model (Fig. 6) represents adequately the system response with a small error.

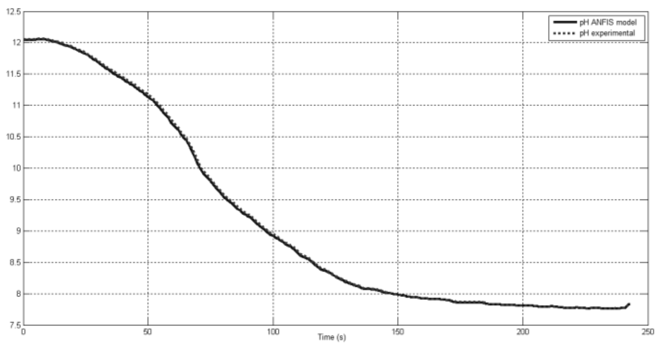

Fig. 6. Model versus validation data of the pH response for a step from 0 $L.min^{-1}$ to 7.5 $L.min^{-1}$in the flowrate.

IV. Conclusions

The implementation and instrumentation of a typical CIP station, with an appropriate monitoring, control and data acquisition of the process variables has been successfully done, as well as the CIP process dynamics identification (in the rising process). This identification has been done using the ANFIS inference system available in the "Fuzzy Toolbox" on MATLAB®/Simulink tool.

The advantage observed in the ANFIS system modeling is possibility on using a tool to easily and quickly generate a model independently of the production, operational condition and equipments used.

The development of a virtual sensor based on the obtained models for the process variable considered in this paper, reveals an attractive industrial application perspective. An optimized control strategy based on a virtual sensor, in which a target objective function is related to the cost minimization, represents a potential application for process control industries.

V. Acknowledgment

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