Research, Society and Development, v. 9, n. 9, e13996321, 2020
(CC BY 4.0) | ISSN 2525-3409 | DOI: http://dx.doi.org/10.33448/rsd-v9i9.6321

Controle nebuloso do pH do caldo de cana para produção de açúcar

Fuzzy pH control of sugarcane juice for sugar production

Control difuso del pH del jugo de caña de azúcar para la producción de azúcar

Recebido: 04/07/2020 | Revisado: 19/07/2020 | Aceito: 23/07/2020 | Publicado: 09/08/2020

Manuel Ferreira Silva Neto
ORCID: https://orcid.org/0000-0003-1299-9504
Universidade de Uberaba, Brazil
E-mail: netomfs@hotmail.com
Antonio Manoel Batista da Silva
ORCID: http://orcid.org/ 0000-0003-1082-7637
Universidade de Uberaba, Brazil
E-mail: tomanel.tamanel@gmail.com
Edilberto Pereira Teixeira
ORCID: http://orcid.org/ 0000-0003-3953-2891
Universidade de Uberaba, Brazil
E-mail: edilberto.teixeira@gmail.com
Marcelo Lucas
ORCID: http://orcid.org/0000-0001-6111-0834
Universidade de Uberaba, Brazil
E-mail: marcelo.lucas.eng@gmail.com

Resumo

Uma proposta para controlar o pH do caldo em usinas de açúcar é apresentada neste trabalho. Por ser um sistema com distúrbios e características não-lineares, os métodos de controle convencionais não atendem aos requisitos usuais do processo. Entre esses métodos convencionais, destacamos o controlador PID, que é basicamente linear. Ampliando-se as possibilidades de ação, a proposta de controle apresentada neste trabalho mostrou-se bastante satisfatória, utilizando lógica nebulosa de maneira preditiva na consideração do efeito das perturbações de maneira inteligente. Os detalhes do controlador proposto são apresentados, incluindo alguns resultados de simulação. A eficácia do controlador proposto é ilustrada por simulação, mostrando graficamente os distúrbios e a consequente ação de controle, o que elimina o erro no estado estacionário. A comparação dos resultados obtidos com os controladores PID convencionais e com os controladores *fuzzy* mostra a ação preditiva desses controladores, permitindo uma redução significativa na variabilidade do erro no estado estacionário. Além disso, essa arquitetura pode ser modificada para incluir outros distúrbios para outras aplicações. Assim, a presente proposta pode ser usada em geral para controlar sistemas não-lineares e multivariáveis.

Palavras-chave: Controle nebuloso; Controle pid; Controle de pH; Sistemas não lineares; Processo agroindustrial.

Abstract

A proposal to control the pH of the broth in sugar mills is presented in this work. Because it is a system with nonlinear characteristics and disturbances, the conventional control methods do not satisfy the usual requirements of the process. Among these conventional methods, we highlight the PID controller, which is basically linear. Extending the possibilities of action, the control proposal presented in this work proved to be quite satisfactory, by using fuzzy logic in a predictive way in the consideration of the effect of the disturbances in an intelligent way. The details of the proposed controller are presented, including some simulation results. The effectiveness of the proposed controller is illustrated by simulation, showing graphically the disturbances and the consequent control action, which eliminates the steady state error. The comparison of the results obtained with conventional PID controllers and the fuzzy controllers shows the predictive action of the fuzzy controllers allowing a significant reduction in the variability of the steady state error. In addition, this architecture can be modified to include other disturbances for other applications. Thus, the present proposal can be used in general to control non-linear and multivariable systems.

Keywords: Fuzzy control; Pid control; pH control; Nonlinear systems; Agro-industrial process.

Resumen

En este trabajo se presenta una propuesta para controlar el pH del jugo en ingenios azucareros. Como se trata de un sistema con perturbaciones y características no lineales, los métodos de control convencionales no cumplen los requisitos habituales del proceso. Entre estos métodos convencionales, destacamos el controlador PID, que es básicamente lineal. Al ampliar las posibilidades de acción, la propuesta de control presentada en este trabajo demostró ser bastante satisfactoria, utilizando una lógica difusa de manera predictiva al considerar el efecto de las perturbaciones de una manera inteligente. Se presentan los detalles del controlador propuesto, incluidos algunos resultados de simulación. La efectividad del controlador propuesto se ilustra mediante una simulación, que muestra gráficamente las perturbaciones y la acción de control consiguiente, que elimina el error en el estado estacionario. La comparación de los resultados obtenidos con los controladores PID convencionales y con los controladores *fuzzy* muestra la acción predictiva de los controladores *fuzzy*, lo que permite una reducción significativa en la variabilidad del error en el estado estacionario. Además, esta arquitectura se puede modificar para incluir otras perturbaciones para otras aplicaciones. Por lo tanto, la presente propuesta se puede utilizar en general para controlar sistemas no lineales y multivariables.

Palabras clave: Control *fuzzy;* Control pid; Control de pH; Sistemas no lineales; Proceso agroindustrial.

1. Introduction

The pH control is a common action in the clarifying process of the sugarcane juice during the production of white sugar (Pinheiro & Finzer, 2016). The broth treatment is an important step to obtain a final product of high quality, and an increase in the useful life of the process equipment (Elfatni & Tijani, 2006). These treatments are also responsible for maintaining the nutritional characteristics of sugarcane that are necessary for the yeast metabolism (Alcarde, 2020). In the industrial process of sugar production, the control systems are fundamental to the good performance of the plant. These systems include pH control, which indicates the acidity, neutrality, or alkalinity of an aqueous solution. The process has the characteristics of strong nonlinearity, multiple inputs and time varying properties, making it difficult to calculate parameters in real time to maintain pH without manual adjustments (Singh at ali., 2014, 2015; Karthik & Senthilkumar, 2010; Vijayaragavan at ali., 2015). Some actuators and sensors may also exhibit nonlinearities, causing control instability, dead zone, and stationary error. There are also some time varying characteristics that makes the control system sensitive to minor disturbances when the controller works near the setpoint (Suchithra at ali., 2016).

The objective of this work is to show the performance of the fuzzy controller in nonlinear systems, such as the pH control for sugar production. The dynamic model of the plant is simulated, including the proposed controller and some possible disturbances. The performances of the fuzzy and the PID controllers are compared to emphasize the effectiveness of each one.

2. Methodology

This work was developed using computer simulation as the basic tool. The transfer functions describing the dynamic systems analysed in this paper have been estimated by authors considering their experience in sugar production plants. This kind of research can be considered as quantitative, since the results are analysed in terms of the industrial plant loop error, and as qualitative, since the performances of the conventional PID and the fuzzy controllers are compared. The work was carried out in the university computer laboratory, but the industry experience in sugar plants was important for obtaining the mathematical description of the dynamic equations. Therefore, it can be considered both an industry and laboratory computer work. The basic criteria to analyse the results was a performance comparison of the step responses of the controllers used in this work. The simulations have been performed using the Matlab/Simulink system, and the Matlab/Fuzzy Toolbox. The industry process that is used to test the approach presented here is the control of sugar juice pH. The steps for its production, the control of the sugar juice pH, the fuzzy controller applied and its characteristics, including the implication rules are presented in the next sections.

2.1 Steps of the sugar manufacturing process and pH control

The complete sugar production process includes the following steps: sugar cane washing, crushing, extraction, lime addition, carbonization, filtration, sulfur dioxide addition, concentration, crystallization and drying. Lime addition, carbonization and sulfur dioxide addition are critical process steps and require continuous pH control. After washing the cane, grinding occurs with flow of hot water in opposite direction. The crude broth thus obtained must be treated with a lime solution, prepared with calcium hydroxide (CaOH). The addition of lime is necessary to neutralize the acids from sugarcane to prevent sucrose from becoming starch by hydrolysis or the inversion to other forms of sugar. Lime milk is added to the sucrose solution to neutralize its pH around the value of seven (Karthik at ali., 2011).

The control of pH is vulnerable to process disturbances (Norquay at ali., 1999; Wan at ali., 2006). Therefore, the application of multivariable control techniques is very appropriate to consider the influence of these disturbances and treat them properly (Abdullah et ali., 2012). The nonlinear characteristics of the process must also be considered, which justify the application of advanced control techniques, such as fuzzy control (Arun at ali., 2015; Barros at ali., 2006; Hassani & Zarei, 2015). Therefore, the option was the use of fuzzy controllers. This can also be justified by:

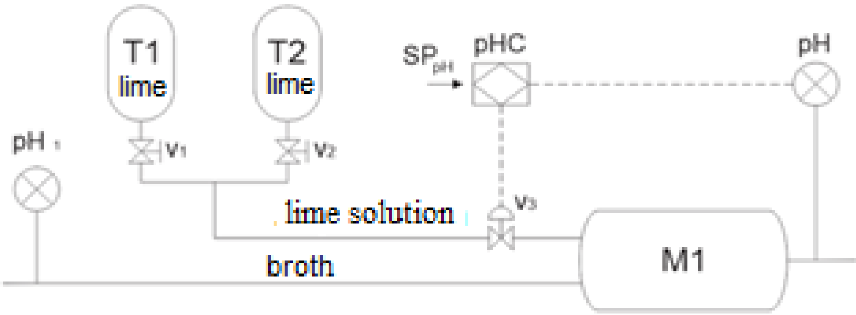
- Not requiring a priori knowledge of the dynamic process equations (Yordanova, 2016).
- Fuzzy control rules are independent, which makes the system reliable and less sensitive to external disturbances.
- Fuzzy control rules are created based on the knowledge obtained from the process operators (Song at ali., 2020).

Some details of pH control of sugar broth as shown next.

2.2 Control of broth pH

The liming process consists of adding Ca (OH) lime milk to the broth to obtain a neutral pH condition. In general, the lime solution is prepared in more than one tank to avoid plant shutdowns due to lack of this component. The process is performed manually by the plant operators. There are several configurations for this process, and, in some cases, there is an intermediate level-controlled tank, which allows the lime feed to be conducted directly to the control valve. To avoid settling, there is recirculation by pumping between the intermediate tank and the preparation tanks. In other cases, there is not an intermediate tank, causing a variation of the pressure in the valve which makes the control action difficult. This variation causes a disturbance in the control variable. The final control element is the valve V_3, in Figure 1.

Figure 1. pH broth control diagram.



Source: The authors (2020).

Figure 1 shows a simplified process diagram showing the following elements: pH1 and pH represent the input and the output pH transmitters, respectively; pHC refers to the pH controller; T1 and T2 are the tanks containing the hydrated lime solution; V1 and V2 are manual valves; V3 represents the control valve for hydrated lime injection and M1 is the broth tank.

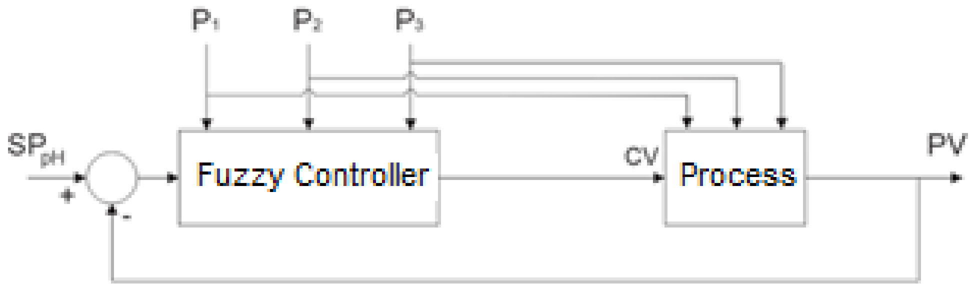
Consideration should also be given to the variation in broth pH at the process inlet. This disturbance, here called P2, also influences the control variable, but with a different periodicity than disturbance P1. On the other hand, applying a broth inlet flow control to the dosing tank ensures that the process is fed in a most homogeneous manner, facilitating lime dosing control. Providing a relationship between broth volume and lime volume to raise the pH value is of great relevance in this process. In this case, in the model presented in this paper, it is considered that this disturbance, now called P_3, would have a direct action on the final process variable, with a different periodicity than the other disturbances.

A simplified process model using a first order transfer function is considered, as shown in equation 1, despite the nonlinear characteristics of the dynamic pH model, as proposed by (Sunori at al., 2016), and (Cavalcanti at ali., 2008). One can physically see that there is no dead time, because the fluid is not compressible. However, the transport delay shown in equation 1 refers to an approximation of a higher order system to a first order function.

$$G(s) = \frac{Y(s)}{F(s)} = \frac{ke^{-\theta s}}{\tau s + 1} \quad (1)$$

In equation (1), G(s) is the transfer function, Y(s) is the Laplace transform of the output variable, corresponding to the broth pH after lime addition, on a scale from 0 to 14, and F(s) is the Laplace transform of the valve opening, on a scale of 0 to 100%. Moreover, K is the system gain, θ is the dead time and τ is the process time constant, both expressed in minutes. Considering that the established ranges are correctly implemented in the transmitters, in this case, the dimensionless gain (K = 1) can be considered. Dead time and process time constant values were estimated at 30 seconds and 2 minutes, respectively. These values come from the practical experience of process operators in sugar mills. Because it is a simulation-based procedure, it is unnecessary to use accurate values from a specific plant. However, the order of magnitude of values is consistent with the practical cases of the visited mills. Figure 2 presents the process control diagram, including disturbances.

Figure 2. Process and instrumentation diagram for broth pH control.



Source: The authors (2020).

In this analysis, we simulate the specific case of the process, where lime is fed by gravity with a valve as the final control element. Thus, due to the variation of the tank level, different flow values are obtained for the same valve opening. For this reason, the tank level is treated by the fuzzy controller as a disturbance. Two other disturbances used in the rule base are the pH variation of the broth inlet and the variation of the broth inlet flow. Thus, it is essential, for the application of the control strategy, the installation of transmitters to represent variables corresponding to pH, flow, and level.

These disturbances are fed into the fuzzy controller in derivative form, so that they only influence the final control element when they vary. When these variables are at rest, the valve opening will be under the action of the integral term of the controller to ensure the elimination of the steady-state error. The anticipatory characteristic of the disturbance derivative produces the desired effect of practically eliminating the undesirable influences of these three quantities. However, there are other disturbances that are not considered in the rule base. Among them, there is the variation in the lime concentration, which is not considered in the fuzzy controller rule base because, in general, no transmitters are installed to measure them in sugar mills.

To illustrate such disturbances in the simulation, first order transfer functions were used, with time constants compatible with the reality of sugar mills. For the purpose of simulation, the functions presented in equations (2), (3) and (4) were used, corresponding to the level of the lime tank $G_{P1}(s)$, the pH variation of the input broth $G_{P2}(s)$ and the variation $G_{P3}(s)$ in the broth inlet flow, respectively.

$$G_{P1}(s) = \frac{k_1}{\tau_1 s + 1} \qquad (2)$$

$$G_{P2}(s) = \frac{k_2}{\tau_2 s + 1} \quad (3)$$

$$G_{P3}(s) = \frac{k_3}{\tau_3 s + 1} \quad (4)$$

In these equations, (k_1, τ_1), (k_2, τ_2), and (k_3, τ_3) are the gains and time constants corresponding to disturbances P_1, P_2 and P_3, respectively. For simulation purposes the gains were arbitrarily adjusted to show their influence on the control process. However, time constant values were obtained empirically by observations in sugar mills at $\tau_1 = 4$ min, $\tau_2 = 3$ min, and $\tau_3 = 20$ min.

To perform the controlled process simulation, the Matlab/Simulink system was used, together with the Matlab/Fuzzy Toolbox. The fuzzy controller model includes the influences of disturbances in its rule base. In this specific case, the variations of the lime tank level, the inlet pH and the variation of the sugarcane juice inlet flow were used as a rule base. Although variation of lime concentration is not considered in the rule base, it enters as a disturbance in the control variable and its influence is minimized by the integral effect of the controller.

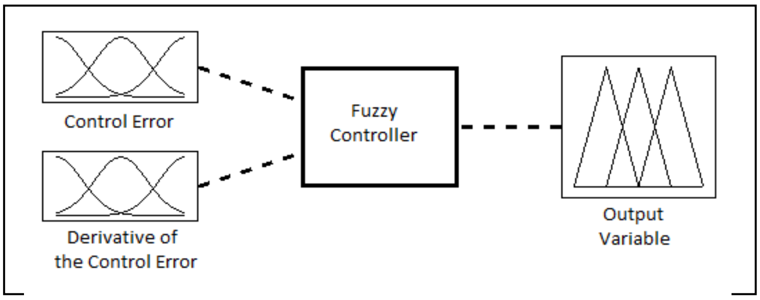
2.3 Fuzzy Controller

The fuzzy controller presented in this paper considers, in a predictive way, the most important disturbances that affect the control of the broth pH. Therefore, these disturbances must be measurable, as is the case of the lime tank level, the broth inlet pH, and the broth inlet flow rate.

Theoretical and conventional ways of dealing with this problem apply predictive control techniques based on the multivariable model of the plant. This model should involve the output response to each disturbance. However, the determination of this model is generally very difficult. Thus, the option for fuzzy control is a viable solution due to the possibility of solving the control problem without knowing the plant model.

The use of two control modules acting simultaneously is then proposed in this paper. The control module 1 operates with the error and the control error derivative, shown in Figure 3, with an integrator on its output.

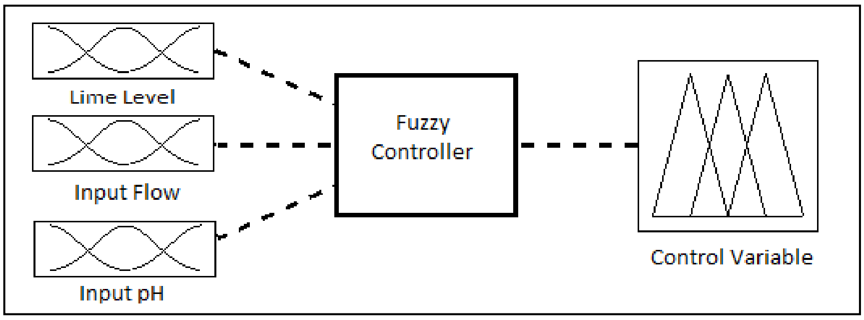
Figure 3. Fuzzy controller - Module 1.



Source: The authors (2020).

The fuzzy controller in module 1 acts to control the opening of the control valve, depending on the control error. The output of the fuzzy controller of this module is part of the control variable. The output of the second fuzzy controller described in module 2 completes the control variable, as shown in Figure 4.

Figure 4. Fuzzy controller - Module 2.



Source: The authors (2020).

The second module receives the derivatives of the perturbations, shown in Figure 4. The use of derivatives allows their action, which is already predictive by acting on input variables, to present an extra degree of anticipation by considering the predictive characteristic of the derived function. Thus, module 2 only influences the moments of the disturbance variation, increasing or decreasing the control variable to decrease the control error. Eventually, module 1 may be replaced by a simple PI controller. The membership functions used in both fuzzy controllers are presented in the next section.

2.4 Membership Functions

The membership functions represent the way that each element belongs to a set. In this work, triangular membership functions were used for the input and the output variables of each controller.

The universe of each variable was standardized from -1 to 1 to guarantee the conditions of increment and decrement for the control variable. Thus, the quantities corresponding to the inlet pH at the tank level, the inlet flow of the sugarcane juice and the valve opening were scaled from their range of variation to the range of -1 to 1, in the fuzzification phase.

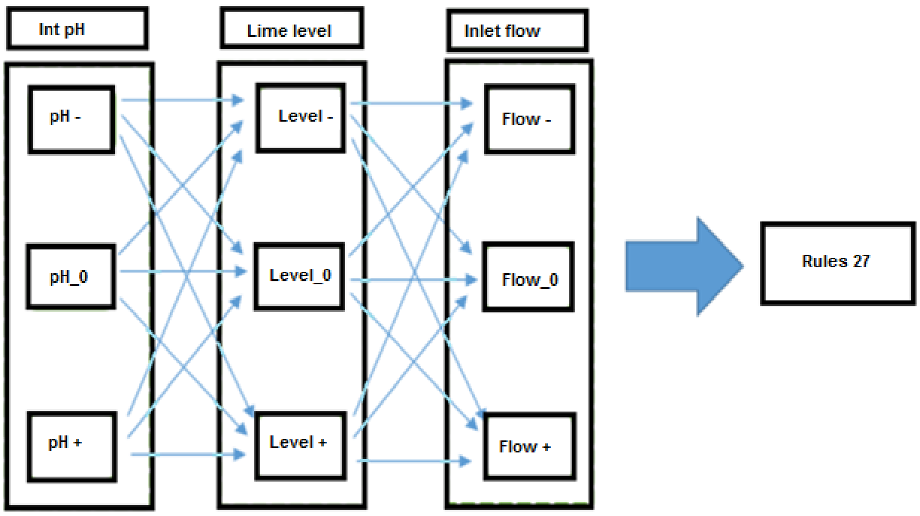
For controller module 2, three membership functions are associated to each of the variables involved in the process control. The membership functions were classified as negative (-), zero (0) and positive (+).

2.5 Implication Rules

An important component of the fuzzy controller is the rule base. It translates the experiences of process operators in a linguistic way. For the fuzzy controller, module 2, the attributes negative variation (-), zero variation (0) and positive variation (+) were used. Thus, there are three operating conditions for each of the quantities involved. For example, the negative (-) tank level condition implies a need for a larger lime valve opening to compensate for the lower flow caused by the lower pressure at the lime withdrawal point. This situation conflicts with the positive variation (+) of the pH of the inlet flow and negative variation (-) of the inlet flow conditions, which would require a reduction in the lime valve opening. These conditions and possible conflicts are perfectly handled in the rule base. It is essential to emphasize that, for each disturbance, the derivative function is applied, so that there is not an accumulation of effects on the final control variable when the input variable is accommodated. When this occurs, it is up to the integral function to correct the steady-state error. An example of an implication rule applied to this process would be: if the input pH variation is negative and the lime solution level variation is also negative and the broth input flow variation is positive, then the increment to be given to the lime valve opening should be large.

Following the same procedure for module 2 of the fuzzy controller, twenty-seven implication rules were established, corresponding to the three input fuzzified variables with three membership functions for each one. They act to interfere on the control valve, opening and closing as a function of the disturbances of the broth inlet flow, inlet broth pH, and lime tank level. Each rule considers a membership function of each entry. Figure 5 shows how the arrangement of the combinations is made to obtain twenty-seven possibilities that will compose the rule base that make up module 2.

Figure 5. Possibilities of membership functions for the creation of the rule base for module 2.



Source: The authors (2020).

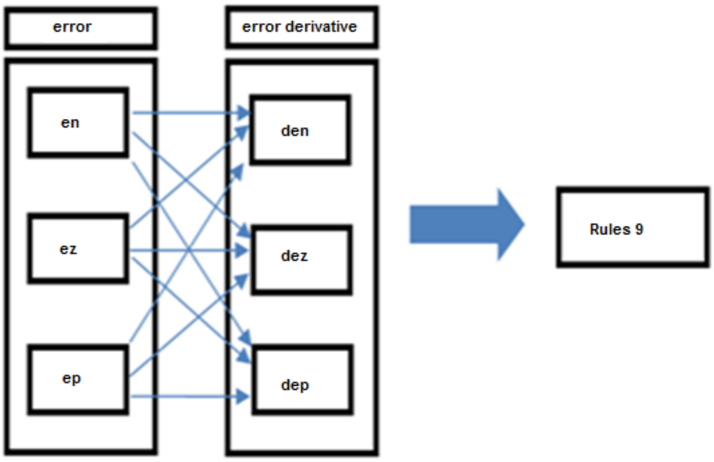
Some of these rules are:

- If the derivative of the lime level is positive and the derivative of the inlet broth flow is positive and the derivative of the inlet broth flow is positive, then the increment of the lime valve opening should be negative.
- If the derivative of the lime level is positive and the derivative of the inlet broth flow is positive and the derivative of the inlet broth flow is zero, then the increment of the lime valve opening should be negative.
- If the derivative of the lime level is positive and the derivative of the inlet broth flow is positive and the derivative of the inlet broth flow is negative, then the increment of the lime valve opening should be zero.

Module 1 of the fuzzy controller is illustrated in Figure 6, where nine implication rules were established corresponding to two input fuzzified variables with three membership functions for each one.

(CC BY 4.0) | ISSN 2525-3409 | DOI: http://dx.doi.org/10.33448/rsd-v9i9.6321

Figure 6. Possibilities of membership functions for the creation of the rule base for module 1.



Source: The authors (2020).

These rules actuate to control the opening and closing of the control valve as a function of the error and the derivative of error. The error is equivalent to the difference between the values of the setpoint and the process variable. The membership functions in module 1 are: negative error (en), zero error (ez), and positive error (ep). For the derivative of error, the membership functions are negative derivative of error (den), zero derivative of error (dez), and positive derivative of error (dep). The output of each rule is the increment in the lime addition. Some of these rules are:

- If the error is negative and the derivative of error is negative, then the increment of the lime valve opening should be negative.
- If the error is negative and the derivative of error is zero, then the increment of the lime valve opening should be negative.
- If the error is negative and the derivative of error is positive, then the increment of the lime valve opening should be zero.

The result of the premise of each rule is a membership function obtained by the application of the logical AND among the individual membership functions of the rule arguments. In fuzzy logic, the AND operation is obtained by determining the minimal membership value of the arguments, for the whole universe of discourse. The result of each rule is a membership function that is calculated by the minimal of the premise and the membership of the output. After obtaining the resulting membership functions for all the rules, an OR operation is performed among them, obtaining a single membership function that is the result of a simultaneous application of all rules. In fuzzy logic, the OR operation is obtained by determining the maximum membership of the arguments, for the whole universe of discourse. The next step is known as defuzzification. In this step the resulting membership function is transformed in a single value, in the universe of discourse in the range of -1 to 1. In this work, the weighted mean defuzzification method was chosen. In the next section, some simulation tests are presented.

3. Results and Discussions

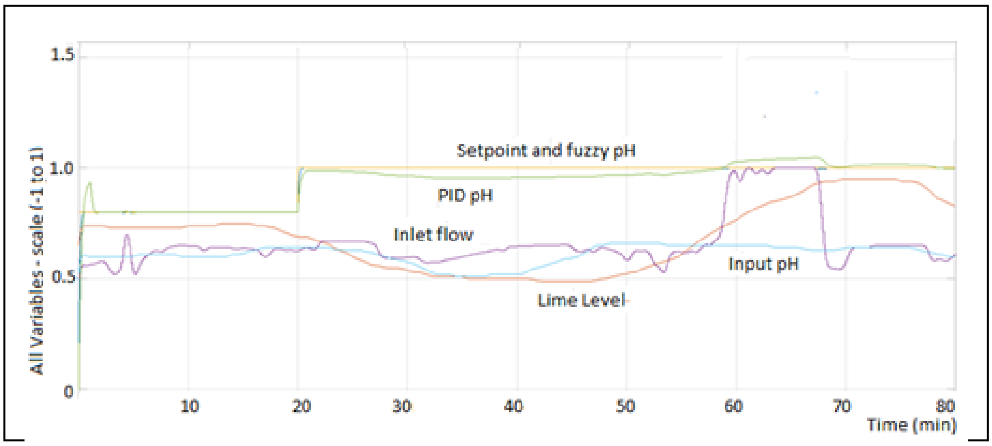
To validate the method proposed in this work, the transfer functions 1, 2, 3, and 4 were simulated using the Matlab/Simulink system. Both fuzzy controllers were implemented using the Matlab/Fuzzy toolbox and the resulting modules were exported to Simulink. The disturbances discussed in section 4 were represented by random signal generators. The parameters used to represent disturbance values and the transfer functions representing the dynamic system were obtained using values which are compatible with some observations made in sugar mills.

Several simulation tests were performed to illustrate an actual process condition as well as some cases that cause difficulties for the process control. The differences between fuzzy and PID controllers are emphasized, considering adverse situations for disturbances. The following situations are presented:

- Variations of the three disturbances (lime tank level, inlet broth flow, and inlet broth pH).
- The lime level in the tank was kept constant and the inlet broth flow, as well as the inlet pH could vary randomly.
- The pH of the inlet broth was kept constant while the tank level and the process inlet flow could vary randomly.
- The input broth flow rate was kept constant while the tank level and the pH of the process input broth could vary randomly.

In the simulation tests, all variables were scaled from -1 to 1 to facilitate the visualization of the results. Figure 7 presents the results of the first test, comparing the results of the fuzzy controller with a simple PID controller.

Figure 7. Step response including variations in pH and broth flow.

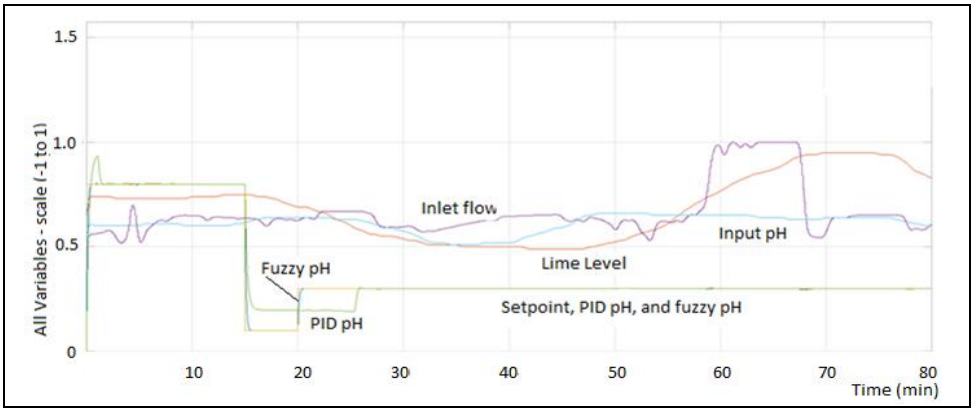


Source: The authors (2020).

Note that in this first test, the tank lime level and inlet broth pH vary randomly and there are also two variations in the pH setpoint. The fuzzy controller was able to make the process variable follow the setpoint. In addition, it is clearly shown that the fuzzy controller had a more satisfactory and anticipatory performance, making the output pH closer to the setpoint most of the time, when compared with the PID controller.

For the simulation result shown in Figure 8, the inlet pH, the lime tank level, and inlet flow were randomly varied and the setpoint varied three times.

Figure 8. Step response including changing in pH, lime level and broth flow.

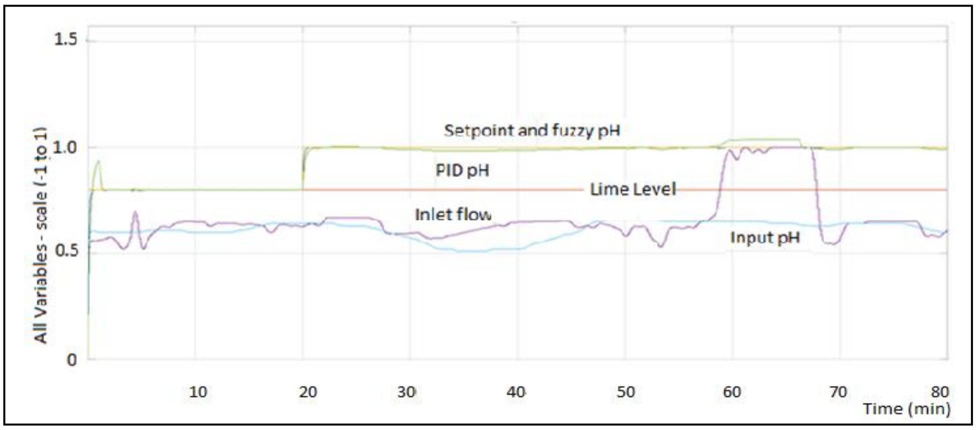


Source: The authors (2020).

The fuzzy controller presented once again a better performance than the PID controller, keeping the process variable following the setpoint at practically the entire time interval. In this case, the setpoint shows changes around 15 and 20 minutes shown in the plot. The fuzzy controller could keep the variable under control. However, the same cannot be said for the PID controller for this range, making even more evident the effectiveness of the fuzzy controller in the compensation action for the setpoint changes. Compensation is performed by the rule base action that alters the control variable as a function of the disturbance changings.

For the simulation presented in Figure 9, the inlet pH and the inlet flow rate varied randomly and the lime tank level remained constant at 0.8.

Figure 9. Step response for input flow pH and the broth flow. Constant lime level at 0.8.



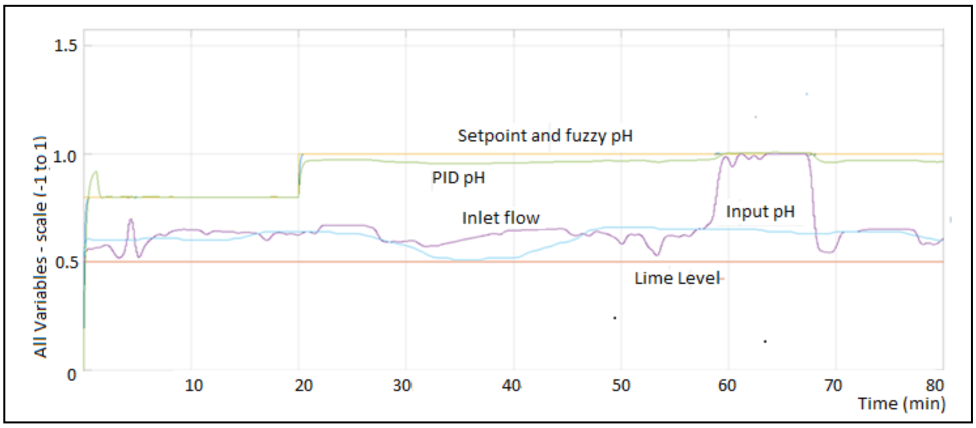
Source: The authors (2020).

In this case, both the fuzzy controller and the PID controller were able to accommodate the process variable at the setpoint value, although the fuzzy controller was able to accommodate faster than de PID module. The same happened at point 20, because of a setpoint change. Close to point 60, there is a disturbance in the flow of the inlet broth. The fuzzy controller shows its anticipatory capacity, compensating for the disturbance variation, and keeping the process variable within the desired value, close to the setpoint. The PID at the same point could not keep the process variable close to the setpoint.

The anticipatory action of the fuzzy controller was possible because the disturbances could be measured. Therefore, this example makes clear that to take a full advantage of the fuzzy capacity it is important to have enough plant instruments for measuring the important variables. The way the PID and fuzzy controllers are combined in this paper makes possible to eliminate the control error and take advantage of the anticipatory capacity of the fuzzy rules. This could be seen in the results presented in Figure 9, and in the next figures.

For the simulation presented in Figure 10, the inlet pH and the inlet flow varied, and the tank lime level remained constant at 0.5.

Figure 10. Step response for the input flow pH and broth flow. Constant lime level at 0.5.



Source: The authors (2020).

The setpoint was initially changed to 0.8 and, around 20 minutes, it was changed to 1. The fuzzy controller was able to accommodate the process variable close to the setpoint. But the PID controller showed an overshoot in the process variable and it was not able to keep track of the process variable after the setpoint change.

For all simulations, a very satisfactory result was obtained from the fuzzy controller compared to the PID controller. We can highlight the following points for the fuzzy controller:

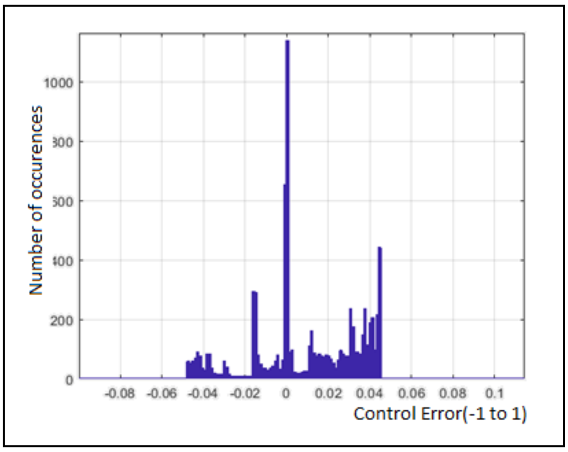
- A significant reduction of the error between the process variable and its setpoint.
- Higher reliability of the control system, as it is less sensitive to disturbance changes.
- Decreased overshoots and delayed responses of the process variable in relation to the disturbance and setpoint variations presented to the system.

Therefore, the results indicate the feasibility of using the proposed fuzzy controller for pH control of the juice in sugar production. Thus, the obtained model can be applied in predictive control strategies and therefore it is expected that the results presented by these simulations could contribute to a practical application of pH control in sugar mills.

To better represent the superior performance of the fuzzy over the PID controller, Figures 11 and 12 show the histograms of the PID and fuzzy controllers, respectively. The presented deviations refer to the simulation of Figure 7, where the response of the process variable is the result of variations in the pH setpoint, lime level and broth flow.

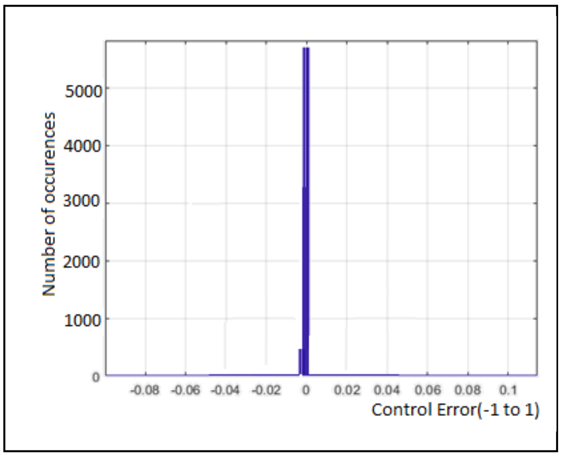
Analysing the PID controller error histogram (Figure 11), a large dispersion can be observed, indicating that the sample values are more dispersed than around the mean when compared to the histogram of the fuzzy controller error (Figure 12), which displays the error sample values around zero.

Figure 11. Histogram of the PID control error.



Source: The authors (2020).

Figure 12. Histogram of the fuzzy control error.



Source: The authors (2020).

Figure 11 shows that the control error different from zero of the PID controller can be significant and occurs many times during the simulation. That does not occur in Figure 12 showing the histogram of the fuzzy controller, since almost all the time the control error was close to zero.

In this analysis between the two controllers, it can be inferred that there was less error variation of the fuzzy controller indicating that the difference between the process variable values and the setpoint value is smaller. This indicates that the fuzzy controller presents a better tracking of the process variable.

4. Conclusion

The results of the simulations indicate the convenience of using fuzzy systems for controlling nonlinear systems, such as the pH control of sugarcane juice. When compared with the PID, the fuzzy controller showed the following results: - a decrease in the error between the process variable and the desired value; - lower sensitivity to disturbance variations; - smaller overshoots; smaller accommodation times and response delays; - the predictive action of fuzzy controllers allowed a significant reduction in steady-state error variability.

The fact of using a fuzzy controller working directly with the disturbances, in order to anticipate the correction of their variations, in the architecture of the proposed fuzzy controller, allowed us to effectively use the information attributed to the level, pH and flow values to adjust the lime valve opening in a predictive way.

This predictive action is evident in the obtained results since the process variable follows the setpoint all the time. Furthermore, the presented architecture can be modified to include other disturbances for other applications.

The next step in the development of the approach presented in this work is its implementation in the pH control of sugarcane juice. One possibility is the combination of conventional PID and fuzzy blocks available in commercial programmable controllers. A ladder or block program should be developed to accommodate this combination. Another possibility would be to make all the development in advanced controllers.

Acknowledgment

The authors would like to thank the Minas Gerais Research Support Foundation (FAPEMIG) and the University of Uberaba (UNIUBE) for the support available to prepare this work.

References

Abdullah, N. H. S., Karsiti M. N. & Ibrahim, R. (2012). A review of pH neutralization process. 4th International Conference on Intelligent and Advanced Systems (ICIAS2012), doi.org/10.1109/ ICIAS.2012.6306084.

Alcarde, A. R. (2020). Tratamento do caldo. Agência Embrapa de Informação Tecnológica (AGEITEC). Recuperado de https://www.agencia.cnptia.embrapa.br /gestor/cana-de-acucar/arvore/CONTAG01_104_22122006154841.html.

Arun, U. P., Georges, S., & Mobeen, S. A. (2015). Control of pH Neutralization Process using Fuzzy Logic: A Review. International Research Journal of Engineering and Technology (IRJET), 02 (03), 1081-1084. Recuperado de https://www.irjet.net/archives/ V2/i3/Irjet-v2i3160.pdf.

Barros, L. S., Moura, D. F. P. & Mota, W. S. (2006). Matrix Methods for Linearization and Representation in the State Space of Electric Power Systems Containing Double Powered Induction Machines Operating as Wind Generators. Brazilian Symposium of Electrical Systems (SBSE), Campina Grande, Paraíba, doi.org/10.1109/TDCLA.2006.311613.

Cavalcanti, A. L. O., Maitelli, A. L., & Fontes, A. B. (2008). A Phase Margin Metric for Multi-Model Multivariable MPC. 16th IEEE Mediterranean Conference on Control and Automation, doi.org/10.1109/MED.2008.4602126.

Elfatni, O., & Tijani, B. (2006). Mathematical modeling and simulation of acidification process for sugar extraction. IMACS Multiconference on Computacional Engineering in Systems Aplications, Beijing, China, doi.org/10.1109/CESA.2006.4281824.

Hassani, H., & Zarei, J. (2015) Interval Type-2 fuzzy logic controller design for the speed control of DC motors. Systems Science & Control Engineering, 03 (01), 266-273, doi.org/10.1080 /21642583.2015.1013644.

Karthik, C., & Senthilkumar, M. (2010). Intelligent Based Modelling, Control and Fault Detection of Chemical Process. IEEE International Conference on Communication Control and Computing Tecnologies, Ramanathapuram, India, doi.org/10.1109/ICCCCT.2010. 5670574.

Karthik, C., Valarmathi, K., & Prasanna, R. (2011). Modelling and Control of Chemical Process in Sugar Industry, ICVCI, 24-28. Recuperado de https://www. ijcaonline.org/icvci/number16/icvci1612.pdf.

Norquay, S. J., Palazoglu, A., & Romagnoli, A. J. (1999). Application of Wiener Model Predictive Control (WMPC) to a pH Neutralization Experiment. IEEE Transactions on Control Systems Tecnology, 07 (04), 437-445, doi.org/10.1109/87.772159.

Pinheiro, W. C., & Finzer, J. R. D. (2016). Broth callus in the manufacture of sucrose. COBEQ 2016, Brazilian Chemical Engineering Congress XXI, Fortaleza, Brazil. Recuperado de https://proceedings.science/cobeq/cobeq-2016/papers.

Singh, P. K., Bhanot, S., & Mohanta, H. K. (2014). Differential Evolution Based Optimal Fuzzy Logic Control of pH Neutralization Process. International Conference for Convergence of Technology, India, doi.org/101109/I2CT.2014.7092060.

Singh, P. K., Bhanot, S., Mohanta, H. K., & Bansal, V. (2015). Self-Tuned Fuzzy Logic Control of a pH Neutralization Process. Proceedings of the 21st International Conference on Automation & Computing, University of Strathclyde, Glasgow, UK, doi.org/10.1109/ IConAC.2015.7313935.

Song, B., Xiao, Y., & Xu, L. (2020). Design of fuzzy PI controller for brushless DC motor based on PSO-GSA algorithm, Systems Science & Control Engineering, 08 (01), 67-77, doi.org/10.1080/21642583.2020.1723144.

Suchithra, R., Sruthilay, V., Sneha, V., Shanmathi, R., & Navasselan, P. (2016). pH Controller for Water Treatment Using Fuzzy Logic. IEEE International Conference on Technological Innovations in ICT For Agriculture and Rural Development (TIAR), doi.org/10.1109/ TIAR.2016.7801238.

Sunori, S. K., Juneja, P. K., Chaturvedi, M., & Saini, P. (2016). Model order reduction of a higher order model of pH neutralizer of sugar mil. 80 th International Conference on Computational Intelligence and Communication Networks, Tehri, India, doi.org/10.1109/ CICN.2016.134.

Vijayaragavan, V., Vivek, S., Athy, S. A., Raagav, S., & Saranya, N. (2015). pH Automation in Sugar Industries. International Conference on Computer Communication and Informatics (ICCCI -2015), Coimbatore, India, doi.org/10.1109/ICCI.2015.7218160.

Wan, F., Shang, H. & Wang, L. (2006). Adaptive Fuzzy Control of a pH Process (2006). IEEE International Conference on Fuzzy Systems Sheraton Cancouver Wall Centre Hotel, Vancouver, BC, Canadá, doi.org/10.1109/FUZZY.2006.1682031.

Yordanova, S. (2016). Fuzzy logic approach to coupled level control, Systems Science & Control Engineering, 04 (01), 215-222, doi.org/10.1080/21642583.2016.1228486.

Research, Society and Development, v. 9, n. 9, e13996321, 2020
(CC BY 4.0) | ISSN 2525-3409 | DOI: http://dx.doi.org/10.33448/rsd-v9i9.6321

Percentage of contribution of each author in the manuscript

Manuel Ferreira Silva Neto - 30%

Antonio Manoel Batista da Silva - 25%

Edilberto Pereira Teixeira - 25%

Marcelo Lucas - 20%