Diagnosis the Process Dynamic a the Model of Drinking Water Production

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Abstract—Currently, many of the processes for water purification are processes that require special care in the control of each of the stages to perform it. The scarcity of online sensors that enable a real-time monitoring of the process states is one of the main obstacles of the study. The development of a virtual sensor has partially permitted to avoid the need of online sensors. The important element of this development is the establishment of dynamic behavior models applied to the important process variables, being the area in which this research focuses. This approach estimates the effect of control actions on the variable to characterize, allowing integrating intelligent diagnostic scheme globally, reducing costs and facilitating the monitoring of the process of drinking water production. The experimental results shown are taken from the data of water treatment plant of Tuxtla Gutierrez, Mexico.

Index Terms—dynamic model; intelligent diagnosis; plant of drinking water production.

I. INTRODUCTION

Currently, the operation of industrial processes is not only based on its controllability, but also in monitoring and troubleshooting to increase the reliability, safety, and to assure a cost reduction.

The production of water intended to human consumption is a process that requires a careful control at every stage. The scarcity of online sensors that enable real-time monitoring of the process states is one of the main obstacles of the study. The development of a virtual sensor has partially permitted to avoid the need of online sensors. An important element of this approach is the establishment of dynamic behavior models applied to the important process variables, being this area in which this research focuses.

The water industry is striving to produce higher quality water at a lower cost due to increased regulatory standards. Improved process control through the introduction of new technologies has increased the operational efficiency of chemical process plants.

In this paper addresses the problem of control of coagulation based on raw water characteristics such as turbidity, temperature and pH addresses. The innovative aspect of this work lies in the integration of the method for obtaining models through Matlab and System Identification Tool program in a global system, including analysis and determination of the functional states and detection of fault.

II. METHODOLOGY

A. Stages of purification

Water treatment involves chemical and biological processes that transform it into water intended to human consumption. Drinking water must meet a set of quality standards at a reasonable price, while respecting the environment.

The treatment water plant (Municipal Potable Water and Sewerage) SMAPA 2010 [1]. The city of Tuxtla, Mexico, which was used as a test site for this study, provides water to more than 800,000 inhabitants and has a nominal capacity of 800 l/s of water.

Figure 1. Typical water treatment plant drinking
and therefore their values can be estimated according to the behavioral model. This is done taking into account the variables of involvement. The reaction forms a precipitate which attracts solids and colloidal particles (negative particles). This precipitate, as sludge, is positioned in the bottom of the tank by gravity.

The next stage is filtration, where particles exist even if the water is trapped by sand layers.

Cloudiness is a measure of the degree of water transparency due to the presence of suspended particles. The more suspended solids in the water, it looks dirtier and more turbid. Therefore, cloudiness is considered and effective measure of water quality. The suspended particles absorb the sunlight heat, causing turbid waters to become warmer, and thus this reduce the concentration of oxygen in the water (the oxygen it is better dissolved in cold water). In addition, some organisms cannot survive in turbid water.

Cloudiness is measured in Nephelometric Turbidity Units (NTU). The instrument for measurement is the nephelometer and the turbidimeter measures the intensity of light scattered at 90 degrees when a light beam passes through a water sample [3], [4].

B. Obtaining dynamic model

Means a system identification experimentally obtaining a model that reproduces with sufficient accuracy the purposes intended, the dynamic characteristics of the process under study. Depending on the cause, repeat the process from the point corresponding identification. Therefore, the identification process is an iterative process; the steps can be seen in the flowchart of Fig. 2 [5].

The model can be a system of equations containing the relationships mentioned, which allows applying some suitable mathematical theory already established. So the modeling process is a set of operations, which, after the appropriate study and analysis, construct the actual behavior of the process.

Thereby reducing the analysis of all the process information that is available. This permits to debug the calculations and reprocess them, so that it can be transcribed to a mathematical language for transcription to a computational simulation language. It is also necessary to consider the initial conditions to determine the evolution of the variables to be taken into account during the time frame evaluation.

The model will be suitable once the errors have been corrected and convenient improvements were introduced. After this the model was ready for use under the proposed scheme and values were estimated in the present investigation. Next, some values found in the literature are presented. Such values were applied to the purification process model, particularly in the coagulation-flocculation stage.

The value for aluminum sulfate was not found in the literature any mathematical expression that modeled the relationship between color and the amount of salt used. So we proceeded with the data provided by the water treatment plant using a polynomial interpolation process and assisted numerical differentiation of Matlab [7], obtaining the equations shown in (1) and (2):

\[
\frac{dC_i}{dt} = \left( a_1 - 2* a_2 t + 3* a_3 * t^2 - 4* a_4 * t^3 \right) 
\]

(1)

\[ C_f = C_s \frac{Sal}{C_i} \]

(2)

where:

- \( dCs \) = Color variation in different stages Color predicted
- \( C_f \) = entry in mg / l
- \( C_s \) = Color of experimental raw water
- \( C_i \) = Real color of raw water
- \( Sal \) = Amount of aluminum sulfate in mg / l.

For the determination of the mathematical model of the polymer, taking into account studies [8][9], where indicate that in the flocculation stage is very important in the destabilization of particles known in rapid mixing time (1 minute, for example). Thus, flocculation stages are influenced by rapid mixing operations, which are suggested in the relationships shown in equations (3) and (4).

\[ G*T*C^{1.46} = 5.9x10^6 \]

(3)

\[ C = \left( \frac{K}{G*t} \right)^{1.46} \]

(4)

where:

- \( T \) = optimum rapid mixing time in seconds
- \( C \) = coagulant dose in mg / l
- \( G \) = average velocity gradient in s-1
- \( K = 5.9x106 \)


\[ \frac{dD}{dt} = C_1 \left( d_1 + n \right)^{2/3} \left( \frac{1}{n} \right)^{1/3} \] (5)

where:

- \( dD/dt \) = Rate of destabilization
- \( d_1 \) = Colloidal particles (m³)
- \( C_1 \) = Constant (mg / l)
- \( m \) = Microscale
- \( n \) = number of iterations

III. RESULTS

Taking into account the dynamic behavior model equations of the coagulant, aluminum sulfate dosage (equations 1 and 2). The application of the methodology described above yields the following results. The database consists of 180 measurements of three coagulant dose variables calculated with the dynamic model for a period of six months (May to October 2010). For the generation of functional states of the purification process and according to the proposed method, which uses a fuzzy classification algorithm as a general, strategy to obtain the plant model (using historical data).

The recognition of the functional states in real-time, according to the on-line measurement of the characteristic variables of the inlet water to the plant, was possible. Figure 3 shows the graph of the results for five classes, resulting from the application of the fuzzy classification method. These five classes are associated with five functional states (shown in Fig. 3), with the assistance of expert station drinking water treatment.[10]

The states of the existence of algae increased the backwash and water cloudiness during the process. This is of great interest to be considered for purposes of water monitoring in the treatment plant.

IV. CONCLUSIONS

We presented an approach for a solution to the problem of estimating the characteristic variables in the coagulation-flocculation process of a drinking water production plant. The method was based on the dynamic modeling of key variables in the process of production of drinking water. The model integrates the constitutive relations and structural process, where it incorporates not necessarily an expression that fully describes the dynamic behavior of the parameters required to estimate. From the results obtained in the validation test of the dynamic model, it can be concluded that the proposed method can reliably be used to predict the evolution of the dose (%) of coagulant (aluminum sulfate) and polymer. The major disadvantage of this method of parameter estimation is its sensitivity to measurement noise. However, its advantages are the ease of implementation, low cost and simple calibration. An additional advantage is the incorporation of process faults detection and diagnosis of the plant. In this work, it is also proposed a monitoring tool for diagnostic drinking water treatment plants. These studies are based on the exploitation of the data of the water at the entrance of the plant, including the coagulant dose determined with the dynamic model, to be performed during the monitoring process. In general, the multivariable controller behaves with accuracy to changes above values applied coagulant doses at steady state.

Fig. 4 shows the results in 2004 which compares the input and output of the plant turbidity in the months of the year, this response is a large variation in Mexico since this period is the rainy season, but turbidity output should remain in the ranks of established quality.

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