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DEVELOPMENT OF COMPUTATIONAL DEVICE APPLIED TO SYSTEM IDENTIFICATION PROCESS IN INDUSTRIAL SYSTEMS

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Abstract. *In this paper is purposed a development of a computational device applied in the system identification process in industrial environments. The device is composed by a data acquisition hardware, linked a computer. This hardware is responsible by the get the experimental data that is generated by the industrial plant, and send to computational application. After the data acquisition, the data are processed by the software kernel that is responsible to prove the system identification process. The final step, a computational module computes the relatives errors between the identified model output and the real output. If the identified model is valid, this model is used in others steps, like process control tools development and others. One of the main objectives of this project is to provide a support for a students in the classes that involve process control and automation on the university, where there is a need to bring the industrial reality to the students.*

Keywords: *System identification; Process Control; Industrial automation.*

1. INTRODUCTION

Dynamic modeling techniques comprehend a class of mathematical modeling, used to describe the dynamic behavior of a physical system. These techniques are considered important on the development of control systems (IWASE et al., 2002).

Mathematical models can be obtained by two methods: the analytical method, also named theoretical modeling, is based on models derived from one or more differential and/or algebraic equations. The second method, named experimental method is based on mathematical models obtained from experimental information where the relationship between input and output data of a dynamic process is recorded. Such model is represented by difference equations (COELHO, 2004).

An analytical model is composed by the system physical descriptions, in other words, the model is described upon theoretical laws (mechanical, thermo dynamical and electrical laws, etc.) and necessary empirical laws to describe the dynamic behavior of a given system, and such approach permits the description of internal dynamic relationships, besides the input-output relationship (RODRIGUES, 2000). This modeling technique is also named white-box modeling (AGUIRRE, 2004), due to the fact that analytical relations, through constructive equations, describe the dynamic behaviors. The main advantage is the fact that the model has a clear physical interpretation. Meanwhile, as stated in (SANTOS, 2000), the analytical approach may have a drawback in relation to the structure complexity, that is, the model can have up to hundreds of constructive equations, and usually the equations are time-continuous despite of the inputs and outputs of a digital control system are discrete. By fact that this modeling technique is more traditional, there are some difficulties when one has to apply them to complexes systems, such as non-linear, stochastic or time-variant systems. Therefore, the construction of an analytical model for this nature of system is usually a hard task considering the computational cost and also the time consume (PAIVA, 1999).

The process of modeling a system by theoretical laws can become quite complicated for large and complexes systems, the more interactions between the parameters, the more complex is the mathematical description. Consequently the precision of a given model is gradually restricted as the system complexity increases (RODRIGUES, 2000).

Despite of the described limitations, the industry has been demonstrated an increasing interest in attaining autonomy on the production processes. Although there are some concerns on the increasing complexity of production processes that contradict such autonomy, as stated before (PAIVA, 1999).

On the experimental modeling, also named System Identification technique, it is necessary to submit the plant to experiments in order to build a mathematical model based on the plant input and output acquired data, in contrast to the analytical modeling (LJUNG, 1999). It is not mandatory the theoretical neither the physical understanding of a plant for a system identification, once all information is collected from experimental procedures. For this reason, an experimental model is classified as a black box model. Internal states or properties of a black box model are ignored, (LJUNG, 1999), (SIMANI et al., 2000).

One meaningful advantage of this technique is the readiness to adjust a model, enabling the formulation and the resolution of process control problems. On the other hand, all model parameters do not carry any physical meaning, what can be considered as a drawback (SANTOS, 2000).

2. SYSTEM IDENTIFICATION

In concept, the system identification is a simple procedure: using the discrete input signal u(k), where k is the time instant, and the output signal y(k) of a given plant, a mathematical model is obtained and this model maps entirely or partially the behavior of the original plant (AGUIRRE, 2004), as represented on Fig. 1:

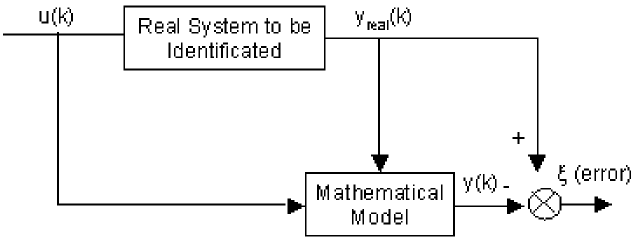

Figure 1. System Identification Technique

The sequence of stages for system identification can be presented (AGUIRRE, 2004), (RODRIGUES, 2000), (LJUNG, 1999) as:

1 – Dynamic tests and data acquisition;
2 – Test the experimental data for non-linearity detection.
3 – Mathematical structure selection;
4 – Model structure determination;
5 – Parametric Estimation;
6 – Model Validation.

The stages listed are used for both linear and non-linear systems, and the main differences among those are variations on how each stage is performed and implemented. The technique described on this work is applicable just on linear systems; applications of the described technique on non-linear systems can be referred on (RODRIGUES, 2000), (LJUNG, 1999), (AGUIRRE, 2004).

The listed system identification stages are described on the following subsections.

2.1 Dynamic Tests and Data Acquisition

This stage consists in perform the data acquisition of the dynamic system to be identified. Therefore it is very important to define the experiment characteristics, like values of input signals, sampling time, number of samples, experiment time interval and pre-processing of samples. The input signals must be defined in order to have a desirable frequency bandwidth able to excite some important plant modes, guaranteeing, this way, well representative experimental data (RODRIGUES, 2000).

2.2 Test the experimental data for non-linearity detection

All plants are in practice non-linear, if one considers that there is always non-linearity even in a very smooth presence. In this case it is possible to represent a non-linear system by a linear model. The author (RODRIGUES, 2000) describes techniques to test non-linearity of a system based on the method of non-linear cross-correlation, however in this paper this stage will not be completed due to presented technique restriction to linear structures. There is not a specific literature on non-linear systems identification, what emphasizes the importance for the non-linearity test procedures.

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2.3 Mathematical structure selection

The selection of a mathematical model to describe the plant dynamics is done in this step. Such decision must be justified on the knowledge of the identification process and also on the a-priori knowledge of the dynamic system. In fact, the mathematical, as stated before, are used to describe the properties of a given system, which can be eventually partially described. This fact justifies the relation between the mathematical structure and the experimental data (AGUIRRE, 2004). This step, therefore, has great importance for the identification process.

A polynomial linear model can be represented by the following structure:

$$y(k) = \sum_{i=1}^{n} \varphi_i^T(k)\theta_i + e(k) \qquad (1)$$

Where:

- θ_i is an array or a matrix with the parameters that must be estimated according to the chosen structure;
- *e(k)* is the prediction error, consists in the difference between the outputs of the real system and the identified model.
- φ_i is the regression vector or matrix that containing the experimental input and output data of the system to be identified.

Therefore, the following equation is obtained from the system identification method:

$$y(k+1) = \sum_{j=0}^{n_a-1} A_j y(k-j) + \sum_{j=0}^{n_b-1} B_j u(k-j) \qquad (2)$$

Considering the Eq. (2), *y(k)* and *u(k)* are respectively the output and input samples on the discrete time k, n_a is the number of output regressors and n_b is the number of input regressors. The prediction error is given by the Eq. (3):

$$e(k) = y(k) - y'(k) \qquad (3)$$

Where y(k) is the experimental data obtained from the didactic plant and y'(k) is output that was predicted by the identified model. The steps of the system identification are given on the next subsections.

2.4 Determination of the model structure

After the selection of the representation for linear systems, some aspects must be defined: the number of poles, number of zeroes and the response time delay. For non-linear systems, on the other hand, the number of terms of the polynomial model must be verified, once the number of such terms increases with the observed non-linear behaviours. In this work an ARX model MISO (Multiple Inputs and Single Output) is used to characterize system behaviour.

2.5 Parametric estimation

With the mathematical structure defined, the parametric estimation stage provides the parameters that will be used on the mathematic model. In this stage, the Least Square algorithm is used to evaluate the parameters θ at each sample of output (y(k)) based on the samples acquired during the system operation condition, and processed off-line in batches afterward the operation condition.

2.6 Model Validation

To validate the model it is necessary to check whether the model incorporates or not the main characteristics of the original system. If possible, it is desirable to compare different model and make a decision for an eventual more appropriate (AGUIRRE, 2004).

This comparison is technically a subjective task and the result will depend on the application and the quantity of available information concerning the original system. The verification of the candidate model is done by comparing the outputs of the model with the outputs of the original system for a defined set of input signal (RODRIGUES, 2000). Among several methods to validate a model, the Crossed Test and the Linearity Test can be cited (AGUIRRE, 2004). On the Crossed Test, two series of data are applied to the model. A parameter set is estimated for the first data set. The outputs are computed for the second data set using the estimated parameters set from the first data set.

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To validate a model using the Linearity Test, experimental tests must be performed with different input signals amplitudes, applying a signal (ex. step or impulse) with positive and negative amplitudes to verify the limits of the identified model under different operation conditions.

3. PROJECT DEVELOPMENT

The system identification process has been applied in a hydraulic didactic plant. The plant operation consists in pumping water from a lower reservoir to the upper reservoir and one heat even in the latter that provides the water for industrial use for didactical example. The plant can representing in a more compact a specific industrial process with the same characteristics and situations encountered by professional instrumentation coupled with high-tech features available on the market. In this study, we used data from the process of pumping water from the lower reservoir to the upper. The Fig. 2 show the plant didactic schematic.

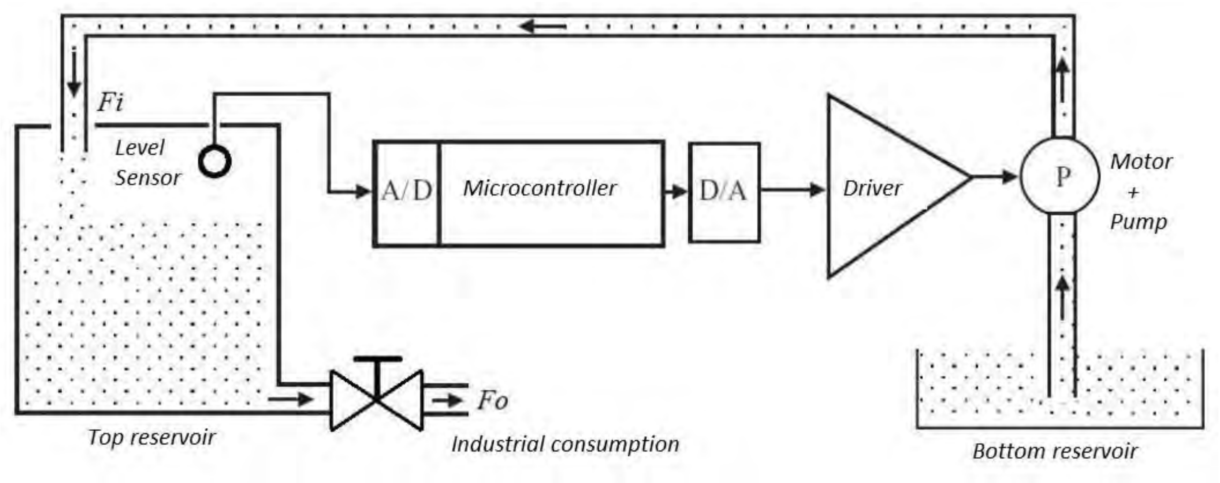

Figure 2. Plant basic schematic

The computing device proposed in this work consists of two modules: one interface hardware responsible for the integration with the plant instrumentation and data acquisition, and another software part containing the processing modules in order to obtain the process model identified.

The hardware consists of energy conductors, responsible for the activation of the pump motor and the solenoid valves. For each element of the power plant is a driver which basically consists in a chopper, a switch operating with cutting or saturation, turning on or off. Transistors TIP120 (Darlington) are used to drive inductive loads, and a free-wheeling diode is inserted to prevent overvoltage generated every time the switch is commanded to open. The drive a schematic is shown in the Fig 3. There is also a conditioning circuit responsible for amplifying the output signal from the RTD, as we can see in the Fig. 3 below. Thus, the signal output of the resistance equivalent to a range of voltage is amplified by a signal amplifier and limited by a zener diode in a range between 0-5V. The voltage Ratio X Sensor temperature is given by a curve equivalent to a quadratic equation, and the temperature value ranging from 0 to 100° C.

This circuit is coupled to a microcontroller Arduino, where all the system signals are mapped plate pins.

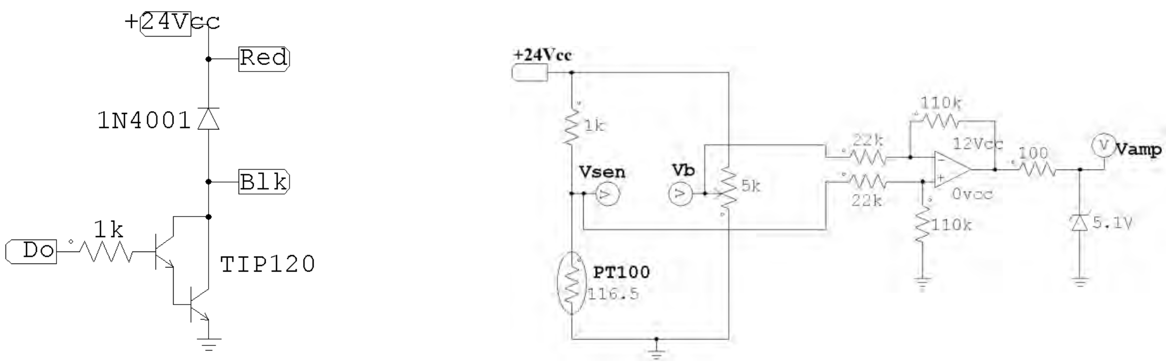

Figure 3. Electronic circuit schematic

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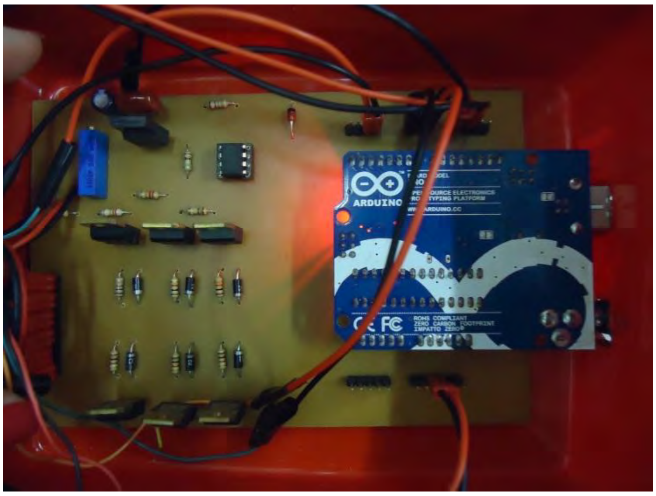

Figure 4. Circuit board

Before the data acquisition step, it is necessary to define which variables will be stored and will be used in the system identification process. The analyzed variables are shown in Table 1. The Tab. 1 describes the information on the variables, if the variable is input or output variable and its description.

Table 1. Variable's description

Variable	Type	Description
Water Pump PWM	Input	Duty cycle controlling the power of the pump that feeds the upper tank of the plant. It consists of an input variable, as is specified by the user of the device and its operating unit is given in percent of the nominal power of the pump.
Level bottom tank	Input	Value of the level of the water column the tank bottom, that the pump which supplies water to the supply tank top. It consists of an output variable and its unit is given in centimeters.
Level top tank	Input	Value of the water column the tank top, that it is fed by the water pump and supplies the same to the industrial use. It consists of an output variable and its unit is given in centimeters.
Input flow	Output	Flow of water entering the tank top, coming from the water pump to fill the tank. It consists of an output variable and its unit is given in liters / hour.

The data acquisition module consists of a code Arduino implemented in software that runs on hardware where a step is given to the value of the variable pump PWM initially from 0 to 50% and thus the values listed variable output over a range of time. We used a sampling rate of 0.5 second and stored for later use these data for analysis thereof via the software module.

The software module, that is responsible to obtain the model, it was developed in the Matlab platform. In this module, we have modules that do the data treatment, data processing and the model validation.

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4. TESTS AND RESULTS

To demonstrate the applicability of the identification module systems, we used data from the sensors used in the instrumentation of the bottom tank of the plant. From the experimental data we identified a mathematical model that represents the behavior of the process. The model is identified through the process of system identification, which provides a mathematical framework for multi-ARX variables. The experiments were conducted by the disturbance of the pump power, the PWM, as shown in Fig. 5.

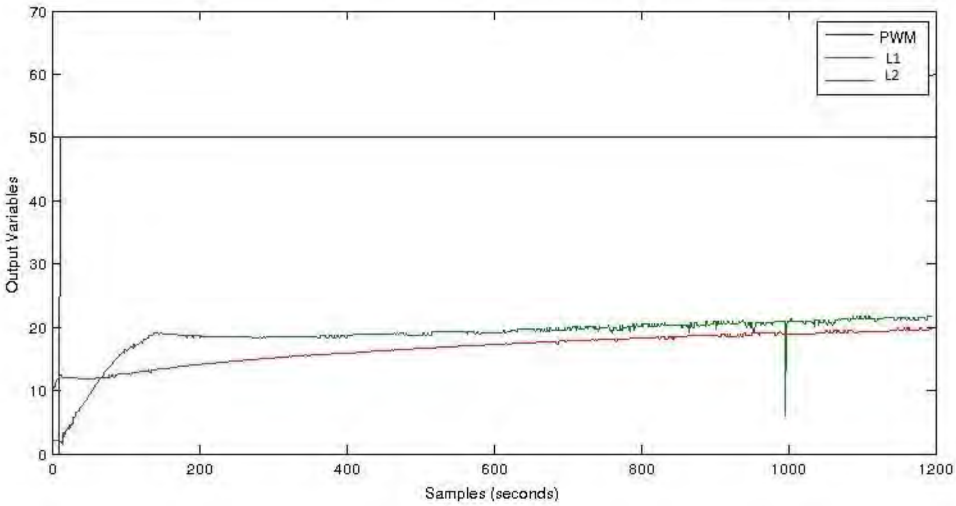

Figure 5. Level values for PWM 50%

Where:
L1 = level of the tank top;
L2 = level of the tank bottom.
Furthermore, the values of the variables shown above level is given in centimeters.

For the identification of the studied system was used which has a Matlab toolbox called System Identification Toolbox that allows the entry of the variables collected input and output of the plant and provides the user the choice of model to be used for identification system, as well as allow the specification of characteristics. Thus the software performs the estimation of the parameters of the chosen model and enables the user to compare the model and found real value of the measured data. The tests were conducted at each switch input flow behavior of the external tank, through the variation of the PWM pump. Thus, two scenarios were considered for this variation, 50% and 60%, with a sampling rate of 0.5 seconds. Such behaviors can be observed in Fig. 6 and 7 for the variation of the PWM 50% and in Fig. 9 and 10 for the PWM 60%.

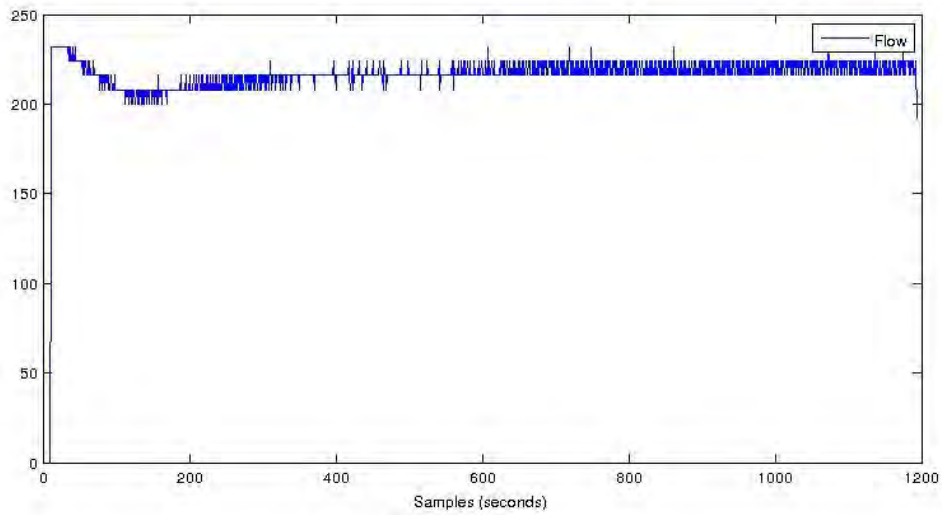

Figure 6. Flow value for PWM 50%

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Where we have given the unit of flow in liters / hour.

From this information, a MISO ARX model with two regressors input and two output regressors. Thus, the difference equation of the MISO ARX model is:

$$\begin{aligned} y(k) &= -0.178y(k-1)+0.1958y(k-2)+4.562u(i-1,1)-0.5067u(i-2,1) \\ &-1.108u(i-1,2)-0.7235u(i-2,2)-4.598u(i-1,3)+7.303u(i-2,3) \end{aligned} \quad (4)$$

The Fig. 7 shows the response of the system identified in the Eq. (4).

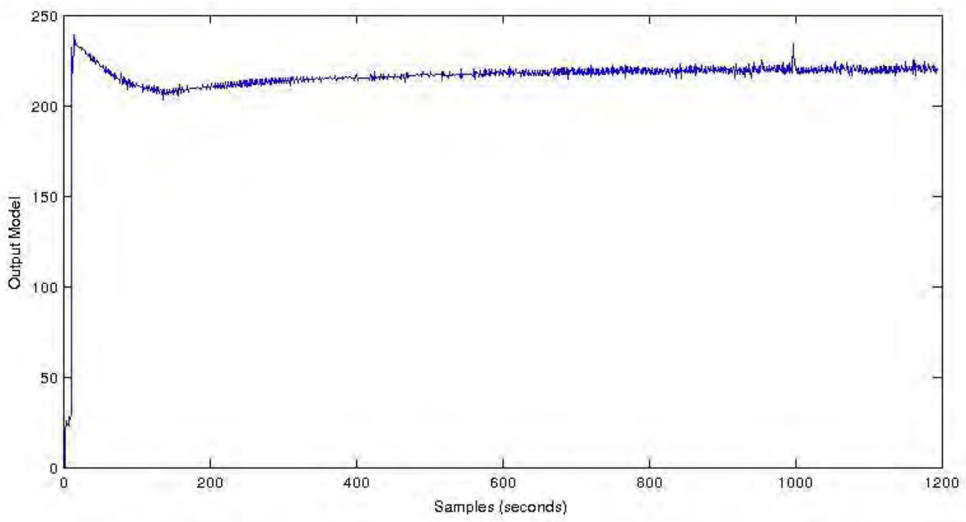

Figure 7. Model's response

To analyze the response generated by the model identified index was used to analyze the feasibility of the model, from the responses generated by the identified models and actual responses obtained by plant hydraulics. These factors show how the identified model is close to the actual output of the system. The coefficients are:

- Coefficient of determination (R^2): indicates that how much of the observed variability is accounted for by the estimate model;

$$R^2 = \frac{\sum_{i=1}^{n}(P_i-\overline{P})^2}{\sum_{i=1}^{n}(P_i-\overline{P})^2+\sum_{i=1}^{n}(O_i-P_i)^2} \quad (5)$$

Where P_i are the predicted results, O_i are the observed values and N is samples.

- Correlation coefficient (R): quantifies the global description of the model, and a high value of R implies a significant correlation between the observed results and the predicted values.

$$R = \frac{\frac{1}{n}\sum_{i=1}^{n}(O_i-\overline{O})(P_i-\overline{P})}{(\sigma_o)(\sigma_p)} \quad (6)$$

Where P_i are the predicted results, O_i are the observed values, and N is samples.

Therefore, the coefficients calculated for the first scenario are showed in Tab. 2.

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Table 2. Validation coefficients

Factor	Value
R^2	0.9307
R	0.9675

The same procedure was done for the PWM 60%. Fig.(8) shows its input variables and their corresponding output in Fig.(9):

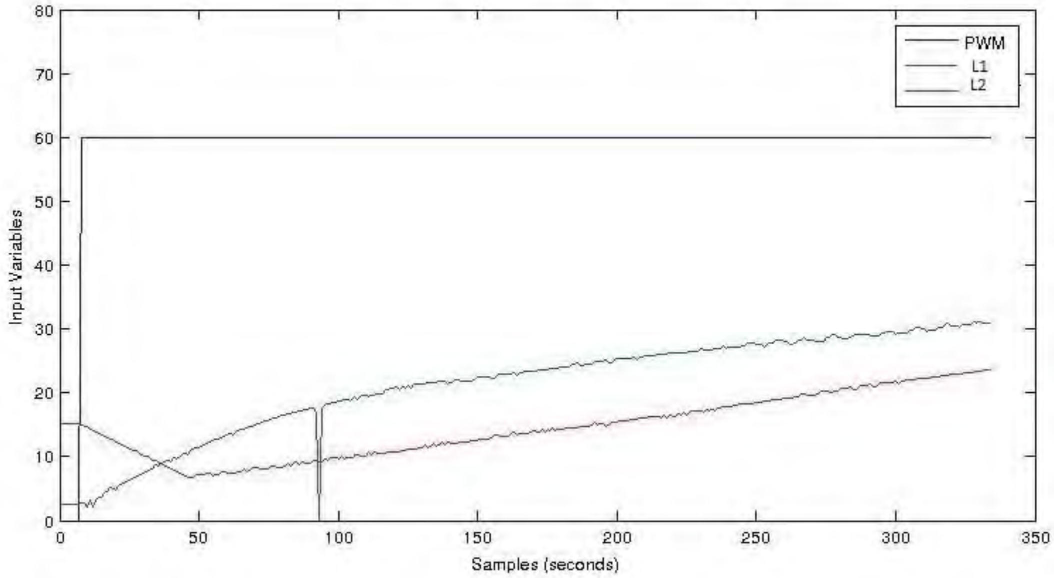

Figure 8. Levels values for PWM 60%

Where:
L1 = level of the tank top;
L2 = level of the tank bottom.
Furthermore, the values of the variables shown above level is given in centimeters.

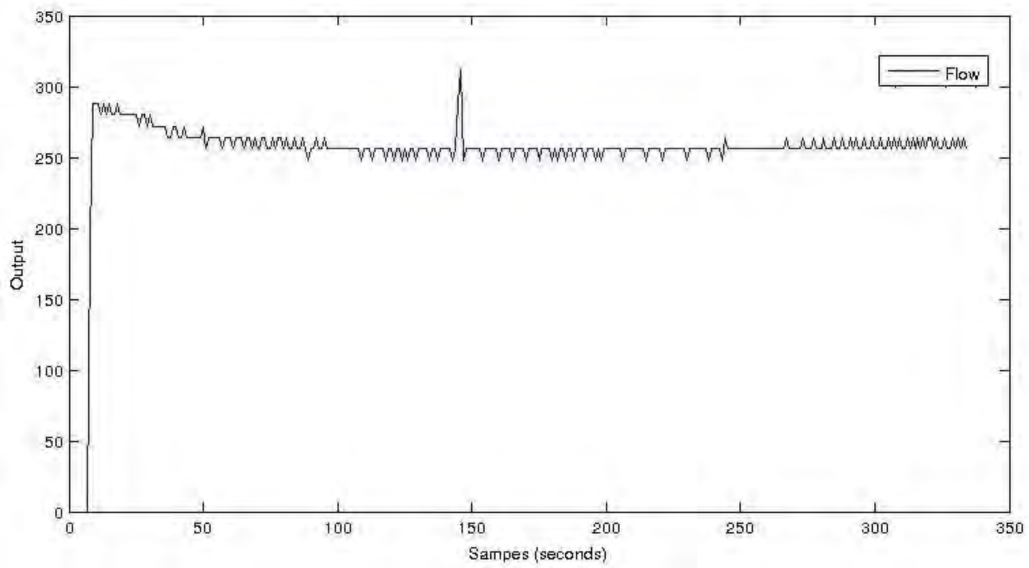

Figure 9. Flow value for PWM 60%

Where we have given the unit of flow in liters / hour.
A new experimental data ARX model is identified, as can be seen in Eq. (7):

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$$y(k) = -0.02708y(k-1) - 0.06555y(k-2) + 4.493u(i-1,1) + 0.3882u(i-2,1) \\ -0.6999u(i-1,2) - 1.016u(i-2,2) + 3.049u(i-1,3) - 1.172u(i-2,3) \quad (7)$$

From the identified model, the following response was generated:

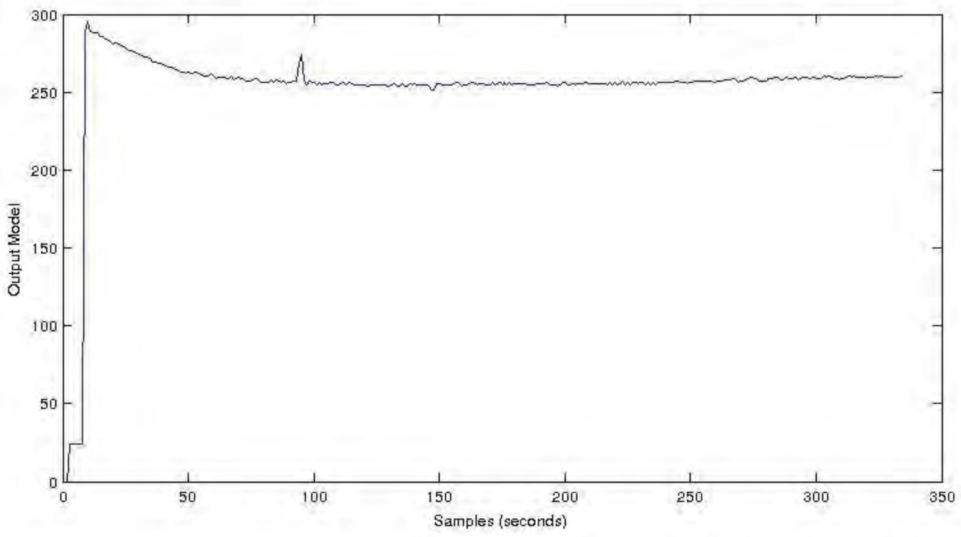

Figure 10. Model's response

The Tab. 3 shows the indices calculated from the response of the identified model and the actual response of the system:

Table 3. Validation coefficients

Factor	Value
R^2	0.9224
R	0.9559

From Tab. 2 and the Tab. 3, it is possible to observe that the models identified for the different scenarios have a good approximation of the real model. If the values is closer than 1, more reliable is the model.

5. CONCLUSION

This article proposes the project and development of a computational device that is able to collect experimental input and output for a didactic industrial plant and find mathematic models that represents a system behavior.

The device proposed consisting of two modules, the hardware and the software. To demonstrate its application was done two tests, through the hardware developed, that collect the outputs values for two different inputs values. Thereby, through the software proposed, it was done the data analysis and was found the system representation models. Lastly, was done the models validation through the validation coefficients. According to these results we can conclude that the device managed to find model representation, with experimental data, so close to the real industrial plant.

Thus, we proved the feasibility of use the system identification method in industrial area, where several times, we do not have access to the whole process behavior. So, through the experimental data it is possible to do the process identification, and finding the reliable representation models, that is possible to make simulations and to help in the controllers conception, to be used in the new controllers that will be used the industrial plants.

6. ACKNOWLEDGEMENTS

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