

Robust Design with Dynamic Features: Laboratory Level Case

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Abstract – A major trend in engineering arising from Taguchi methodology are the systems with dynamic characteristics, also called signal-response systems. This methodology is a basic tool which has a response that varies depending on level changes made in the factor called "signal", the classic example is the accelerator pedal car in which you get one acceleration response depending on the depth at which the pedal is pressed. The main objective of this methodology is to generate the dynamic response of the product that is robust to noise factors present in the system. In addition, it can improve the sensitivity of the product by using a control system. In this paper, an experiment using a prototype that simulates a control system is performed. The idea is that a student perform this work in a laboratory in order to understand and apply the concepts of robust design with dynamic characteristics.

Keywords – Robust Parameter Design, Control Systems, Quality Engineering, Experimental Design, Teaching Process.

I. INTRODUCTION

The robust parameter design is a part of quality engineering methodology, in order to find the best conditions in the control factors, to the effect produced by noise factors in the quality response. In the whole system there is one factor, known as factor signal M , which can be constantly changed based on the performance requirements of the system [1].

Control factors (X) are those that can be adjusted by the process operator to establish the optimum operating values, and keep it under some tolerance for system operation. Noise factors (Z) are those which in practice is difficult and expensive to keep in control, among which can be mentioned the environmental temperature, dust, variation in voltage, human factor; such factors are random during operation of the system.

The linear relationship between signal M and the quality response is given by

$$Y = \beta(X, Z)M + \varepsilon \quad (1)$$

Where ε is a random variable with mean zero and variance σ^2 . In each treatment of the experimental design, an estimation model (1) is obtained. From there it is obtained the signal to noise ratio between the coefficients β squared of the model and the mean squared error.

Referring to the system with dynamic model features in (1) it must be incorporated a control factor with this factor, it seeks to reduce variation by an element that corrects continuously the value of this factor by measurements and continuous corrections. In many processes there are strong noise factors that cannot be desensitized by using the robust parameter design. The use of control systems is inevitable in such cases [2].

In this article, the latest techniques of the methodology are applied to a laboratory case in which the fall time of balls through a liquid mixture is measured. Using statistical techniques, the system behavior is modeled, and based on appropriate optimization techniques [3], levels to control factors which may reduce the sensitivity of the response to noise factors are obtained. Also, a comparison with the addition of a control element is performed in order to check the reduction of variation in the system.

Conducting this design in the laboratory is aimed to engineering students to play a situation that can occur in practice. This is a methodological approach in order to contribute to the learning process of engineering students.

II. THEORETICAL BASIS

In a system with dynamic features, it has control factors X , noise factors Z and the signal factor M . Elements' interaction generates a response Y . The system is shown in figure 1.

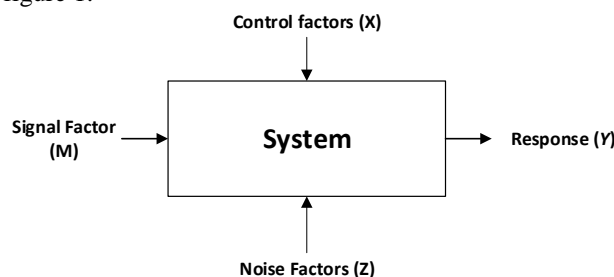


Fig.1. System with dynamic features.

Taguchi [4] used a performance measure of variation from the linear relationship (1) which is called dynamic signal to noise ratio given by

$$SN = \beta^2 / \sigma^2 \quad (2)$$

Where β are the slopes estimated by least squares model and σ^2 corresponding to the variance regression models commonly estimated using mean square error of the analysis of variance for each treatment, which are averaged over the levels of the signal factor [5]. The assumptions in (2) are that the ratio in the response must be linear and robust to uncontrolled factors.

III. TEACHING PROPOSAL

The scheme of Figure 1 shows an abstract idea of what a process is. From there it arises a series of strategies in quality engineering systems in order to build a model in increasing productivity and controlling the variability of the products and processes. In that direction the application of statistical methods for building strategies generated elements in the development of competitiveness.

On the other hand, in the curricula of industrial engineering careers there is the course of design of experiments. When engineers find employment in an industry, it seems that they have not acquired the ability to perform an experiment. Teaching the course has a technical focus and when some teachers pose these practices do not relate to real processes, or with the statistical concepts in experimental design.

The idea is to integrate the problems of the industry and the preparation of engineers. In both directions it is important to research and development of teaching materials.

Considering the situation in the teaching-learning process, the goal is to develop a guide to a practical project to conduct an experiment to represent a real situation that simulates a manufacturing process, and so that teachers have options for teaching. This practical project is a learning strategy that focuses on the core concepts of experimental design and optimization with a control system. So that, a workshop level involving students and engineers in solving industrial problems, with the idea of allowing them to work independently to build their own learning. With this type of project a learning strategy is proposed and it is intended that students develop their skills and encourage some new ideas.

In the project description it states that students will be giving solution to non-trivial problems, so that they raise and debug questions, discuss ideas, work plans and design experiments, collect and analyze data and establish their own conclusions to return to make new approaches that lead to continuous improvement concepts.

The experiment at laboratory allowed properly manipulate both control noise factors. These strategies allow students awareness of the importance of each of the experimental factors and their effect on the desired response of quality, allowing that if need for implementation of an experiment in a real industrial case, they already acquired the ability and vision necessary to create a suitable design that integrates all the elements necessary for obtaining information and for taking appropriate decisions.

IV. EXPERIMENTAL MODELING

The purpose of the experiment is to properly identify which are the controlling factors affecting the performance of the system. The performance measure modeling scheme (PMM) is an experimental strategy that requires a two stages modeling procedure, in which are obtained answers as averages and variances for each of the treatments. The arrangement contains experimental factors combined with signal-factor levels.

The primary array for proposed experiment is a 2_{IV}^{7-3} array [6], [7] which has design generators: E= ±ABC, F= ±BCD y G= ±ACD, this array is showed in Appendix A. The orthogonal matrix allows to analyze the effect of seven experimental factors and the number of experimental runs or treatments is 16. An extra column is added to the orthogonal arrangement with levels of 1 to 5

in order to represent the dynamic characteristic in the experiment, this implies that the orthogonal array is replicated in each of the signal levels of the factor (the weight of the balls). The experimental results can be consulted by the reader in the hyperlink in Appendix B.

V. MODELING WITH CONTROL

One of the latest trends within the robust parameter design for dynamic features methodology is the use of additional control elements online [8], [9]. This type of systems are known as double signal systems or systems with multiple target control, scheme is shown in Figure 2

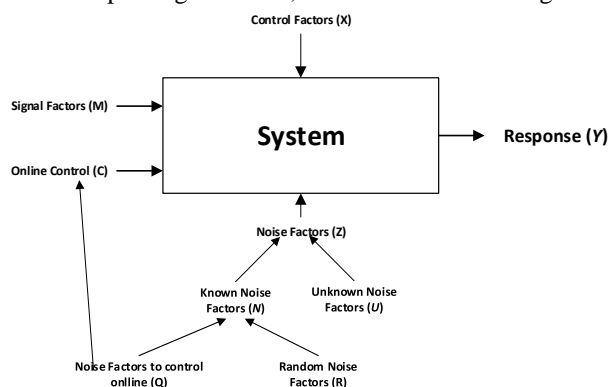


Fig.2. System with dynamic features and control

The diagram shows that the system is influenced by a dynamic characteristic and a online control element, which is continuously performing correction according to the measurement of the variable, in the system control factors X can be kept fixed, noise factors Z are subdivided into known noise factors N and unknown noise factors U . the noise N is subdivided into random noise R and the noise factor to be controlled online Q .

The model (1) is now a function of the control factors, noise factors and the element corrected by controlling as

$$Y = \beta(X, Q, R)M + \varepsilon \quad (3)$$

Where $E(\varepsilon) = 0$ and $Var = V(X, Q, R)M$. The variance of the model is expressed in (3) using the following formula.

$$Var(Y) = E[V(X, Q, R)] + Var[\beta(X, Q, R)] \quad (4)$$

Substituting the formula of the variance in (4) the expression of the signal to noise ratio that characterizes the control system is obtained.

$$SN = \frac{E^2[\beta(X, Q, R)]}{E[V(X, Q, R)] + Var[\beta(X, Q, R)]} \quad (5)$$

Equation (5) it is a measure of performance in each experiment treatments. Statistical analysis of this measure will find the levels of the control factors X with which the robustness of the system is achieved.

VI. STUDY CASE

The response variable is the time it takes the ball to reach the bottom once released, on these values the statistical analysis is done. In each treatment, the balls drop on a liquid mixture that is formed with the following substances: Glycerine, Sugar and carbonate. Experimental

factors and levels are shown in Table 1.

Table 1. Experimental factors and their levels

	Low	High
Glycerin	220 grs	260 grs
Carbonate	60 grs	80 grs
Sugar	25 grs.	50 grs.
Mixing time	5 min	10 min
Ambiental Temperature	15°C	32°C
Mix temperature	10° C	50 °C
Person	1	2

The mixtures were prepared in 1 liter test tubes, the total mixture of components is also one liter, the liquid mix was mixed using laboratory mixer and their times were measured. The ambient temperature could be controlled by air conditioners, the temperatures of the mixture in the low and high levels were obtained by laboratory refrigerators and ovens, the person who rolls the balls also was varied in order to add noise factors in the experiment.

The signal factor are the 5 balls with different weights in order to vary their levels, the weights are shown in Table 2

Table 2. Weights of the balls (signal factor)

	Weight
Ball 1	10.14 grs
Ball 2	11.31 grs
Ball 3	12.78 grs
Ball 4	14.14 grs
Ball 5	15.40 grs

The factor signal is added as an additional column in the Table 1 in accordance with coded 1 to 5 in order to vary the runs with each of the different balls in the experiment runs levels.

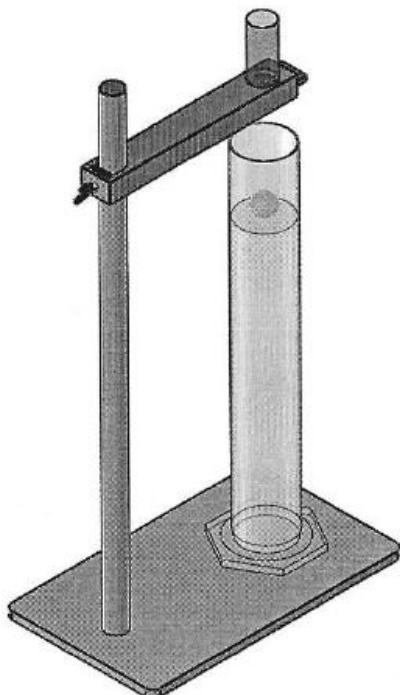


Fig.3. Pitcher device for the experiment

The controlling element is showed in Figure 3, it is a tower that allows to adjust the height of release according to the weight of the balls, to achieve there was made an Excel table which relate Heights of release with weights of the balls with the objective that the discharge height is adjusted based on the weight of the ball so that the theoretical impact force of the ball against the surface of the liquid is the same regardless of the weight of the ball.

To determine the relationship between the variables involved were taken into account the following physical relationships:

Distance d traveled by an object in free fall with time t

$$d = \frac{1}{2}gt^2 \quad (6)$$

Elapsed time t for an object in a fall distance d

$$t = \sqrt{\frac{2d}{g}} \quad (7)$$

Instantaneous velocity v_i of an object in free fall after an elapsed time t

$$v_i = gt \quad (8)$$

Instantaneous velocity v_i of an object in free fall which has traveled a distance d

$$v_i = \sqrt{2gd} \quad (9)$$

Mean speed v_a of an object which has fall in a time t

$$v_a = \frac{1}{2}gt \quad (10)$$

Mean speed v_a of an object in free fall which has traveled a distance d

$$v_a = \frac{\sqrt{2gd}}{2} \quad (11)$$

Mean force F of an object en free fall with a mass m

$$F = m \cdot g \quad (12)$$

In the Figure 4 are observed the main Height calculations, the height of liquid in the test tube filled with a liter of the mixture is 37.40 cms, relating the formulas (6) - (12) in an Excel table, are obtained release corresponding heights which are shown in Table 3.

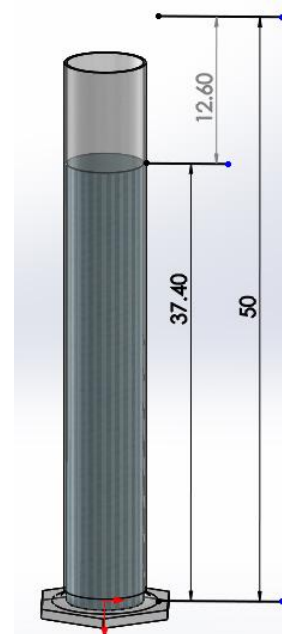


Fig.4. Heights for the test tube and the initial values for pitcher device

Table 3: Release heights according to the weights of the five balls

Mass of the ball (grs)	Real height (cms)
10.4	55.6
11.31	54.1
12.78	52.2
14.14	50.8
15.4	49.7

What is sought in the model is that the person performing rolls should adjust the height of the pitcher before making the run, the goal is to reduce variation that causes launches performed manually since the device will control the rolls and thus the factor signal (ball) and the online control (height adjustment of pitch based on the mass of the ball) will be related, the idea is illustrated in Figure 5.

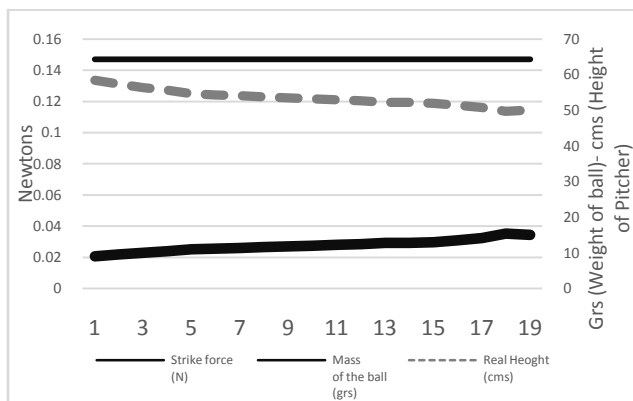


Fig.5. Relationship between strike force vs. the weight of the ball and height of the pitcher

The goal is to make height adjustments to launch as they are changing the balls to form a force of this blow against the surface is obtained with constant liquid Surface strike force value (0.1471 N).

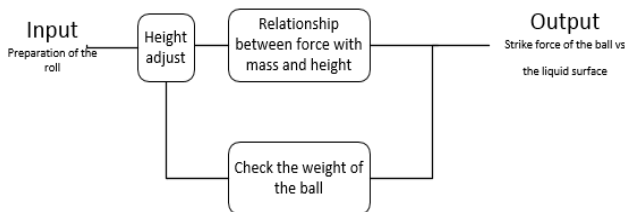


Fig.6. Control model for the rolls

In Figure 6 is showed the diagram of the control model that will be acting in the experiment, the input is the preparing of the roll in the experiment sample, the person doing the work of the control to adjust the height of the device based on the weight ball, here acting physical relationships between variables and an output that is the force of hitting the ball against the surface of the water, if the following experimental treatment includes a ball change is due to reset the corresponding height according the weight of the ball.

VII. OPERATIONAL METHODOLOGY

Operational methodology proposed for the experimental analysis is shown in Figure 7, the aim of the study is to determine the levels of the control factors.

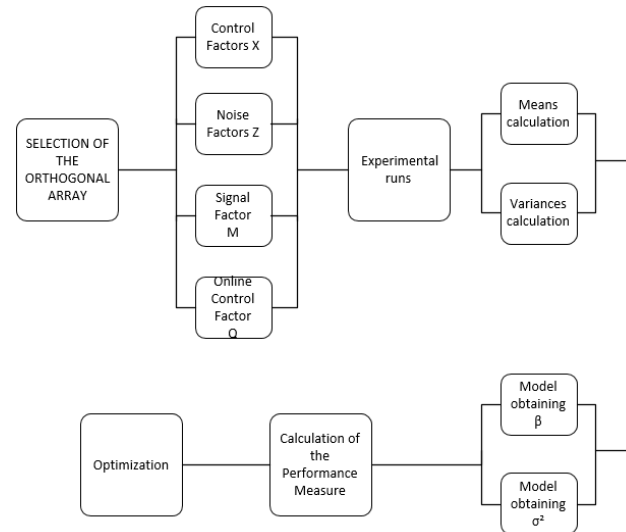


Fig.7. Operational Methodology

To obtain optimal levels in the control factors, conducting the experimental runs are required, the response variable is the time to drop the ball through the liquid mixture and the conditions set by the other experimental factors, once were made runs we proceeded to calculate averages and variances of each of the combinations of treatments (See Appendix B).

It is better to fit the mean model by the weighted least squares [10] with weights $1/V(X, Q, R)$ and to fit the variance model by a Generalized linear model (GLM) Gamma with log link [11] in order to avoid the impact transfer error between models.

Results in experimental runs are showed in Appendix, the 2^{7-3} array replicates through different levels of the factor signal, each of the five balls in the experiment is represented by encoded values from 1 to 5.

Runs for each of the treatments were replicated 4 times, this way the values for the mean and variance of each of the treatments can be calculated. Through the full orthogonal array e fitted models for mean and variance are obtained.

To optimization basis is the inverse of equation (5) which is called Performance Measurement (PerMIA as acronym) which is defined as

$$PM = \frac{E[V(X, Q, R)] + Var[\beta(X, Q, R)]}{E^2[\beta(X, Q, R)]} \quad (13)$$

To obtain the estimated levels of the control factors, equation (13) is minimized through some nonlinear programming algorithm, the estimates obtained are the most appropriate levels for controlling factors in which the robust solution for the model is obtained.

VIII. RESULTS

Based on the experimental results, initially a Generalized linear model Gamma with Log link is fitted to

responses σ^2 , which is used to model the variation, following this, the significant elements are selected using the step- back method, so the model is obtained as follows

$$\hat{V}(X, Q, R) = \exp(1.9551 + 0.41118x_1 + 0.47481x_2 + 0.45789x_3 - 0.06466x_4 + 0.37171x_5 + 0.06486x_6 + 0.02891x_7 + 0.45141x_1x_6 + 0.28824x_2x_4 + 0.15549x_2x_5 - 0.06413x_6x_7)$$

Using the means \bar{x} as a response and by the weighted least squares method with weights $1/\hat{V}(X, Q, R)$ is obtained the model for the mean

$$\hat{\beta}(X, Q, R) = 2.74554 + 0.18732x_1 + 0.24177x_2 + 0.16968x_3 - 0.025325x_4 + 0.028579x_5 - 0.14337x_6 - 0.057562x_7$$

From previous models, we define the elements necessary to evaluate the performance measure (13) being

$$E[V(X, Q, R)] = \exp(1.9551 + 0.41118x_1 + 0.47481x_2 + 0.45789x_3 - 0.06466x_4 + 0.37171x_5 + 0.06486x_6 + 0.02891x_7 + 0.45141x_1x_6 + 0.28824x_2x_4 + 0.15549x_2x_5 - 0.06413x_6x_7)$$

$$E^2[\hat{\beta}(X, Q, R)] = [2.74554 + 0.18732x_1 + 0.24177x_2 + 0.16968x_3 - 0.025325x_4 + 0.028579x_5 - 0.14337x_6 - 0.057562x_7]^2$$

For the model $Var[\hat{\beta}(X, Q, R)]$ It should take into account the factors x_5, x_6 y x_7 were introduced to the experiment as noise factors and its effect are considered as random, because its effect could not be kept fixed or constant in the system, so that the model remains as

$$Var[\hat{\beta}(X, Q, R)] = 0.028579x_5\sigma_5^2 - 0.14337x_6\sigma_6^2 - 0.05756x_7\sigma_7^2$$

We assume in this example that σ_5^2, σ_6^2 y σ_7^2 is approximately distributed $N(0, I)$. Substituting the equations, the model for the Per MIA is obtained:

$$PM = (\exp(1.9551 + 0.41118x_1 + 0.47481x_2 + 0.45789x_3 - 0.06466x_4 + 0.37171x_5 + 0.06486x_6 + 0.02891x_7 + 0.45141x_1x_6 + 0.28824x_2x_4 + 0.15549x_2x_5 - 0.06413x_6x_7) + 0.028579x_5\sigma_5^2 - 0.14337x_6\sigma_6^2 - 0.05756x_7\sigma_7^2) / [2.74554 + 0.18732x_1 + 0.24177x_2 + 0.16968x_3 - 0.025325x_4 + 0.028579x_5 - 0.14337x_6 - 0.057562x_7]^2$$

Experiment levels are encoded as -1 and 1. The best option is to perform the optimization algorithms using restricted nonlinear programming [12] in order to obtain the best combination of levels for the experimental factors, with the help of MATLAB software, 4 different algorithms were applied, the results shown in Table 4.

Table 4: Levels obtained by using NLP algorithms

Factor	Algorithm			
	SQP	Interior Point	Active Set	Thrust Region
x1	-1	-1	-1	-1
x2	-1	-1	-1	-1
x3	-1	-1	-1	-1
x4	1	1	1	1
x5	-1	-1	-1	-1
x6	1	1	1	1
x7	1	1	1	1

The levels obtained for each of the experimental factors are the same in each of the four algorithms nonlinear programming, with which we have a good level of confidence in the results obtained theoretically.

It should be noted that the levels that were obtained by the optimization scheme are consistent with treatment levels of the treatment 9. In table 5 are shown the values for means and variances for the treatment 9

Table 5: Means and variances for the levels of the signal factors in treatment 9

Run	Signal	\bar{x}	s^2
9	1	3.0775	0.02883
9	2	3.0425	0.01283
9	3	1.365	0.00230
9	4	1.205	0.00670
9	5	1.115	0.00297

The overall variance by run in the treatment 9 is the smallest among the 16 experimental runs, indicating that the solution found by the algorithms of nonlinear programming is the best because it is the one with a lower combined variance from 5 factor signal levels, comparing the variance combined by treatment shown in Figure 8.

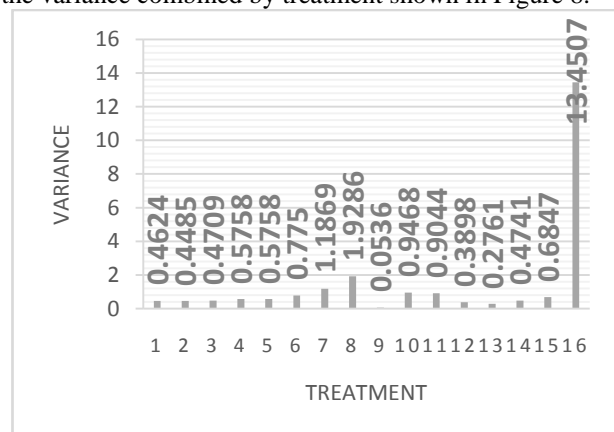


Fig.8. Combined Variances by treatment

Defining appropriate control factors in the experiment, the liquid mixture that has less variation and consequently greater resistance to noise factors is the one containing 220 grams of glycerin, 60 grams of carbonate and 25 grams of sugar, mixing time in 10 minutes is the ideal level and therefore this is the combination of control factor levels in which the process robustness is obtained. The ideal model of the System is showed in Figure 9

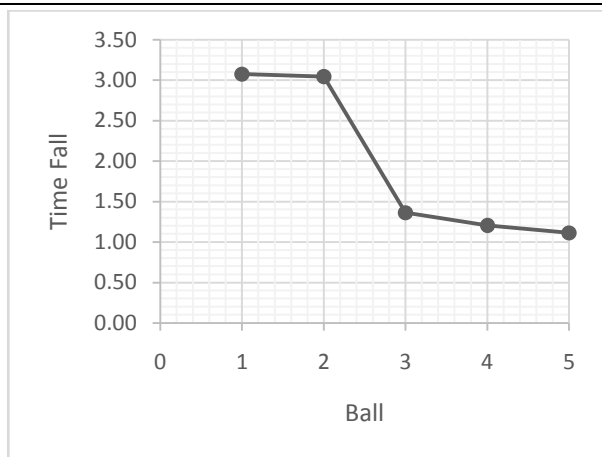


Fig.9. Dynamic Model of the experiment

In the figure 9 the average fall time for each one of the factor's signal levels are shown, the behavior is nonlinear for the difference in weights of the balls, despite this, the methodology showed efficiency for obtaining optimal levels experiment robust. In additional runs that were made for verifying Similar results they were obtained in the runs.

Is Important to note that the levels obtained by optimization have consistency, since when a major sample of Glycerin reacts greater with temperature especially when the element factor is in high level, when the temperature is low, Glycerin tends to crystallize, while at high temperatures tends to become thick, it was also observed that these mixtures with low levels of experimental factors tend to mix more easily in the mixture even in low mixing times.

When is used an online ítem control, a further reduction of the overall variation in the system is guaranteed, the use of such systems is handled can improve the quality processes of industrial type but must adequately justified

its use because it implies an additional cost.

In this work was conducted a laboratory application to model this kind of level systems with satisfactory results, the methodology is scalable and fully applicable to industrial cases. Robust systems modeling can be used to justify the use of an investment before it is performed if the model shows significant benefits and a significant reduction in its performance.

IX. CONCLUSION AND DISCUSSION

Statistical concepts usually represent a major challenge for engineering students because it's difficult to apply the theoretical concepts in practical cases. This paper presented a methodology of engineering and statistics to improve quality in systems with dynamic features, the example was a laboratory level application representing a simulated industrial process.

Because experimentation on industrial scale represents a significant amount of resources consumed, it is important that students can develop their skills and knowledge adequately before facing real industrial problems.

Laboratory level experimentation allows an adequate awareness of the effect by each one of the current variables in a process, and its influence on the quality response of importance.

The experiment helped to obtain the adequate combination of levels for the control parameters with which, it has the least sensitivity to the effect of noise factors –the robust response-. The dynamic model obtained showed consistency in the check runs, which allowed to validate the concepts of the proposed methodology, thus its effectiveness has been proved, and it can be expected a positive impact in its application to industrial level.

APPENDIX

A: Basic orthogonal array for experimental runs

Run	X1	X2	X3	X4	X5	X6	X7	Repetitions				- x	- s
	Gliceryn	Carbonate	Sugar	Mix Time	Amb. Temp	Mix Temp	Person	x1	x2	x3	x4		
	A	B	C	D	E	F	G						
1	-1	-1	-1	-1	-1	-1	-1						
2	1	-1	-1	-1	1	-1	1						
3	-1	1	-1	-1	1	1	-1						
4	1	1	-1	-1	-1	1	1						
5	-1	-1	1	-1	1	1	1						
6	1	-1	1	-1	-1	1	-1						
7	-1	1	1	-1	-1	-1	1						
8	1	1	1	-1	1	-1	-1						
9	-1	-1	-1	1	-1	1	1						
10	1	-1	-1	1	1	1	-1						
11	-1	1	-1	1	1	-1	1						
12	1	1	-1	1	-1	-1	-1						
13	-1	-1	1	1	1	-1	-1						

14	1	-1	1	1	-1	-1	1						
15	-1	1	1	1	-1	1	-1						
16	1	1	1	1	1	1	1						

B. Hyperlink to experimental results

<https://www.dropbox.com/s/f0n8ix2npplet8h/Experimental%20Results%20for%20Article%20authors%20Mares-Dominguez.pdf?dl=0>

C. Calculations for the launcher device

Ball Mass (grs)	Ball Mass (Kgs)	Gravity (mts/seg ²)	Height (cms)	Real Height (cms)	Height (mts)	Height (mts)	Force (N)	Force (N)	Mean Speed (mts/seg)	Instant Speed (mts/seg)	Time (Seg)	Time (Seg)
9	0.009	9.8066	21	58.4	0.306	0.21	0.147099	0.08825985	1.22491528	2.4498305	0.249813	0.1603023
9.5	0.0095	9.8066	19.89474	57.29474	0.296	0.198947	0.147099	0.09316318	1.20473407	2.4094681	0.245697	0.1603023
10	0.01	9.8066	18.9	56.3	0.286	0.189	0.147099	0.0980665	1.18420899	2.3684179	0.241511	0.1603023
10.4	0.0104	9.8066	18.17308	55.57308	0.276	0.181730	0.147099	0.10198916	1.16332183	2.3266436	0.237251	0.1603023
11	0.011	9.8066	17.18182	54.58182	0.266	0.171818	0.147099	0.10787315	1.14205273	2.2841054	0.232913	0.1603023
11.2	0.0112	9.8066	16.875	54.275	0.256	0.16875	0.147099	0.10983448	1.12037993	2.2407598	0.228493	0.1603023
11.31	0.01131	9.8066	16.71088	54.11088	0.246	0.167108	0.147099	0.11091321	1.09827954	2.1965590	0.223986	0.1603023
11.6	0.0116	9.8066	16.2931	53.6931	0.236	0.162931	0.147099	0.11375714	1.07572519	2.1514503	0.219386	0.1603023
11.8	0.0118	9.8066	16.01695	53.41695	0.226	0.160169	0.147099	0.11571847	1.05268772	2.1053754	0.214688	0.1603023
12	0.012	9.8066	15.75	53.15	0.216	0.1575	0.147099	0.1176798	1.02913468	2.0582693	0.209885	0.1603023
12.2	0.0122	9.8066	15.4918	52.8918	0.206	0.154918	0.147099	0.11964113	1.00502982	2.0100596	0.204969	0.1603023
12.4	0.0124	9.8066	15.24194	52.64194	0.196	0.152419	0.147099	0.12160246	0.98033244	1.9606648	0.199932	0.1603023
12.78	0.01278	9.8066	14.78873	52.18873	0.186	0.147887	0.147099	0.12532899	0.95499657	1.9099931	0.194765	0.1603023
12.8	0.0128	9.8066	14.76562	52.16562	0.176	0.147656	0.147099	0.12552512	0.92896996	1.8579399	0.189457	0.1603023
13	0.013	9.8066	14.53846	51.93846	0.166	0.145384	0.147099	0.12748645	0.90219285	1.8043857	0.183996	0.1603023
13.5	0.0135	9.8066	14	51.4	0.156	0.14	0.147099	0.13238978	0.87459630	1.7491926	0.178368	0.1603023
14.14	0.01414	9.8066	13.36634	50.76634	0.146	0.133663	0.147099	0.13866603	0.84610014	1.6922002	0.172556	0.1603023
15.4	0.0154	9.8066	12.27273	49.67273	0.136	0.122727	0.147099	0.15102241	0.81661018	1.6332203	0.166542	0.1603023
15	0.015	9.8066	12.6	50	0.126	0.126	0.147099	0.14709975	0.78601459	1.5720291	0.160302	0.1603023
Variable	Variable	Constant	Variable	Variable	Variable	Variable	Constant	Variable	Variable	Variable	Variable	Constant

D. Values for the mean and variance in the experiment

Signal: 1			Signal: 2			Signal: 3			Signal: 4			Signal: 5		
Run	\bar{x}	s^2	Run	\bar{x}	s^2	Run	\bar{x}	s^2	Run	\bar{x}	s^2	Run	\bar{x}	s^2
1	4.09	0.2246	1	3.51	0.2102	1	1.66	0.0043	1	1.465	0.0188	1	1.1875	0.0045
2	4.97	0.1387	2	4.15	0.2980	2	1.30	0.0032	2	1.225	0.0022	2	0.98	0.0065
3	4.35	0.0414	3	4.30	0.3706	3	1.55	0.0385	3	1.36	0.0134	3	1.0575	0.0070
4	4.42	0.0498	4	4.50	0.4997	4	1.47	0.0045	4	1.1925	0.0208	4	1.1125	0.0011
5	3.79	0.3763	5	3.35	0.1761	5	1.37	0.0068	5	1.1425	0.0104	5	1.035	0.0062
6	4.78	0.0648	6	4.19	0.6862	6	1.44	0.0100	6	1.25	0.0125	6	1.07	0.0015
7	6.19	1.0784	7	5.74	0.0947	7	1.43	0.0046	7	1.3175	0.0089	7	1.1125	0.0002
8	11.77	1.7183	8	11.48	0.1470	8	1.85	0.0125	8	1.555	0.0454	8	1.1975	0.0055
9	3.08	0.0288	9	3.04	0.0128	9	1.37	0.0023	9	1.205	0.0067	9	1.115	0.0030
10	4.23	0.4669	10	4.26	0.4596	10	1.55	0.0063	10	1.2225	0.0042	10	1.0975	0.0098
11	4.34	0.0523	11	4.19	0.8378	11	1.34	0.0094	11	1.29	0.0045	11	1.0325	0.0004
12	5.56	0.1040	12	5.03	0.2628	12	1.79	0.0158	12	1.595	0.0042	12	1.1025	0.0030
13	4.44	0.1202	13	4.20	0.1038	13	1.60	0.0285	13	1.405	0.0218	13	1.12	0.0018
14	4.89	0.3135	14	5.15	0.1427	14	1.45	0.0092	14	1.335	0.0079	14	1.185	0.0007
15	4.62	0.1894	15	4.95	0.4760	15	1.41	0.0088	15	1.145	0.0102	15	0.955	0.0004
16	10.35	9.2414	16	11.12	4.1799	16	1.48	0.0075	16	1.225	0.0014	16	1.02	0.0205

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