Integral Dynamic Control System IDCS: A hybrid approach to meeting the quality specifications.

R. Baeza-Serrato[1], J. Yáñez-Mendiola[2] J.AVazquez-Lopez[3]

[1]Department of Industrial Engineering & Manufacturing Science,
Centro de Innovación Aplicada en Tecnologías Competitivas A.C.
robaeza66@hotmail.com

[2]Department of Industrial Engineering & Manufacturing Science,
Centro de Innovación Aplicada en Tecnologías Competitivas A.C.
jyanez@ciatec.mx

[3]Department of Industrial Engineering,
Instituto Tecnológico de Celaya.
antonio.vazquez@itcelaya.edu.mx

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ABSTRACT.
Historically, control charts have been used (*CC*) to monitor the quality of the production of industrial processes. The use of *CC* for this purpose has limiting operation, which only determines the moments in time the presence of special causes, but does not imply the correctness of its effects on poor quality, or take into account the rate of process capability. Consequently, an alternate to the *CC* that would achieve adjustments in the manufacturing process during production and increase the rate of process capability is useful. This article presents an approach that allows this situation, determining "what and how to" make adjustments in the process according to their "outputs." The operation of *IDCS* be explained by processing the "error signal", calculated by the system and reduced by a fitting algorithm, this algorithm incorporates an offset variable to a linear regression model that represents the experimentally obtained controlling element of the system. The *IDCS* presented here was validated by system dynamics. This approach is a novel process control application for the case exposed. The *IDCS* consists of four basic elements. The elements of *IDCS* are: i.- controlling element, which represents one of the major contributions of research, proposing a fitting algorithm and incorporating a variable compensation, ii. processing element, iii. measuring element and iv. comparator element. The test results were compared with the control chart of individual measurements and show the impact in restoring the ability of a textile production process to produce parts conforming to quality specifications. To close the research, simulations of random samples with normal distribution have been used to analyze the efficiency of the proposed adjustments *IDCS*.

Keywords: System dynamics, control engineering, regression models, control charts, process capability index.

1. INTRODUCTION

Being P a manufactured product with different characteristics of quality. For a certain characteristic of quality (C) of P, the limits of superior specification and limits of inferior specifications are known as USL and LSL, respectively. If Y is the random variable representing C, then Y will have as parameters the measurement (μ) and the standard deviation (σ). The P non-conformity to the specifications of quality in C is determined in two ways:
First: according to the values of the Y parameters. Assuming Y~N (μ,σ2), if any of the next three cases are accomplished:

a. $\{\mu \neq (USL - LSL)/2\}$ y $\{\sigma<(USL - LSL)/6\}$
b. $\{\sigma > (USL - LSL)/6\}$ y $\{\mu = (USL - LSL)/2\}$
c. $\{\mu \neq (USL - LSL)/2\}$ y $\{\sigma > (USL - LSL)/6\}$

Normally, in a production process the values μ and σ are unknown so they must be inferred through statistical techniques -previous to the CC construction- and adjusted periodically.
Second: According to the individual measurements of Y. If for any measurement yi of Y, where Y= $[y_1, y_2, y_3,\ldots,y_n]$, any of the following two conditions is present:

a. $y_i > USL \quad i = 1,2,\ldots,n$
b. $y_i < LSL \quad i = 1,2,\ldots,n$

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The CC are employed as means of detection of moments in time in which a special cause of variation is present through "observable anomalies" in the control charts. However, knowing this is not enough to eliminate it and guarantee quality; according to Guh (2005), the CC indicate only "when" it is necessary to execute a search of special causes of variation in order to make the required adjustment to the process, but it does not show either "what to do", or "how to make the adjustment". Other disadvantages of the CC are the probabilistic requirements of normality and independency in Y, which are not always easily observed.

Nowadays, there are alternative ways different from the CC to establish mechanisms of control of quality in the production process. Two tendencies predominate: the first corresponds to the use of artificial neuronal nets to recognize patterns (which equivalent in the CC is to detect special causes; with higher efficiency, though.) For example, Vázquez et. al (2010) proposed a method to determine the appropriate values of the control parameters of a Fuzzy ARTMAP net in order to increment its efficiency in the recognition of patterns associated to special causes of variation. Guh y Shiue (2009) proposed a Time Delay Neural net to detect the patterns which vary over time, and that cannot be simulated by traditional neuronal nets such as the Backpropagation. Pham y Chan (1998) described an auto-organizational neuronal net to recognize basic patterns of the control charts, which learns to recognize new patterns. The second tendency for controlling the quality of the processes instead of the CC, consists of the implementation of hybrid systems of adjustments to the process during the production, based in the output. Georgieva y Feyo de Azevedo (2009), proposed a hybrid system with two alternatives of control (first a predictive model of control and second a linearized feedback system), by using neuronal nets as a transference function of the analyzed closed loop feedback system. Zhao et al. (2008) proposed a hybrid system of predictive control and the programming design which is applied to generate predictions of control for every closed loop system. Black et al. (2001) considered the impact of using statistical process control and engineering process control together; in a hybrid system denominated integral process control, which uses an integral controller to realize the adjustments by using a first order dynamic model ARIMA with disruptions.

Research in these two tendencies proposes prediction methods by using neuronal nets and hybrid systems of control, which give not answer to "what" and "how" to make the necessary adjustments, glimpsing an opportunity area considered in this research to explain the "what and how to do" to return the control of the process.
Any system of quality control has as an ultimate purpose: to make that the production process delivers products complying with the specifications. The current requirement for these systems is to be able to answer the questions "When is a non-conformity present?", "What to do to correct it?" and "how to do it?" This article presents an integral system of dynamic control which answers these questions without necessarily looking for the special causes of variation that act on the process itself in accordance with its output. This allows making the necessary adjustments to the manufacture process during the production in order to guarantee fulfilling the required specifications of quality. The developed integral system of dynamic control uses four elements: processing element, controlling element, measuring element and comparator element, based on tools and techniques of industrial engineering applied to continuous improvement of any industrial process.
With this hybrid approach of control of processes it is proposed to perform the control of quality during the manufacture process without looking for special causes, detecting special patterns or using estimation statistical techniques; thus the IDCS can be considered a tool of industrial engineering for making the adjustments in the production process and increasing the indicator of the process capacity. This research presents three main contributions.

a. An advanced control system which allows executing actions of control when the conditions of non-compliance are identified by comparing individual measurements to specifications, through the adjustment algorithm that incorporates a variable of compensation and represents the controlling element; explained in section 2, sub-topic 2.3
b. An Analysis of the performance of the IDCS adjustments, through the transference function of a dynamic characteristic; explained in section 2, sub-topic 2.5
c. Design of a control and adjustment chart for the IDCS; explained in section 2, sub-topic 2.6

In order to validate the IDCS, the result of the experimental design obtained during this research was used in a system of textile production, analyzing knitted fabric of a SHIMASEIKI machine, where the experimental tests, the simulation and the validation were carried out on a piece of fluted fabric, made with Apollo thread consisting of 50% lycra and 50% polyester. The characteristic of quality considered was the fabric length, measured in centimeters.
After section 1, this article is organized as follows: section 2 describes the IDCS methodology and each element conforming it, as well as the transference function used as indicator of the efficiency of the adjustments executed. Section 3 shows the IDCS validation with an approach of systems dynamics, which allows identifying and understanding the behavior of the adjustment zones ($\alpha 1$, $\alpha 2$, $\alpha 3$), for the construction of the IDCS control charts.

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Section 4 describes the working method for the IDCS application in an actual process. Finally, section 5 contains the comparison of the IDCS control chart to the individual measurements chart, as well as the conclusions and future works foreseen.

2. METHODOLOGY

The IDCS proposed in this research, allows keeping control of quality in the production during the process, understanding the existing relation between the independent variables X and the random variable Y which represents the characteristic of quality C, and explaining it through a regression model. Usually, in regression models the X variable is used as a predictor of Y, which implies that given X, Y is obtained. In the IDCS the opposite happens, in other words, given Y, X is obtained (inverse regression); this allows determining the necessary adjustments in X given a Y measurement that does not fulfill the required specifications, which explains "what and how to do it" to make the necessary adjustments and return the control of quality to the production process. This way, it is possible to calculate the error signal in relation to the specifications.

The IDCS elements (image1), are the processing element (PE), the measuring element (ME), the comparator element (CME), and the controlling element (CE).

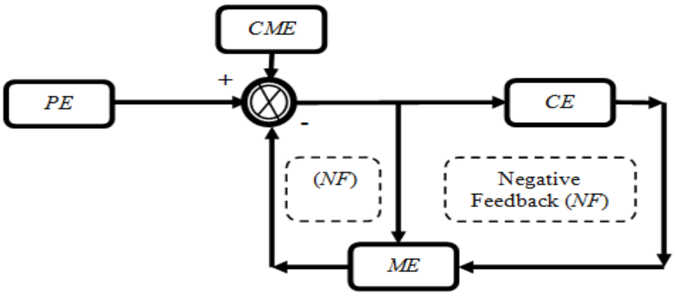

Image 1. Integral Dynamic Control System of closed-loop control with negative feedback

2.1 Processing element (PE)

Assuming that for a characteristic of quality represented by the random variable Y, there will be a multiple lineal regression model with xk independent variables expressed in the equation 1- that explains the relationship between them.

$$\mathbf{Y} = \boldsymbol{\beta}_o + \boldsymbol{\beta}^T\mathbf{X} + \phi \qquad (1)$$

Where:

$$\boldsymbol{\beta} = [\beta_1, \beta_2, \dots \beta_k]^T; \mathbf{X} = [x_1, x_2, \dots x_k]^T$$

Then it is possible to assign the element PE to the model in image 1

2.2. Comparator element (CME)

The CME calculates and processes the error signal (ϕ) through the equation 2. In order to fulfill this, it is necessary to use the n measurements of negative feedback (NF) of the system and compare them with the nominal value NV[1] of the specifications of quality. If ρ_1 = LSS-NV y ρ_2 = NV-LIS, then

$$\phi_i = NV - NF_i \;\; to \; i = 1,2, \dots, n \qquad (2)$$

2.3 Controlling element (CE)

In order to obtain the controlling element, it is necessary to understand the relationship between the operation variables and the quality characteristic of Y interest. Thus, it is necessary to obtain a regression design which explains such a relationship. See equation 1.

Since the X values are operation parameters, there will be combinations in X that will cause values in Y out of specifications and other values in X complying with the specifications in Y. This way and through inverse regression,

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for the cases where $\phi_i > \rho_1$ ó $\phi_i > \rho_2$, adjustments can be made to the machine, as long as the rule of impact of the X factors is given. The inverse regression implies clearing X in equation 1, in order to obtain the equation 3.

$$\mathbf{X} = \frac{\mathbf{Y} - \boldsymbol{\beta}_0 - \boldsymbol{\phi}}{\boldsymbol{\beta}^{\mathrm{T}}} \quad (3)$$

Given that in the equation 3 a scalar is present in the numerator and a vector is in the denominator, it turns difficult to find out the values of the corresponding X operation parameters. That is why it is necessary to find out a G vector with variables of compensation, which can estimate the necessary adjustments to X, which is in function of the error signal ϕ; just as it is pointed out in the equation 4 and indicted in the equation 3.

$$\mathbf{G} = \mathbf{f}(\phi) \quad (4)$$

Using an adaptation of the technique of ascendant scaling of response surfaces (Montgomery, 2001) it is determined the necessary increments or decrements of the G vector which represents the variable of compensation, in order to make the respective adjustments to the X significant factors, through the function of error signal.
The ascendant scaling technique to determine the increments and decrements is as follows:

1. The increment or decrement of a variable of process is chosen. Usually, the variable with the greatest coefficient of absolute regression $|\beta_j|$ would be selected.
2. The sizes of the increment of the variables are

$$\Delta x_i = \frac{\beta_i}{\left(\frac{\beta_j}{\Delta X_j}\right)} \quad i = 1, 2, \ldots, n$$

3. The increments are converted into decrements Δx_i from codified variables to natural variables.

To each Y simulated value through the regression model of the equation 1, it corresponds a respective value of the error signal ϕ. This signal represents the necessary adjustment to be made to the X significant factors. This research proposes an algorithm of dynamic control which distributes in a hierarchical way the error signal in the significant factors of the regression model, using the basic concepts of the ascendant scaling technique, through the G compensation vector, in at least an x_k variable of each of the significant factors of X operation, in order to have ϕ tend to zero.
Where:

$$\mathbf{G} = [g_1, g_2, \ldots g_k]^{\mathrm{T}}$$

G= Compensation vector to perform the necessary adjustments to the X vector of the significant factors.

In order to find the G compensation vector, which allows finding the necessary adjustments to X, the following steps are carried out:

1. To identify and assign the dominant factor such as β_m, which can be picked from the values of the coefficients β_j from the significant factors of the regression model. The dominant factor is the one with the absolute highest regression coefficient in the equation 1. The non-dominant factors are the rest of the significant factors of the regression model obtained in the equation 1.

β_m = Coefficient of the dominant factor

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β_j = Coefficiente of the significant factors of the regression model for j= 1, 2,…n.

2. The relationship existing between each non-dominant factor and the dominant factor is determined by using the equation 5. This relationship is used to distribute the error signal in the non-dominant significant factors.

$$\frac{\beta_j}{\beta_m} \quad for\ j = 1,2,\ldots n\ and\ j \neq m \qquad (5)$$

3. Since the relationship existing between the factors of the model was determined in the previous step, the error signal is distributed proportionately between the correspondent factors by using the coefficient of the dominant factor as a hierarchical proportion guideline.

The value of the compensation variable g_i for the significant dominant factor is determined trough the following proportion of the equation 6

$$g_i = \frac{\phi_i}{\beta_m} \qquad (6)$$

The values of the compensation variable g_i for the significant non dominant factors are determined with the following proportion of the equation 7:

$$g_i - \frac{\phi_i}{\left(\frac{\beta_j}{\beta_m}\right)} \qquad (7)$$

4. When adding the error signal (ϕ_i) term in natural units to the statistical regression model, it is necessary to convert the levels of the factors into natural units for the regression model is not modified (ψ_j). See equation 8.

$$\psi_j = \left(\frac{\mathbf{1}}{\textbf{High natural level} - \textbf{Low natural level}}\right) \quad \mathbf{(8)}$$

Thus, the equations (6) and (7) remain as follows:

Compensation variable g_i for the dominant factor:

$$g_i = \frac{\phi_i}{(\beta_m)\psi_j} \quad for\ i = 1,2,\ldots n\ and\ j = 1,2,\ldots k \qquad (9)$$

Compensation Variable g_i for the non-dominant factors:

$$g_i = \frac{\phi_i}{\left(\frac{\beta_j}{\beta_m}\right)\psi_j} \quad for\ i = 1,2,\ldots n;\ j = 1,2,\ldots k\ and\ j \neq m \qquad (10)$$

Where:
n = number of simulated measurements
k = number of significant factors of the lineal regression model
The equations 9 and 10 are used to find the vector of compensation G which represents the increments o decrements in the X significant factors, in function of the error signal ϕ, thus, to obtain the adjusted values the equation 1 is as follows:

$$\mathbf{Y_{Aj}} = \boldsymbol{\beta_o} + \boldsymbol{\beta^T}\mathbf{G} + \boldsymbol{\phi} \qquad \mathbf{(11)}$$

2.4 Measuring Element (ME)

The adjusted values (Y_{AJ}) or non-adjusted (Y) are registered as ME. These registered values represent the negative feedback of the comprehensive dynamic control system of closed loop (NF).

2.5 IDCS Transference Function

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Taking the nominal value as the IDCS input signal, and the NF results of the dynamic simulation as the output system, the transference function is generated through the mathematical model which relates the inputs with the outputs, through the equation (12)

$$\mathbf{Y_{Aj}} = \varphi \mathbf{NV} \qquad (12)$$

Where:
NV = The input signal (Nominal Value)
φ= The response line slop (% efficiency of the relationship input-output)
Y_{AJ}= IDCS adjusted negative feedback

The value φ represents the percentage of the transference function efficiency. If the Y_{AJ} values adjusted were equal to the nominal value wanted or to the input one, the value must be 1, which represents a 100% percent of efficiency.

The sensitivity or slop represents the efficiency of the adjusted values and it is determined by the equation (13):

$$\varphi = \frac{1}{r}\left(NV_1 y_{Aj1} + NV_2 y_{Aj2} + \cdots + \mathrm{Nv} y_{Ajk}\right) \qquad (13)$$

Where:

Y_{AJ}= System adjusted output, and

$$r = n\left(NV_1^2 + NV_2^2 + \cdots + NV_k^2\right) \qquad (14)$$

n = Number of measurements

2.6 Construction of the IDCS Control Chart Form

The IDCS control chart is used to monitor and adjust the quality of production in the process by using inverse regression; in other words, given Y, X is obtained. This allows determining the necessary adjustments in X given a Y measurement not complying with the required specifications; in turn, this permits explaining "what" and "how to make" to perform the necessary adjustments to take control again of the production quality in the process. For the construction of the IDCS Control Chart, the elements shown in chart1 are used.

Chart 1. IDCS Chart Control Elements

Symbol	Meaning	Location in the Chart	Symbol	Meaning	Location in the Chart
USL	Limits of Superior Specification	Graphic section	α2	Adjustment Zone 2	Graphic section
LSL	Limits of inferior specification	Graphic section	α3	Adjustment Zone 3	Graphic section
NV	Nominal Value	Graphic section	Φ_i	Initial Error Signal	Records section
ρ_1	Tolerance 1	Graphic section	Φ_f	Final Error Signal	Records section
ρ_2	Tolerance 2	Graphic section	Cpk_i	Indicator of Initial process capacity	Records section
α1	Adjustment Zone 1	Graphic section	Cpk_f	Indicator of Initial process capacity	Records section

Being P a manufactured product with different quality characteristics. For a certain characteristic of quality (C) of P, the limits of superior specification and limits of inferior specifications are known as USL and LSL, respectively; just the same way, NV represents the nominal value of the quality specifications. These parameters are located in the IDCS graphic section. See image 2.

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The zones α1, α2, α3, are identified by analyzing the adjustments behavior in the IDCS dynamic validation. In this research, every adjustment zone represents the number of times that a proposed adjustment algorithm will be used as a controlling element in order to meet the specification established. The zones are located in the IDCS graphic section. See image 2.

These adjustment zones may or may not be symmetric respect to the NV and to the limits of specifications USL and LSL of the product P to be manufactured, since they depend on the values obtained from the parameters β of the equation 1 and the hierarchical proportion used in the equations 9 and 10.

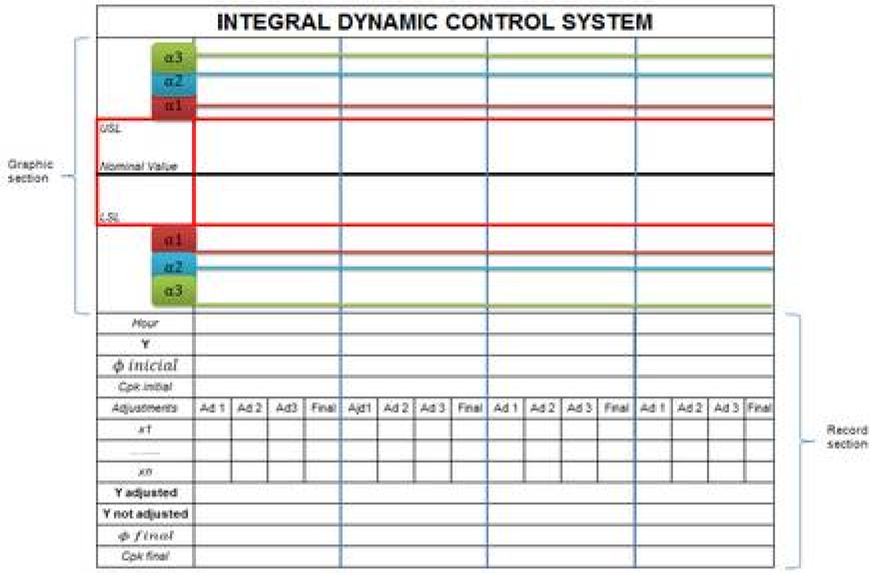

Image 2. IDCS Control Chart Form

Image 2 shows the IDCS Control Chart Form, which consists of two parts: the graphic section and the record section. The graphic section of the form contains the tolerance regions established for the nominal value through the limits of superior and inferior specification, as well as the delimitations of the adjustment zones. The inferior section registers the yi, variable measurements corresponding to the EP, and calculates the error signal by using the equation 2, corresponding to the CME, as well as the initial Cpk indicator, taking the error signal as the standard deviation obtained. If the error signal is within tolerance, no adjustments will be made to the measurement; otherwise it must be made as many adjustments to X by using equations 9 and 10, according to the adjustment zone where the measurement has been located, corresponding to the CE. Finally, the adjusted value Y_{AJ} or non-adjusted Y, are registered, corresponding to the ME, as well as the final Cpk to observe the increment of the indicator, if any adjustment to the process.

When using the IDCS control chart, it is not necessary for the data to present normality or to follow an established pattern, but it is advisable to use the CC previously to get the process stability, and complementarily to use the IDCS to make the required adjustments, explaining “what to do” and “how to make them.”

3. DYNAMIC VALIDATION TO OBTAIN THE IDCS ADJUSTMENT ZONES (αi)

A dynamic model was developed (image 3) to validate the IDCS; this allows understanding the behavior of the adjustment made to the simulated process and identifying the zones (αi) for the IDCS operation, for a further successful implementation in a real process. This model consists of three state variables, which represent the significant factors of the statistical model obtained in the experimental design in a study case of a textile process (see equation 15.) They are dynamically increased through positive feedback loops to understand the actual behavior of the model, which differs from a linear behavior assumed. When the variability exceeds the specification limits on the error signal, the adjustment is made immediately, through the controlling element. The simulation performs up to three adjustments to identify the zones α1, α2, and α3 in the construction and operation of the IDCS control chart, generating knowledge for the process.

$$Y = 87.8813 + 1.15625x_2 - 0.71875x_3 + 1.30625x_4 \quad (15)$$
$$R2= 77.04\%$$

The state variables are increased dynamically with a growing rate established in auxiliary variables, through the positive reinforcement loops. The response variable is calculated over a defined time horizon. The dynamic model is constructed to realize and analyze the response variable behavior across the three adjustments to the dynamic control process to detect and understand which the adjustment zones are for the dynamic model. The dynamic model was developed in the software Stella 9.0.2.

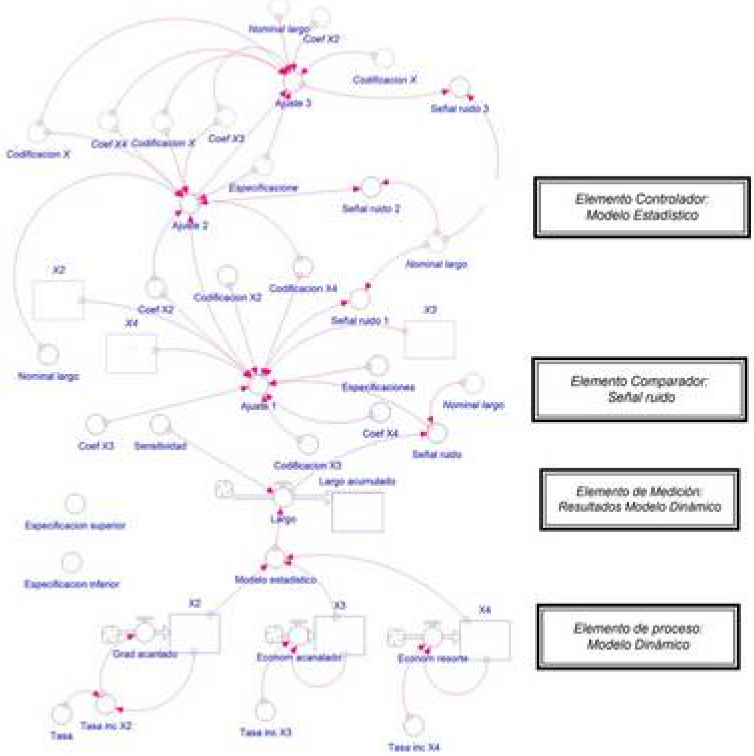

Image 3. IDCS Forrester Diagram

Chart 2 describes the types of variables used in the model.

Chart 2. Types of variables in the model

Variable	Type of Variable	Variables	Type of Variable
X2	State Variable	Coefficient X4	Auxiliary Variable
X3	State Variable	Decoding X2	Auxiliary Variable
X4	State Variable	Decoding X3	Auxiliary Variable
Growing Rate X2	Auxiliary Variable	Decoding X4	Auxiliary Variable
Growing Rate X3	Auxiliary Variable	Adjustment 1 long	Auxiliary Variable
Growing Rate X4	Auxiliary Variable	Adjustment 2 long	Auxiliary Variable
Length	Auxiliary Variable	Adjustment 3 long	Auxiliary Variable
Nominal length	Auxiliary Variable	Coefficient X3	Auxiliary Variable
Coefficient X2	Auxiliary Variable	fluted graduation	Flow variable
Fluted Economizer	Flow variable	Spring Economizer	Flow variable

4. VALIDATION RESULTS

In the simulation of the dynamic model, it was set the nominal value of the response variable long in 89.0 cm. With tolerance of ± 1 cm, through the required specification limits: USL = 90.0 and LSL = 88.0 cm.

Figure 4 shows the behavior of the process element, simulating Y measurements in the curve 1, which has a real behavior of exponential growth, differing from the assumed linear behavior of the regression model, due to the feedback that each state variables has in the system. Each exponential curve point not complying with the specifications was adjusted only once in a dynamic way in real time, which is transformed in curve 2, through the regression model proposed as IDCS controlling element. Chart 4 shows that making a single adjustment satisfies only the region α1 which complies with the specifications.

The permitted tolerance zone that does not require any adjustment is limited by ρ. Chart 4 illustrates that the process is not centered, since the value of the mean of the Y random variable is greater than the USL, so that there are several values of such a variable that make the process unable to fulfill the desired quality and therefore the Cpk is not calculated.

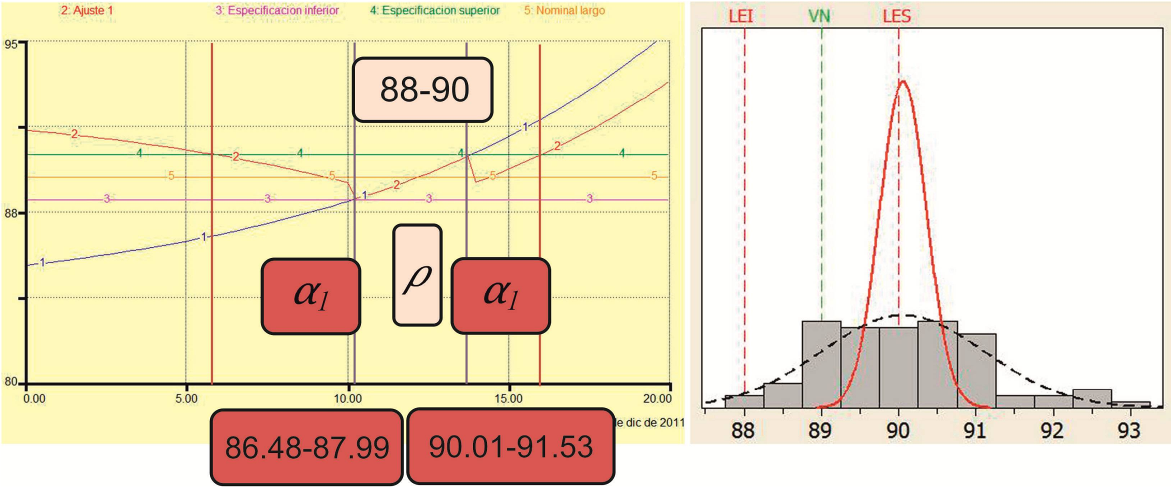

Image 4. Identification of the IDCS zone α1.

In image 5a, curve 1 shows the process behavior. The Y random variable measurement range was modified in the dynamic simulation to obtain the zone α2, which were adjusted twice dynamically, transforming them into curve 2 through the regression model proposed as the IDCS controlling element. In this case, the range in which the proposed model makes the necessary adjustments is wider, giving the values of zones α1 and α2 in which the required specifications meet. Image 5b shows that the process is not centered, since the mean value of the random variable Y, is different from the desired nominal value, and therefore, the Cpk indicator is not calculated.

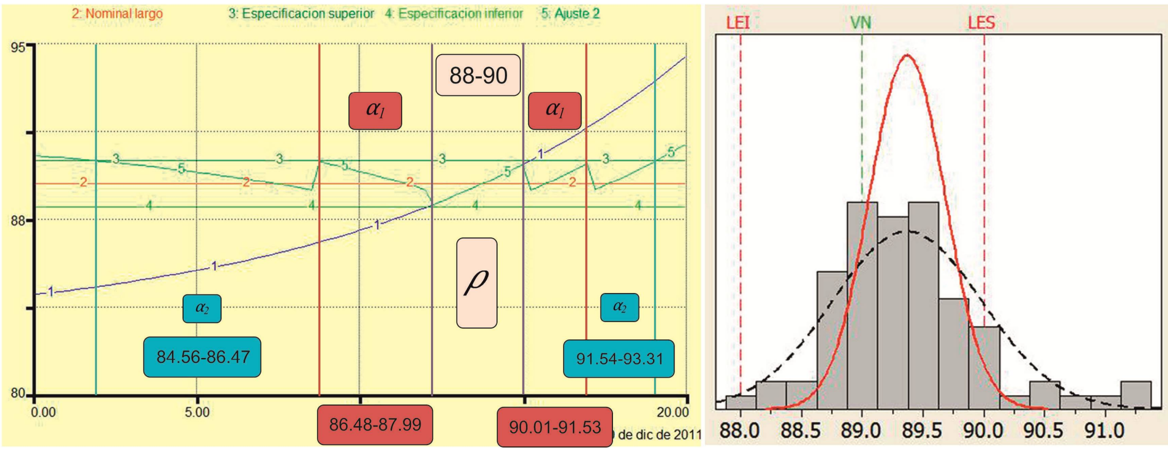

Image 5a y 5b. Identification of the IDCS zones α1 y α2.

The zones α1, α2 and α3 can be seen in the image 6a. For doing that, the rank of the simulated Y measurements was modified. Each point of the exponential 2 curve not complying with the specifications were adjusted in a dynamic way in real time, converting it into the curve 1 through the regression model proposed as IDCS controlling element. Consequently, the total fulfillment of adjustments can be observed. Image 6, shows that the process is centered, for this reason the indicator Cpk was calculated resulting a value of 1.44.

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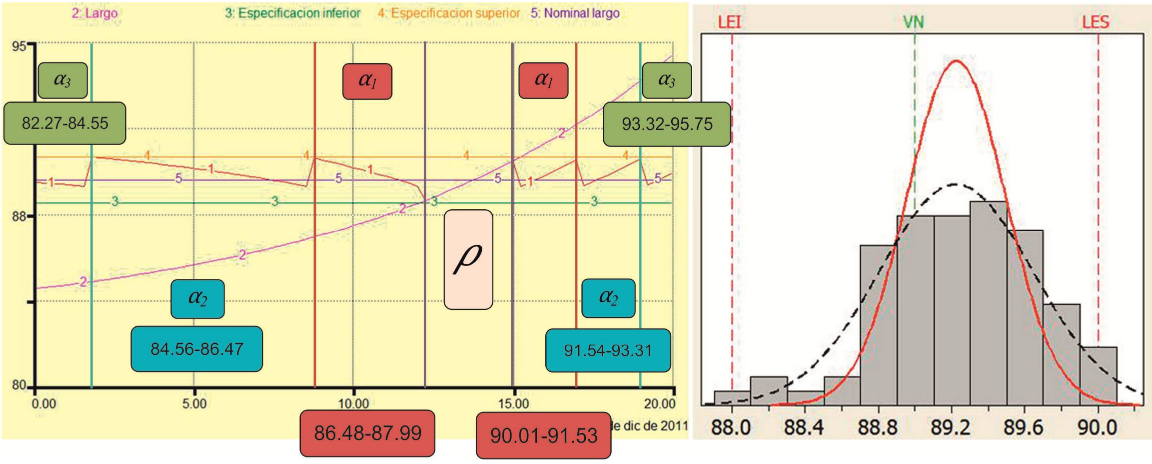

Image 6. Identification of the IDCS zones α1, α2 and α3.

Adjustment Zone (αi):
Knowing the IDCS adjustments behavior carried out, operational policies were designed. These policies validate the fulfillment of the required quality specifications. See chart 3.

Chart 3. IDCS Stability

Interval	Adjustment number (α)
82.27 – 84.55	3
84.56 - 86.47	2
86.48 - 91.53	1
91.54 – 93.31	2
93.32 – 95.75	3

Chart 4 shows the IDCS outputs in the operational range of 3 adjustments which meets all the operation rank

Chart 4. Dynamic Control Process Outputs

Closed- Loop System Outputs of the Dynamic Control Process			
89.59	88.87	88.76	89.35
89.56	88.82	88.05	89.5
89.53	88.77	88.16	89.65
89.5	88.73	88.28	89.81
89.47	89.96	88.4	89.97
89.44	89.9	88.52	88.82
89.41	89.84	88.65	88.97
89.38	89.77	88.77	89.11
89.34	89.7	88.91	89.26
89.31	89.64	89.04	89.41
89.27	89.57	89.18	89.56
89.24	89.49	89.32	89.72
89.2	89.42	89.47	89.89
89.16	89.35	89.62	88.75
89.12	89.27	89.77	88.89
89.08	89.19	89.93	89.04
89.04	89.11	88.78	89.19
89	89.02	88.92	89.34
88.96	88.94	89.06	89.5
88.91	88.85	89.2	89.66
Outputs average = 89.22375			
Error = 0.22375			

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Transference Function

The transference function sensitivity is obtained by using the equations (13) and (14) and the data in chart 6, See equation 16. The studied system has only one input variable which represents the nominal value wanted.

$$r = 68(89^2) = 633680$$
$$\varphi = 1/633680(89(89.59 + 89.56 + \cdots 89.66)$$
$$\varphi = 1.00251404$$
$$\mathbf{Y}_{\mathbf{AJ}} = 1.00251404VN \qquad (16)$$

The reliability of the transfer function of the process of the dynamic control system is meaningful, fulfilling the criterion of almost uniform sensitivity.

5. IDCS METHOD IMPLEMENTATION

1. To apply the CC to identify the moment "when" special causes are present, delete them and get process stability. Monitor to observe low process capability or changes in the global average. If this happens, go to 2.

2. To Perform experimental design to find the relationship in a regression model between the X operation variables and the Y random variable, that represents the quality characteristic C to control, for any product P to manufacture. The model has to comply with the determination coefficient greater than 70% in order to explain the model equation. See section 2, subtopic 2.1.

3. To use a systems dynamic to validate the IDCS proposed in this research and identify the adjustment zones to control the real process, made up of four elements: i) processing element, ii) comparing element, iii) controlling element, and iv) measuring element. See section 3.

4. Construction of the IDCS control chart for monitoring and controlling the actual process, which explains the "what" and "how to make" the necessary adjustments to X for the fulfillment in Y, in order to establish the process control. See section 2, subtopic 2.6.

    - Determine the nominal value NV to control and represent it with a horizontal line as a measurement of central tendency, in the graphic section of the IDCS control chart.
    - Determine the limits of superior and inferior specification and represent them with two horizontal lines, in the graphic section of the IDCS control chart.
    - Determine the adjustment zones obtained through the IDCS dynamic validation. See section 3. Each one is represented as horizontal lines in the graphic section of the IDCS control chart, using different colors for each of them to facilitate the records location.
    - Register the yi measurement obtained in the process (PE), in the record section of the IDCS control chart.
    - Identify the measurement, in the graphic section of the IDCS control chart.
    - Calculate the initial (ϕ_i) error signal as compensation element (CME) in the record section of the IDCS control chart. See equation 2.

        - When complying with the specifications, no adjustment is to be made and the same record is kept as measuring element (ME). Also calculate the Cpk corresponding, using the error signal ϕ_i as a standard deviation.
        - When the specifications are not complied, locate the adjustment zone in the graphic section which represents the number of times to use the adjustment algorithm proposed as controlling element (CE). Perform the arithmetic sum of the results of the algorithm, record it in the IDCS and then make the adjustment to X significant factors, to obtain compliance in Y. Calculate

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the Cpk corresponding by using the final error signal ϕ_f, as a standard deviation to see the increment in the Cpk indicator.

- Register the adjusted and non-adjusted value as measurement value (EM) in the record section of the IDCS control chart.

6. SIMULATIONS AND RESULTS

Comparison of the IDCS adjustments to the control chart of individual measurements.

Image 7 displays the control chart of individual measurements for a random sample of 40 observations with normal distribution, with $\mu = 89$ y $\sigma = 2.5$. The process is considered stable and in control, observing the behavior with no tendency, or abnormal patterns within the superior natural control limits (USL) and inferior (LSL).

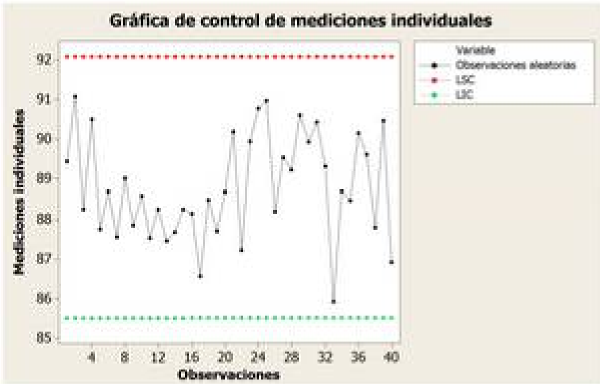

Image 7. Control Chart of Individual Measurements

Image 8 shows the chart of individual measurements of image 7, which were incorporated the specification limits set by the textile company: USL=90 and LSL=88. The comparative of the data behavior was carried out for both limits and the correspondent analysis of capacity.

The chart that showed a stable process and in control, remains stable and in control, but it is unable of fulfilling the specification required.

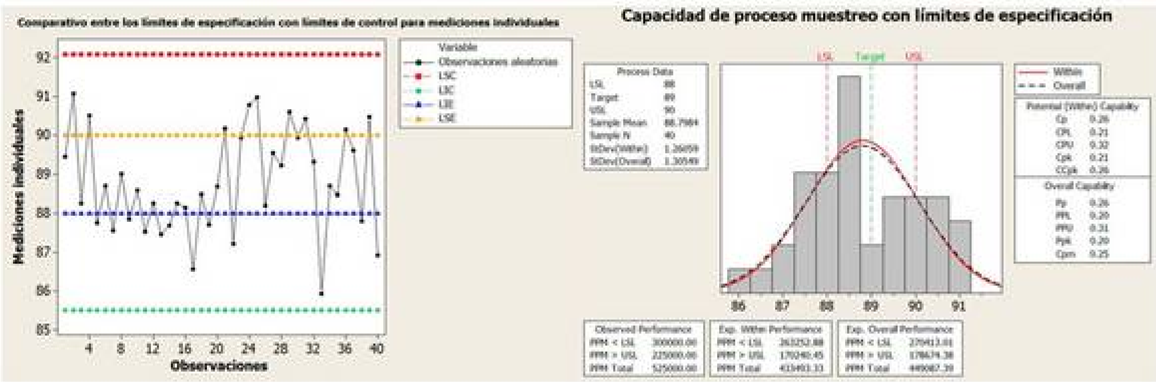

Image 8. Control chart with the specification limits requires by the company and a 0.26 Cpk.

Images 9, 10 and 11 shows the impact of the adjustments performed to X, given the Y measurements, using the controlling element proposed in this research, increasing the process capacity to higher levels than 1.33 and lowering the defect rate than 64 ppm, as it is acceptable for an industrial process (Montgomery, 2009.)

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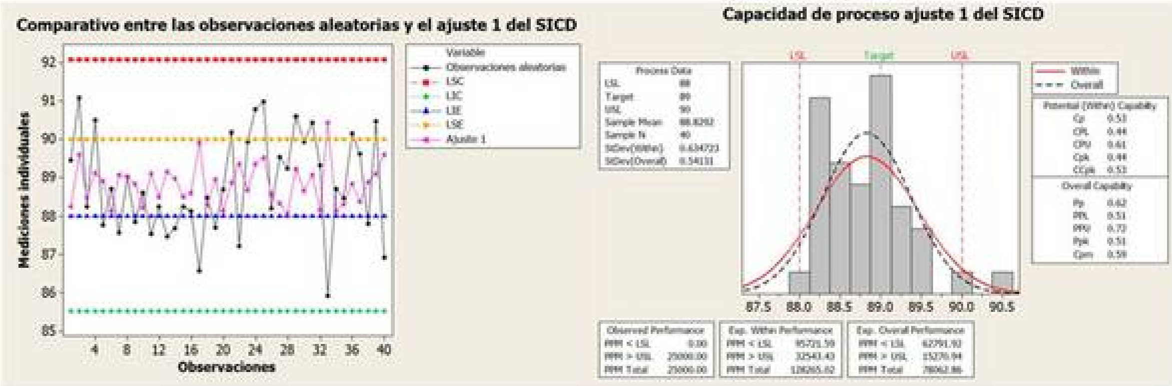


Image 9. IDCS Chart Control with specification limits required by the company and the process capacity for an adjustment, with a 0.53 Cpk.

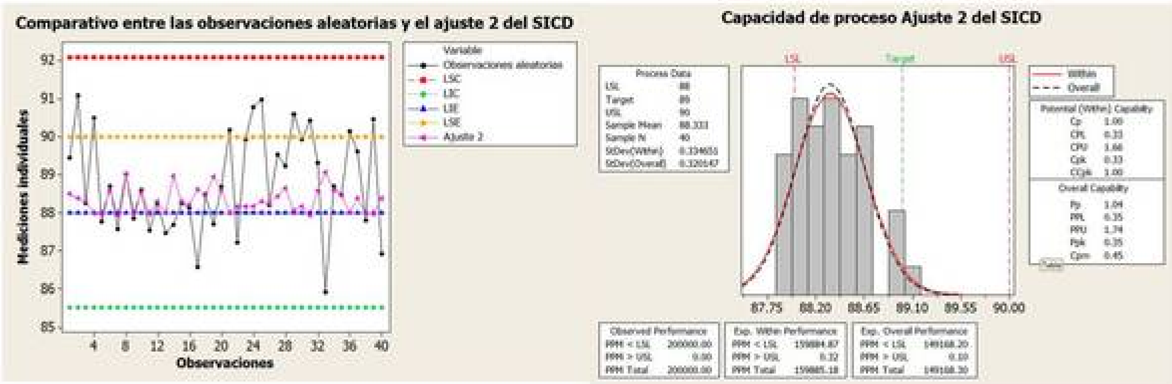
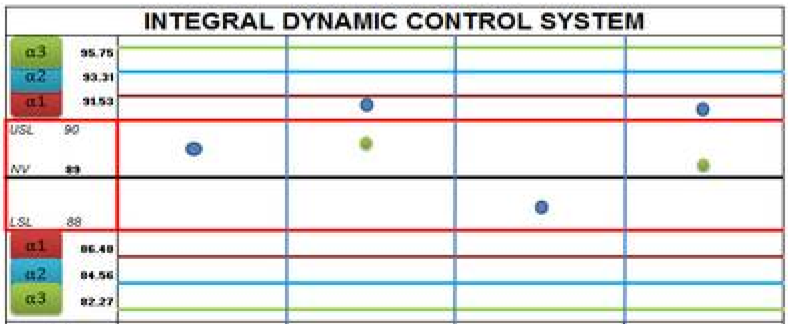


Image 10. IDCS Chart Control with specification limits required by the company and the process capacity for two adjustments, with a 1.0 Cpk.

Image 11. IDCS Chart Control with specification limits required by the company and the process capacity for three adjustments, with a 1.44 Cpk.

IDCS Chart Control:



Hour																
Y	89.4455				91.0816				88.2532				90.5044			
ϕ *inicial*	0.4455				2.0816				0.7468				1.5044			
Cpk initial	0.74822297				0.160133231				0.446348866				0.221572277			
Ajustes	Ad 1	Ad 2	Ad 3	Final	Ad 1	Ad 2	Ad3	Final	Ad 1	Ad 2	Ad 3	Final	Ad 1	Ad 2	Ad 3	Final
x1				-------	1.18			1.18				-------	0.85			0.8
....				-------	0.95			0.95				-------	0.68			0.7
xn				-------	0.8			0.8				-------	0.58			0.6
Y adjusted					89.6018								89.1247			
Y not adjusted	89.4455								88.2532							
ϕ *final*	0.4455				0.6018				0.7468				0.1247			
Cpk final	0.74822297				0.553893874				0.446348866				2.673082064			

Image 12. IDCS Chart

Image12 shows the IDCS control chart to monitor the actual process.
The elements at the top are the NV with a value of 89 and the specification limits established by the company: USL and LSL, with values of 90 and 88respectively. These values are represented by red horizontal lines.
The zone α1 is represented by two maroon lines, the lower adjustment limit α1inf has a range of 86.48-88 and the upper limit α1sup, has a range of 90-91.53.
The zone α2 is represented by two blue lines, the lower adjustment limit α2inf has a range of 84.56-86.48 and the upper limit α2sup, has a range of 91.53-93.31.
The zone α3 is represented by two green lines, the lower adjustment limit α3inf has a range of 82.27-84.56 and the upper limit α3sup, has a range of 93.31-95.75.
The value ranges for every adjustment zone were obtained by using systems dynamic to validate the IDCS recommended in this research.
At the bottom were recorded the first four observations of the random sample in Figure 8, corresponding to the measurement of the quality characteristic C, determined as a random variable Y, corresponding to the processing element PE. The measurements were located in the IDCS chart and the respective error signal was calculated. The comparison was made between the tolerances of ρ by using the comparator CME.
In cases where the error signal was not within tolerances, the necessary adjustments were calculated according to the location of the measurements made by using the controlling element CE. Finally, an adjusted or non-adjusted value was registered by using the measurement element ME. The first measurement did not require any adjustment since the error signal was within tolerances. The second measurement required only once from the use of the proposed adjustment algorithm as controlling element (CE). The third measurement did not need any adjustment since the error signal was within tolerances, and finally, the fourth measurement required once the use of the adjustment algorithm proposed.

5. CONCLUSIONS AND FURTHER WORKS

The validation of the advanced control system was performed allowing executing actions of control when the non-compliance conditions are identified through comparing individual measurements to the specifications and answering the questions “what” and “how” to make the necessary adjustments. The statistical model obtained through the experimental design in a case study of the textile sector which represents the processing element PE was used. The noise signal was used as comparator element CME. The adjustments were made dynamically and immediately complying with the required specifications by using the inverse regression of the statistical model obtained; in other words, given a Y value it is necessary to estimate the necessary adjustments to X, incorporating a compensation variable, used as controlling element CE. For doing so, the specifications deviations (ϕ_i) were calculated, as well as the relation between the (β_j/β_m) for j≠m variable and the levels of the statistical model (ψ_j) were decoded, as knowing process. It was developed a dynamic model which allowed identifying the adjustment zones for the construction of the IDCS control chart, and it was also designed operational policies which comply with the quality specifications by performing 1, 2, or 3 adjustments to the significant factors. The analysis of the IDCS adjustment performance was carried out through a transference function with a dynamic characteristic which has a meaningful reliability to get the almost unitary sensitivity value of 1.0025. The IDCS results obtained were compared to the measurements of the control chart, in which the compliance impact of the required specifications can be seen. In future works the response long variable will be analyzed as a dynamic characteristic. This will deliver a model that minimizes the error signal for different fabric lengths, since one of the main characteristics of the knitted fabric is to have a vast variety of models and sizes respectively. In addition, neuronal nets will be used to design an intelligent control system which optimizes the adjustments to the dynamic control of the process automatically.

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