

Taguchi's loss function: A system dynamics approach.

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Abstract— This paper presents a dynamic approach to the Loss Function (LF) methodology described by Dr. Genichi Taguchi for the three types of quality characteristics, Nominal-is-best, Higher-is-best and Lower-is-best and their corresponding Analyses of Variance (ANOVA), and its corresponding Analysis of Variance (ANOVA). One of the objectives of the model is to replicate the behavior of the different curves described in Dr. Taguchi's methodology, which will be carried out by including graphical functions in the simulation model. The model is designed to be able to include an array of “n” values (measurements), and through its execution it is possible to obtain: the behavior of the curves for the 3 types of quality characteristics and their respective ANOVA with the Sullivan's approach. To develop the model, data taken from literature was used as input: size (n) and values (yi). Within the results, it was possible to replicate the behavior of the curves for each characteristic as well as their numerical values and the calculation of each of the variables that intervene in the mathematical approach of the methodology, as well as ANOVA results for each of the cases, level of variation due to the average and error, corresponding probabilities and also its significance level, therefore, it could be used as a tool for managerial and engineering decision making.

Keywords: anova, decision making, loss function (LF), simulation model, system dynamics (SD), taguchi.

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I. INTRODUCTION

Quality has long been one of the main objectives of manufacturing companies. Based on this need, according to [1], there has been an evolution in quality, starting with inspection, moving to Statistical Process Control (SPC), to Quality Assurance and finally to Business Excellence Models. However, each one defines quality according to the role to play within the production-market chain [2].

In this sense, Taguchi methods, developed by Genichi Taguchi, emerged as a tool to improve the implementation of total quality control in Japanese industry, which he referred to as "quality engineering" [3], despite Although this author has been working on his ideas on quality improvement since the 50's, his methods were practically unknown outside of Japan until the early 80's [4].

Tranco in [6] states, Taguchi sees quality as "something that cannot be characterized solely by the measurement of a desired characteristic. The variability of said characteristic must also be considered". One of the most important contributions of Dr. Taguchi's quality engineering was the concept of On-line and Off-line quality control. Online quality control is defined as the methods used during the manufacturing process to improve and maintain the quality of a product, while offline quality control are all the activities that take place during product planning, design and development and includes the design of tolerance parameters [7], which is the starting point for the present work, with the purpose of measuring the variability in the processes and improving them.

In this way, it is necessary that organizational decision makers can have tools that allow them to reduce their implicit risk, and at the same time optimize the use of available investment resources. However, even so, quality loss is common and easy to understand in the decision-making process [8]. Quality engineering and specifically the Loss Function (LF), allows calculating the loss associated with deviations from a given objective value, for this reason it has been used in manufacturing and process improvement areas obtaining good results.

On the other hand, according to Sterman in [9], System Dynamics (SD) is a method to improve learning in complex systems. Just as an airline uses flight simulators to help pilots learn, system dynamics is, in part, a method for developing management "flight simulators." Initially called industrial dynamics, the field developed from the contributions of Jay W. Forrester [10], deals with the interactions between the flows of information, money, orders, materials, staff, equipment and/or capital in a company, an industry, a national economy, etc. [10], [11].

SD according to [12], is a method that improves learning about the behavior of complex systems, where computer modeling and simulation helps to learn about dynamic complexity, understand the sources of resistance to policies and design more effective policies. In other words, it becomes a source of information and support for the decision making process.

Some of the most notable advantages of SD include: the means to understand the system by identifying relationships between variables, the use of a structured model that allows decision makers to simulate the current functioning of the system and explore opportunities for improvement, improvement, and assistance to decision makers in the prediction, performance metrics and sustainability of the system [13].

In this work, a model is presented with the SD approach based on LF and ANOVA, which allows for a quantification of the loss imparted to society by non-compliance with a quality requirement, whether explicit by the client, due to the elaboration or characteristics of the product or service to evaluate, and that allows the identification of present deviations and the design of policies for their mitigation or control, as well as their deviations from the desired objective value and degree of significance.

II. LITERATURE REVIEW

When carrying out a careful search in the academic literature to identify some of the applications that have been given to the methodologies to be integrated, several works were found, which served as support and theoretical backrest of it.

In [13], develops a System Dynamics (SD) model with the objective of facilitating decision making by integrating systemic thinking in the evaluation of sustainable manufacturing, allowing us to understand the complex interaction of factors from the operational scale (micro) to the business scale. (macro). It is concluded that the SD approach offers an adequate framework to modify manufacturing systems and evaluate both their sustainability and performance.

For his part, Delf in [14], presents a dynamic model to better understand and analyze the dynamics of strategic decisions related to manufacturing and marketing plans in changing systems facing heterogeneous customers, which includes, among other variables, such as: Parameters of demand, the dynamics in the adoption and management of modern platforms for production and parameters involved in the adoption and management of scalable capacity mechanisms to address product volume fluctuations. In this work the author reaches the conclusion that the presented approach will help manufacturers employing modern advanced systems to be able to consider marketing parameters simultaneously with the parameters of perceived value by their customers for both demand mix and volume. The conclusions of this work validate the relevance of this proposal, which seeks to be a support tool for decision makers.

In [15] a model is developed to support the efficient decision-making process that captures the impacts of strategic decisions on production costs and environmental sustainability in which CO2 emissions, energy and water consumption are evaluated. in automobile assembly, in this work the authors conclude that the model results indicated that they can practically help decision makers by providing in-depth knowledge of environmental impacts and associated costs.

Describing other SD integrations with application in the production area, in [16] Cardiel develops a system dynamics model based on the Six Sigma methodology to be implemented in a textile production line in a company in the south of Guanajuato, in this work showed that with the implementation of the model an increase in the performance of the process was obtained, increasing the sigma level.

The approach outlined in [17] integrates System Dynamics (SD) and Fuzzy Logic methodologies to assess supplier performance in terms of sustainability within a fuzzy environment. The model's execution reveals that increasing the investment rate in sustainability leads to an

exponential improvement in overall supplier performance. Furthermore, the investment's return rate is surpassed within approximately 12 months.

The application of System Dynamics (SD) for decision support extends beyond manufacturing and production. For instance, [18] uses the SD modeling method to depict the production cycle of a broiler chicken warehouse, analyzing changes in the chicken population based on parameters defined by the modeler. In [19], SD is utilized to develop a model for planning installed capacity and resource usage based on hospital patient care indicators, thereby enhancing the overall performance of the institution. Additionally, in [20], the authors create an SD model integrating Fourth Industrial Revolution (4IR) technologies to manage preventive and corrective maintenance processes. This work found that incorporating these technologies improved the predictability of equipment defects before failure, potentially reducing costs by 27.46%.

To conclude, Irfani D. in the proposal developed in [21], presents a model that, on the contrary, integrates the SD model, decision-making tools directly to improve performance measurement in a maritime transport company, the which are selected through an exhaustive review of the literature, and determining the attributes described by the authors in their abstracts, and then refining the selection process for full review. Subsequently, it selects the key measurement indicators, includes them in the model and measures their performance through the model. In one of his conclusions, the author expresses that decision makers face conflicting objectives from the social, financial, and legal dimensions.

In the review of the literature carried out, SD has been widely used in the industrial field in order to serve as a support tool for high-level management decisions and so that related parties, can develop a better and more complete understanding of the behavior of the evaluated systems and the relationships that exist between the variables that compose them, which is the starting point and justification of this work, since it seeks to replicate the behavior that the LF will have according to its characteristic quality relates to the costs of non-quality or deviations from it and the values for each of the values of y_i , which in the model are represented by auxiliary variables.

On the other hand, LF has been used recurrently for the evaluation of the performance of industrial and non-industrial processes, some of which will be mentioned below to serve as a framework of reference and exemplify applications in different areas. For example, in [22] the use of the concept of selective assembly used in manufacturing and together with LF is proposed in order to adjust and match the skills of the students and the requirements of the contracting company, the study concludes that by incorporating multi-criteria decision making (ANP), the proposed methodology provides a viable strategy for policymakers in technical institutions in India. This approach can enhance the quality of locations and significantly influence the perceived ranking of engineering institutions.

In [23] Banihashemi, proposes an approach based on Multiple Dependent State (MDS) sampling scheme and process performance index considering Taguchi loss function, to minimize the costs related to the process performance index Spk. performance. in which it seeks to satisfy the opposite requirements of the consumer and the producer, the total expected losses were minimized by imposing two restrictions through which the design parameters are determined, showing the validity and applicability of Dr. Taguchi's methods. In the review, it was possible to find integrations of LF along with other methodologies to optimize the selection of suppliers.

For example, in [24] Taguchi LF is integrated with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to obtain multi-criteria objectives. In the same way, in [25] the authors propose a combined methodology of the Taguchi loss function and AHP to select the appropriate supplier for the outsourcing activity based on the benefit and risk factor which is established through the evaluation of suppliers measuring the loss due to their level of performance. In both studies, the usefulness of LF is highlighted as a reliable methodology to quantitatively establish the loss related to deviations in the supplier selection process.

In the same sense [26], LF applies the intuitionistic method based on fuzzy sets using two different distance measurement approaches, namely, the fuzzy normalized Euclidean distance and LF to evaluate the impact of personal perceptions of the decision makers during the supplier selection process.

To conclude in [27], presents an evaluation of the effect of process variance using the Taguchi methodology. The study provides a detailed description of the methodology's application and its effectiveness in assessing process performance, as well as how LF can be employed to control variation. Two key management applications of the variance reduction model proposed in this article are identified: one in the area of machine replacement and the other in global manufacturing. A static case was considered where process variance had worsened, and the optimal reduction amount was determined based on various cost parameters. In a dynamic context, managers must also assess whether variance reduction is worth pursuing. Factors such as process aging and excessive wear may lead to high variance reduction costs, and the overall process standard deviation (σ^*) may still remain elevated after reduction.

From the above, a relationship of applicability can be established between the two methodologies that supports their use in the improvement of industrial processes, and as a support tool in decision making and evaluation of the performance of the processes that are evaluated, additionally, show the importance of the integration of some methodologies such as management support and projection of the behavior of manufacturing systems with the support of SD.

While previous studies have applied System Dynamics (SD) in manufacturing and decision-making contexts, and Taguchi's Loss Function (LF) has been widely used for quality evaluation, the integration of both approaches into a single simulation model remains unexplored. This paper presents a novel SD-based model that replicates the behavior of the three LF curves and computes the corresponding ANOVA dynamically. Unlike static spreadsheet calculations, our model allows users to observe how changes in input measurements affect the loss and variance components in real-time, providing a more interactive and comprehensive tool for quality engineers and managers.

Recent advances in system dynamics have further expanded its application in quality management and decision support. Manenzhe et al. [20] developed an SD model integrating Fourth Industrial Revolution (4IR) technologies for preventive and corrective maintenance management, demonstrating that incorporating these technologies improved defect predictability and could potentially reduce costs by 27.46%. Their work illustrates how SD can be combined with emerging technologies to enhance quality-related decision-making—a direction that aligns with the present study's goal of integrating SD with quality engineering tools.

In the realm of loss function applications, Turk [26] recently applied Taguchi's loss function within intuitionistic fuzzy sets to evaluate the impact of decision-makers' personal perceptions during sustainable supplier selection. This study demonstrated that LF remains relevant in contemporary multi-criteria decision contexts, particularly when combined with fuzzy logic to handle uncertainty and subjectivity. Similarly, Banihashemi et al. [23] incorporated Taguchi loss function into acceptance sampling plans, showing its continued utility in minimizing costs related to process performance indices.

Despite these developments in both SD and LF separately, no study to date has integrated both methodologies into a unified simulation model. While SD has been used for manufacturing system analysis [13], maintenance management [20], and performance measurement [21], and LF has been applied to supplier selection [24, 25, 26] and process variance analysis [27], the combination of Taguchi's loss function with system dynamics modeling remains unexplored. The present work addresses this gap by developing an SD model that dynamically replicates LF behavior and ANOVA calculations, offering a novel tool that combines the visualization and interactive capabilities of SD with the quantitative rigor of Taguchi's quality engineering.

Complementary to these developments, recent Latin American research has contributed significantly to both SD and Taguchi methodologies. Barrios Sánchez et al. [28] developed a mathematical model for industrial processes in a system dynamics environment, demonstrating how SD can effectively represent complex manufacturing systems and support decision-making through simulation—a foundational approach that informs the present work. Díaz-Ruiz & Trujillo-Gallego [29] proposed an integration of Six Sigma and system dynamics specifically for process variability reduction, achieving significant improvements in industrial process performance. Their work is particularly relevant as it addresses variability reduction, which is the core objective of Taguchi's loss function.

In the specific domain of Taguchi methods, Reynoso Jardón et al. [30] applied the Taguchi method to optimize parameters in plastic injection molding simulation, showing the continued relevance of Taguchi's offline quality control in modern manufacturing contexts. More recently, Medina et al. [31] presented a comprehensive quality improvement methodology that incorporates Taguchi principles within broader quality management frameworks. These studies collectively demonstrate that both SD and Taguchi methodologies remain active areas of research and application, yet none have attempted the specific integration proposed in this paper—a dynamic system dynamics model that replicates and visualizes Taguchi's loss function and its associated ANOVA in an interactive simulation environment.

The quality loss function, often referred to as the "Taguchi Loss Function (TLF)" after its creator G. Taguchi in the latter half of the 20th century, is an engineering tool for quality control. It is used to quantitatively assess the "loss of quality" in a project, product, or service relative to its optimal quality level. Taguchi defines quality as "the loss imparted by any product to society after being shipped to a customer, other than any loss caused by its intrinsic function [27].

As described by [32], the (TLF) is classified into three types: nominal-is-best, smaller-is-better, and larger-is-better. The appropriate function is determined by the magnitude of variation and the allowable direction of deviation from the target value. The target value is typically the midpoint between two specification limits, known as the nominal-is-best loss function, as illustrated in Figure 1 and formulated in Equation 1.

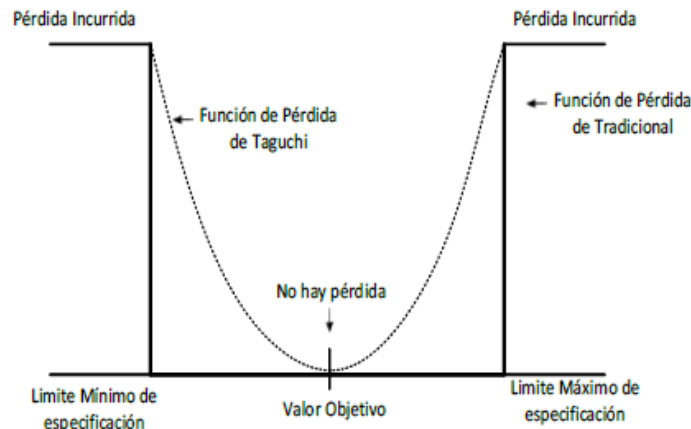


Fig. 1: Loss Function to the characteristic Nominal-Is-Better.

Source: Adapted to Geanie W. Margavio and Southwest Missouri State University, USA.

$$L(y) = k(y-m)^2 \quad (\text{Equation 2.1})$$

$$k = A/\Delta^2 \quad (\text{Equation 2.2})$$

$$L = \frac{A}{\Delta^2} \sigma^2 \quad (\text{Equation 2.3})$$

Where $L(y)$, is the loss associated with the particular value of the equality of the characteristic and, m is the nominal value or value; k : Is a proportionality constant; A : is the loss caused (in monetary units) for each error in production; Δ : They are the limits (tolerance) allowed to the right or to the left $\pm$ of the error of the evaluated quality standard.

Equation 2 exemplifies one of the statistical variations described by Mast in [30], since commonly the σ^2 , which is the variance of the sample, is calculated as the result of squaring the value of σ .

$$\sigma^2 = \sum_{i=1}^n \frac{(y-m)^2}{n} \quad (\text{Equation 2.4})$$

In addition, the other two loss functions include the one-sided maximum and minimum limit specification and one-sided orientation functions, called lower-is-better and higher-is-better, which are shown in Figures 2 and 3 respectively.

Where:

$$k = \frac{A}{\Delta^2} \quad (\text{Equation 2.5})$$

$$L(y) = k * \Delta^2 \quad (\text{Equation 2.6})$$

$$L = k * \sigma^2 \quad (\text{Equation 2.7})$$

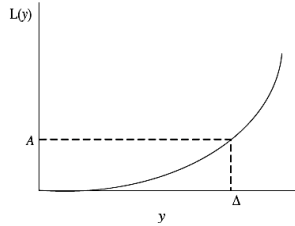


Fig. 2: Loss Function to the characteristic Lower-Is-Better.
Source: Adapted to Liao, C. N., & Kao, H. P. (2010).

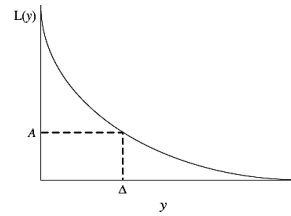


Fig. 3: Loss Function to the characteristic Higher-is-better.

For each of the quality characteristics described, Dr. Taguchi proposes some variations in terms of the language traditionally used in statistics as described [33]. The terminology and techniques that are used by this author are strongly related to engineering knowledge and They differ in some measures from the traditionally used statistical techniques and vocabulary. With this work, we will first replicate the behavior of each of the curves for each quality characteristic from the model developed in SD, this will be achieved through the calculations of each of the variables involved in this method. and the mathematical relationships described in it.

On the other hand, and as a complement to the approach described by Dr. Taguchi, the ANOVA corresponding to each of the functions mentioned above will be analyzed, which is a process diagnostic tool in order to determine the origin of the process variation. that is being analyzed, as well as the value to determine its significance.

III. METHODOLOGY

In figure 4 shows the methodology which is made up of 4 levels of the SD approach, each of which corresponds to 1 stage described by Sterman in [9], and in the same way in each of them the activities carried out throughout the development of the model through which this proposal is developed, a stage is added (Literature Review) with which it is intended to validate the proposed model.

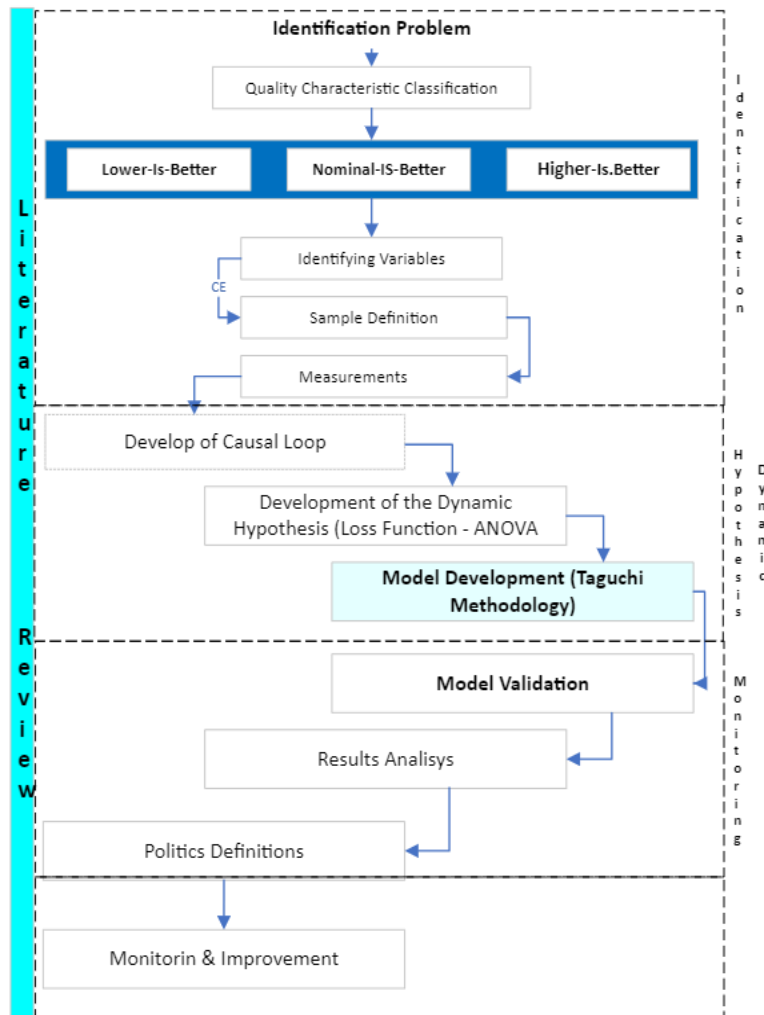


Fig. 4: Metodology.

a. Development Of Methodology

Stage 1: Problem identification

Quality in any of its stages is a challenge for any organization, regardless of its line of business, size, or production sector in which it provides its services or produces its products. Therefore, over time, methodologies have been developed that allow them to companies identify their areas of opportunity in this area. From inspection to total quality management (TQM), it is imperative for companies to control deviations or variations that exist between the satisfactory specifications of a product and the final characteristics of the product when delivered to the customer.

In this sense, quality engineering has been a widely used tool, not only because it allows quality engineers to identify these areas of opportunity, but also through a simple methodological application, it allows calculating the amount of loss (in value monetary), which is incurred due to non-compliance with product specifications, which is of great help in making managerial decisions in terms of adjustments to the evaluated processes.

For this reason, in the present work we aim to give a new approach to the theory described by Genichi Taguchi called LF, in which it is sought that, through SD, it can be established in a simpler way, the way in which the different system variables (LF), and the effect they have on determining the amount of the economic loss.

In the first stage of the methodology proposed for this work, the activities that are related to the understanding of the problem and the identification of the quality characteristics of the process to be evaluated were included, as seen in the graph, this includes from the identification of the problem or area of opportunity, passing through the variables subject to measurement or sample size (n) to the "taking" of the measurements, which are the main tool so that the evaluator has an understanding of the process and the variables that make part of the model.

For this work, an important and critical part within this stage is the selection of the key variables and reference modes since they will provide the main guideline for the analysis of the system's behavior. In this sense, the key variables for the model will be defined by the elements that are part of the LF and ANOVA methodology, that is, each of the variables make up the mathematical equations which can positively or negatively affect the result and that explain the behavior of the system (see equations 1,2, and 3).

On the other hand, the reference modes will be given by the history of the measurements (y_i) that will be used in the calculation of the LF, which will be taken from some application exercises in the academic literature.

Stage 2. Formulation of the Dynamic Hypothesis

This stage is made up of three activities, however, it is the most important in the development of the model since it establishes a holistic understanding of the problem, the elements that are part of it and the relationships that exist between them. Subsequently, through a causal diagram graph, the relationships that exist between the variables that are part of the system which define its behavior and identify the key variables within the system to be modeled.

For this case study, the variables are defined by the relationship established between each of the variables in the LF methodology, and in the calculation of each of its facings. Diagram 2 presents the causal diagram for the LF model, for its 3 different quality characteristics and its corresponding ANOVA, as well as the polarities of each of them. The term "polarity" refers to the relationship between two variables that are interconnected, in such a way that a change in one variable directly affects the other.

In figure 5 shows the relationships between the variables and the feedback existing in the variables that are part of the model, along with the key variables of the system, which are identified by a rectangle to facilitate their identification. In this graph, it can be seen that the relationships between the variables are determined by the mathematical relationships proposed within the model for the calculation of the Loss Function (LF) and the analysis of variance (ANOVA) for the three quality characteristics. The model is dynamic in that the behavior of the system will depend on the values of the input vector included in the graphic function.

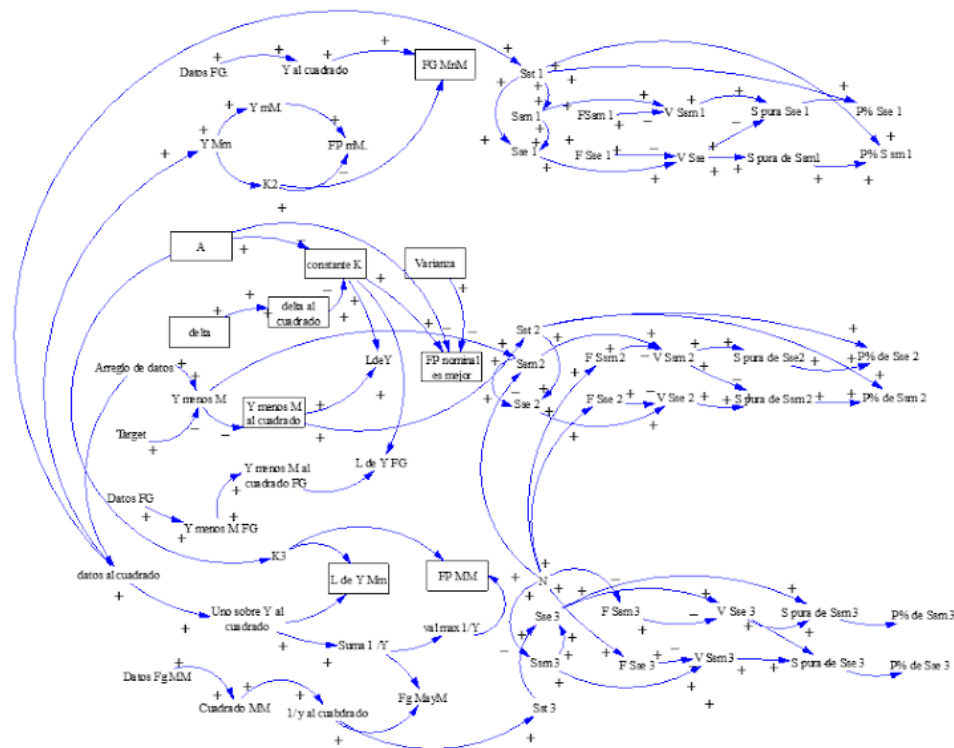


Fig. 5: Causal Loop Diagram.

In this stage, the application of the concepts described by the Taguchi methodology for the calculation of the LF and the variance analysis is carried out, which include modifications to the commonly accepted statistics. The relationships established in the model are those formulated in the method described in [34].

In figure number 6, the Forrester diagram or flow and stock diagram is presented, in which all the variables involved in the system are shown, represented by circular figures or auxiliary variables and their interrelationship, which are indicated with colored arrows. red. In the same way, ghost variables were used because the same mathematical expression can be used to determine the PF for more than one quality characteristic. The model was developed using Stella Software in version 9.1.3.

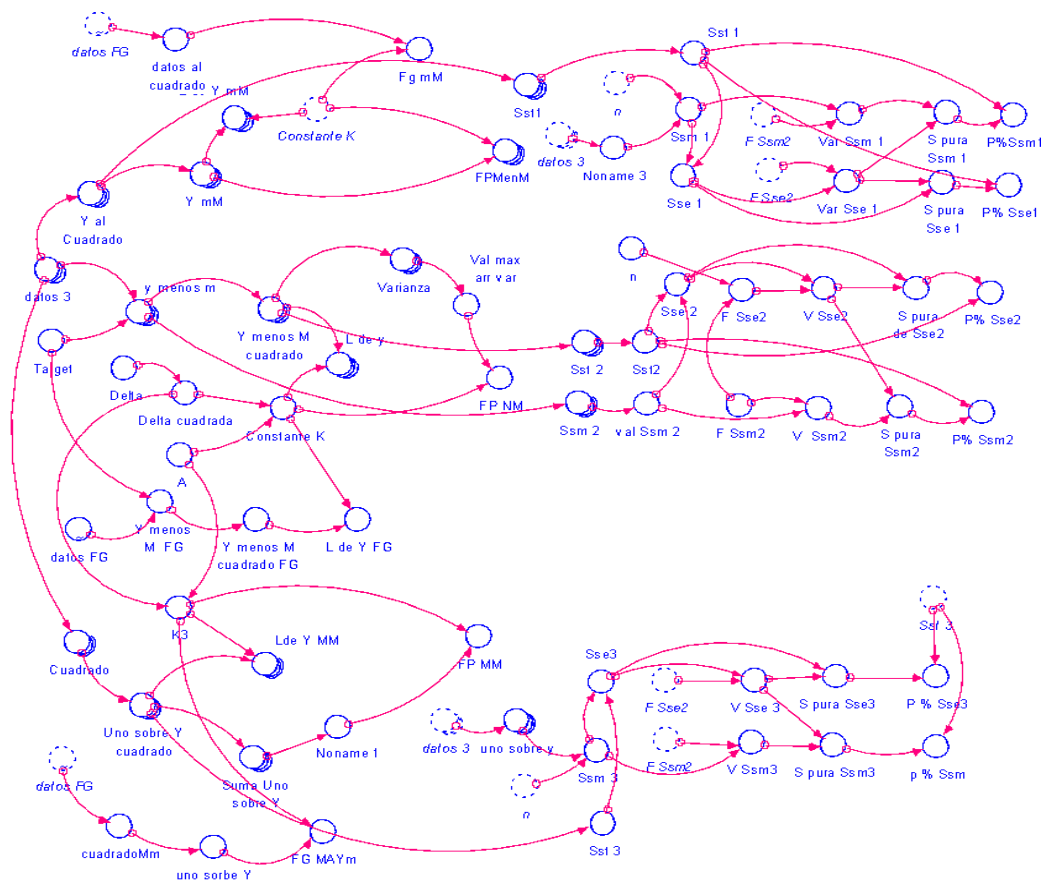


Fig. 6: Stock and Flow Diagram.

Model initialization and boundaries

The model is initialized with user-defined input measurements (y_i) entered via a graphical function. The sample size (n) is fixed per simulation run. The model assumes standard Taguchi loss functions (quadratic for nominal-is-best; one-sided for smaller/larger-is-better) with symmetric loss for nominal-is-best. Constraints include: no interactions between multiple characteristics, ANOVA based solely on Sullivan's approach, and independence of measurements. The system boundaries cover calculation of individual losses, total loss, variance components, and ANOVA tables. The model does not perform optimization, policy design, or simulate dynamic process behavior over time.

In the Forrester diagram it can be seen that the model flow for the Nominal-is-best quality characteristic begins with the insertion of a vector of values into the system through an auxiliary variable "data" that is, the values "y" conditioned with a graphic function, together with or with the Target variable "m" or objective value.

In turn, the variable "Y menos m" is positively affected by the variable "datos" and positively by the variable "Target", the variable "Y menos m cuadrado" is positively affected by the variable "Y menos m", and finally the variable "Ly_i" is positively affected by the variable "k", thus obtaining the LF or economic loss for each measurement which is greater if it is further away from the variable "Target". This behavior is explained by the mathematical relationships that are part of the model as shown in diagram 4.

In the same way as explained previously, the behavior of the other variables that make up the SD model is described.

Stage 3. Model Validation and Analysis of Results

In this stage we seek to validate the operation of the model, to guarantee that the values found through the developed SD model are correct in order to make a correct interpretation of them by the decision makers before generation. of the graphics that will support the main objectives of this work.

To validate the operation of the model, a reference case included in [34] was taken, with a sample size equal to eight (8), an objective $m=115$ and $A=200$, which were processed through a spreadsheet. The results of this process are shown in Table 1.

TABLE I
RESULT OF SPREADSHEET

Measurements	Organized	$Y_i - m$	$(Y_i - m)^2$	L_{Y_i}
113	113	-2	4	1,28
116	113	-2	4	1,28
115	114	-1	1	0,32
113	115	0	0	0
117	115	0	0	0
115	115	0	0	0
115	116	1	1	0,32
114	117	2	4	1,28

The graphic 7 shows the loss function for the Nominal-is-better characteristic corresponding to the values included in Table 1.

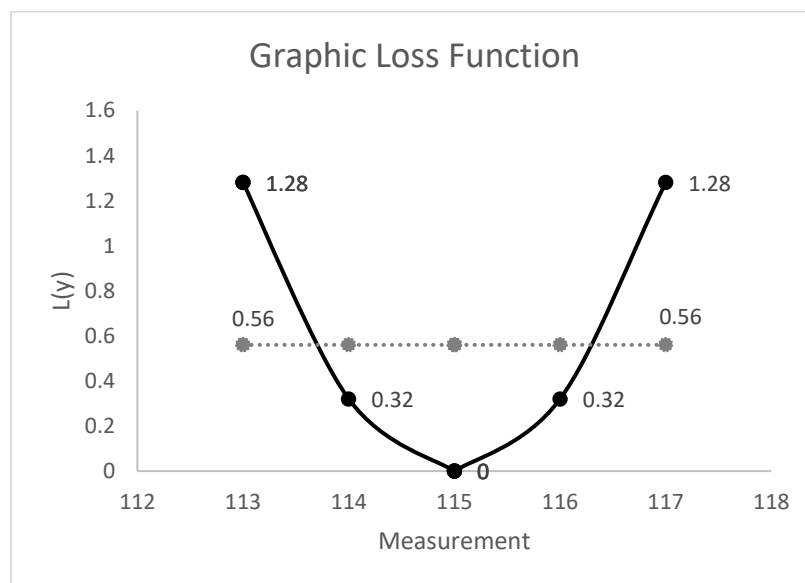


Fig. 7: Loss Fuction for data vector.

Figure 7 shows the graphical result of the model for the graphic function corresponding to the quality characteristic Nominal-is-better, where it can be seen that the values-monetary units corresponding to the LF for each of the measurements included in the model corresponds with a 100% adjustment to those determined through validation in the spreadsheet.

The model's outputs were compared with traditional spreadsheet calculations (see Table 1 and Graphic 1), showing 100% agreement. This confirms that the SD model accurately replicates the static Taguchi loss function while offering dynamic capabilities that traditional methods lack, such as real-time visualization of curve behavior and immediate feedback when input parameters are modified.

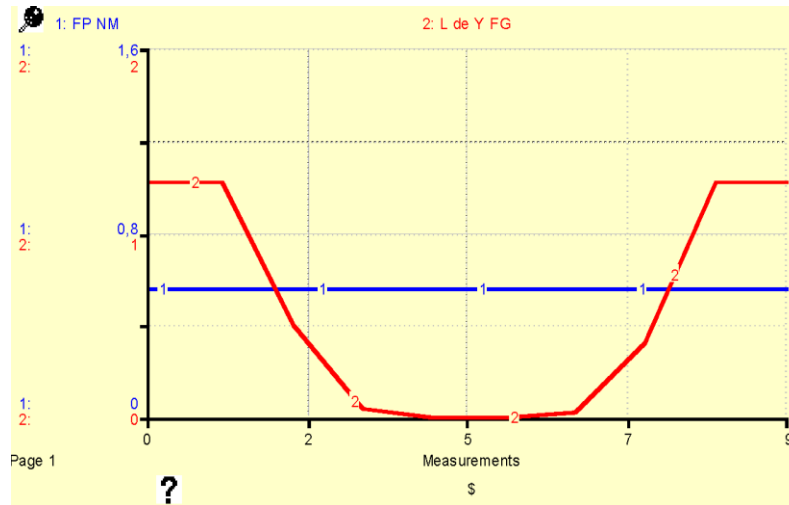


Fig. 8: Loss Function for the Nominal-is-best characteristic of the model.

In table 2 presents the result vector for the variable $L(y)$ for each of the measurements included within the model through the Stella software, which correspond to those calculated through the spreadsheet and which are the input element for the loss function graph for the Nominal-is-best characteristic as can be validated in column 5 of diagram 5. Additionally present the result for the variable L to this model is equal to 0.56 monetary units.

TABLE II
MODEL RESULTS FOR THE VARIABLES L AND $L(Y)$

Loss function (Monetari units)									
Time	FPMN	L de y(1)	L de y(2)	L de y(3)	L de y(4)	L de y(5)	L de y(6)	L de y(7)	L de y(8)
0	0,56	1,28	1,28	0,32	0,00	0,00	0,00	0,32	1,28
1	0,56	1,28	1,28	0,32	0,00	0,00	0,00	0,32	1,28

Stage 4. Analysis of results.

At this stage the evaluator, by observing the behavior of the graphs, through stochastic data and the projection of the losses that would be incurred due to the deviations of the observations with respect to the objective sought in the processes, in other words deviations in compliance with customer requirements, action plans and policies must be formulated in the process, the culés must be oriented towards controlling the sources of variation in the processes and ensuring compliance with customer expectations.

Finally, regarding the ANOVA, they were calculated through the sum of squares methodology and according to the Sullivan approach. The importance of including the ANOVA within the model is based on confirming factors that influence the case studies to determine the control variables and parameters in the processes as described by [35] and help determine their significance. For this model, the data were represented by means of auxiliary variables and ghost variables of the results obtained in the calculation of the LF.

IV. RESULTS

Within the results of this work, by including graphical functions in the model, the behavior of the graphs described in Dr. Taguchi's literature in the loss function is replicated, as can be seen in diagram 7, in which You can see the behavior of the three quality characteristics like this:

- Curve 1: Graphic representation of the LF for the Higher-is-better characteristic, which tends to infinity (see figure 3), meaning that the further the measurement is from 0 "zero", the lower the amount of loss incurred.
- Curve 2: Graphic representation of the LF for the Nominal characteristic is better
- Curve 3: Graphic representation for LF of the lower-is-better characteristic which tends to zero (see figure 2), that is, the closer the value of the quality characteristic is to the value 0 "zero", the lower the amount of the loss incurred.

As presented in the next graphic.

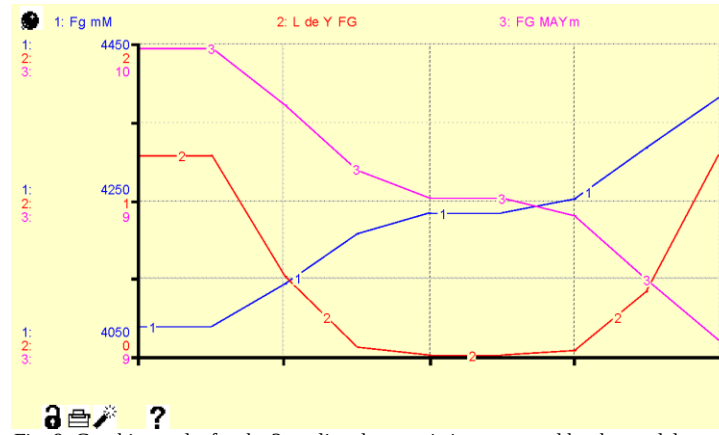


Fig. 9: Graphic results for the 3 quality characteristics generated by the model.

The results produced by the model, for the nominal quality characteristic, is better with data taken from [5] correspond to those described by the author, which validates the behavior of the model, as well as the results for the ANOVA of the data by the Sullivan's sum of squares approach method, the resulting graph is presented below.

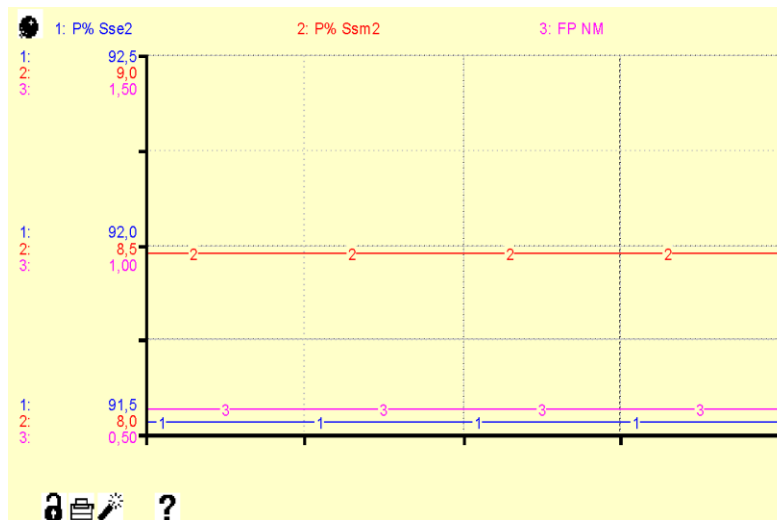


Fig. 10: Validation of LF and ANOVA results.

The graph shows in curve number 1 the amount of social loss incurred due to deviations or non-compliance with the quality specifications for the measurements analyzed, which in this case is 0.56 u.m. per unit. In the same way, the analysis of variance shows us that Pm (%) 8,47% of the variation in this process is due to the error in curve number 1 and the remaining Pe (%) 91,53% corresponds to the average in curve number 3, which suggests a process in which the dispersion of the measurements is what contributes most to the variance of the measurements and deviations of the process. These values can be validated through Table 3.

TABLE III
MODEL RESULTS FOR ANOVA

Table 3 ANOVA Results					
Time	F Sse2	FSsm2	P% Sse2	P% Ssm2	FP NM
0	7	1	91,53%	8,47%	\$ 0,56
1	7	1	91,53%	8,47%	\$ 0,56

The total loss of 0.56 monetary units per unit (Table 3) represents a moderate deviation from the target value. To contextualize this figure, if the process produces 10,000 units annually, the total societal loss would amount to 5,600 monetary units due to quality variation alone, highlighting the economic significance of even small deviations when scaled to production volumes.

The ANOVA decomposition reveals that 91.53% of the variation is attributable to random error (dispersion), while only 8.47% is due to the mean deviation from target. This indicates that the process is well-centered but exhibits high variability—a common finding in manufacturing processes where equipment wear or inconsistent raw materials contribute to spread rather than shift. This result aligns with González-Sosa & García-Carranco [33], who reported similar dispersion-dominated variance patterns in additive manufacturing processes, where 85-92% of variation was attributed to error components rather than mean shifts.

Compared to Banihashemi et al. [23], who reported optimal loss values ranging from 0.32 to 0.78 monetary units in acceptance sampling plans for similar industrial contexts, our calculated loss of 0.56 falls within the expected range. However, their study employed different process

performance indices (S_{pk}), suggesting that direct comparisons should be made cautiously due to methodological differences in loss calculation approaches.

The dispersion-dominated variance structure ($P\% Sse2 = 91.53\%$) also resonates with findings by Mukhopadhyay & Chakraborty [27], who demonstrated that in global manufacturing contexts, variance reduction efforts often yield greater economic benefits than mean adjustments when processes are already centered. Their static case analysis showed that when process variance has worsened, optimal reduction amounts depend critically on cost parameters—a dynamic that our model could potentially explore in future extensions.

Turk [26] recently applied Taguchi loss function in fuzzy environments for sustainable supplier selection, reporting that loss values between 0.45 and 0.65 were typical for moderate-performing suppliers. Our result of 0.56 positions the hypothetical process in this moderate-performance category, suggesting that while not severely off-target, variability reduction should be prioritized over mean adjustment—a conclusion directly supported by the ANOVA percentages.

These quantitative insights demonstrate that the model not only replicates Taguchi's theoretical curves but also provides actionable diagnostic information consistent with contemporary quality management literature. The predominance of error variance suggests that quality improvement efforts should focus on reducing process dispersion through techniques such as Statistical Process Control (SPC), equipment maintenance optimization, or raw material standardization, rather than merely adjusting the process mean.

For the results presented, continuous values of normal behavior were used, which were validated through the MiniTab Software in version 17, the simulation model was developed through the Stella Software in its version 9.1.3.

V. CONCLUSIONS

As has been widely described during this work, through the development of the model presented, it was possible to replicate the behavior of the curves and the ANOVA for each of the quality characteristics. The amount of social loss imparted by the deviations associated with the variability of the measurements was also obtained with 100% measurements.

That is why the model can be used to calculate the variables included within the quality engineering methodology, since it provides a more graphic and direct view of the interrelationships that exist within the mathematical model and how each one behaves. of them and the way their variation affects the behavior of the model.

In this sense, decision makers have a tool that allows them to calculate in a simple and complete way the amount of economic loss in monetary units of any deviation in measurements, during the manufacturing production process or in any other business line. The interpretation and adjustment policies must be provided by the experience of senior management or another methodology that allows projecting results, such as SD. Additionally, a novel integration is carried out between an off-line quality engineering tool and SD.

However, it is pertinent to say that the tool must be interpreted by the decision makers and the results must be correlated with the real behavior of the system. The statistical variations raised in Taguchi's methodology must also be considered in order to correctly interpret the results obtained by the mode

Despite its utility as a decision-support tool, the model presented in this work has several methodological limitations that must be acknowledged. First, the model is static in nature: while it allows dynamic visualization of results when input parameters are modified, it does not capture the temporal evolution of manufacturing processes, such as equipment degradation, process drift, or learning curves. The current version assumes that all measurements are taken at a single point in time.

Second, the model assumes that measurements are independent and identically distributed. In real-world industrial processes, autocorrelation and time-dependent patterns are common, which could affect both the loss calculation and the ANOVA results. This simplification may lead to underestimation of actual process variation.

Third, the ANOVA implementation follows Sullivan's sum of squares approach exclusively. Other variance decomposition methods (e.g., classical Taguchi's signal-to-noise ratios or alternative ANOVA formulations) might yield different interpretations of the sources of variation. Users should be aware that the choice of ANOVA method influences the diagnostic conclusions.

Fourth, the model's accuracy depends critically on the correct specification of input parameters: the target value (m), the loss constant (k), and the tolerance limits (Δ). In practice, these parameters may be uncertain or difficult to estimate, and the sensitivity analysis presented in Section 4.1 shows that small errors in parameter estimation can lead to significant variations in the calculated loss.

Fifth, the model considers each quality characteristic independently and does not account for interactions between multiple characteristics that may be present in complex products or processes. Real-world quality problems often involve trade-offs between competing characteristics.

Regarding the scope, this model is intended as a calculation and visualization tool for the Taguchi loss function and its associated ANOVA. It does not include optimization algorithms to automatically find optimal parameter settings, nor does it provide policy recommendations. The interpretation of results and the design of improvement actions remain the responsibility of quality engineers and managers based on their domain expertise and understanding of the specific process context.

Future work should address these limitations by incorporating dynamic elements (e.g., time series simulation), extending the model to handle correlated measurements, integrating multiple quality characteristics simultaneously, and developing optimization capabilities to suggest parameter adjustments that minimize expected loss.

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