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A SIX SIGMA AND SYSTEM DYNAMIC INTEGRATION FOR PROCESS VARIABILITY REDUCTION IN INDUSTRIAL PROCESSES

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Abstract: *In today's globalized and dynamic world, companies face pressures related to high-quality product offerings that meet customer expectations, with minimum variability. Likewise, they deal with complex systems, such as industrial processes. The objective of this article was to design a five-phase model of the DMAIC cycle by integrating the six sigma and system dynamics approaches for variability reduction in critical quality characteristics. Model validation was carried out via a case study in the electrolytic tin plating process, in a Colombian metal-mechanics company. Thus, the current process was simulated and various scenarios were analyzed, that which would benefit the company the most was selected. The results show significant quality improvement by way of the reduction of variability in the coating thickness, and profit increases achieved through poor quality and reprocessing cost reductions. The proposed model serves as a financial viability tool, given the implementation of a six-sigma project, by guiding management to determine the best scenario for investments in the process, so as to obtain results that benefit companies, in terms of both profits and product quality.*

Keywords: *Quality, Six sigma, System dynamics, Competitive priorities, Multivariate control, Metalworking.*

1. Introduction

Globalization and its highly competitive, dynamic environment, generates pressure on organizations to develop products and services that meet customer expectations, at a competitive price, in the shortest possible time, as well as to meet stipulated product requirements, within customer-set quality ranges (Ahuja & Khamba, 2008; De Carvalho et al. ,2014; Kiatcharoenpol & Seeluang, 2019; Sá et al., 2020; Singh & Singh, 2020; Dagmar & Tarigan, 2021; Ketabforoush & Aziz, 2021; Makwana & Patange, 2021). Consequently, many organizations recognize the importance of quality management strategies as continuous improvement strategies with which to remain competitive (Sá et al., 2020; Alexander et al., 2021).

A globally recognized tool for continuous improvement is Six Sigma (SS), introduced by Motorola in 1980. This has been a great contribution to Total Quality Management (TQM) to reduce process variability (Cardiel-Ortega et al., 2017; Ridwan & Noche, 2018; Ahmed et al., 2020; Singh & Singh, 2020). Sánchez-Rebull et al. (2020) and Ahmed et al. (2020) state that six sigma is a philosophy that

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pursues product and service excellence, reliability, and high quality through two perspectives: On the one hand, six sigma is a powerful methodology that improves the quality, efficiency, and productivity of processes to meet not only customer requirements, but also to achieve enhanced asset use, obtain greater savings, benefits, profitability, and improved corporate image (Freiesleben, 2008; Naeem et al., 2016; Costa et al., 2019; De Mattos et al., 2019; Abdallah, 2020; Sánchez-Rebull et al., 2020; Singh & Singh, 2020; Ketabforoush & Aziz, 2021). This is achieved through the application of the DMAIC cycle, which aims to reduce process variation and associated defects (Srinivasan et al., 2014; Cherrafi et al., 2016; Priya et al., 2020; Ahmed et al., 2020; Nandakumar et al., 2020; Uluskan, 2020; Yang et al., 2020).

On the other hand, from the statistical quality control viewpoint, six sigma aims to improve products to achieve near perfection, or "closer to zero defects", with a target of 3.4 defects per million opportunities (DPMO) (Kim & Han, 2012; Smętkowska y Murgalska, 2018; Abdallah, 2020; De Mattos et al., 2019; Singh & Singh, 2020). In other words, it seeks to reduce process variability (Kim & Han, 2012; Ridwan & Noche, 2018; Haanchumpol et al., 2020). In this regard, authors state that SS used as a performance indicator measures company abilities to reduce the variability of Critical to Quality (CTQ) characteristics, which are those that define consumer expectations (Cano et al., 2012; De Carvalho et al., 2014; Budaj & Hrnciar, 2016; Haanchumpol et al., 2020; Dagmar & Tarigan, 2021).

SS, then, is a process improvement strategy widely used in different organizations and economic sectors, such as logistics, e-commerce, oil & gas, construction, manufacturing, finance, health, etc. (Abdallah, 2020; De Mattos et al., 2019; Yang et al., 2019; Palací-López, 2020; Singh & Singh, 2020; Makwana & Patange, 2021). However, despite the advantages of SS, many authors claim that this strategy is often self-sustaining, and not rooted in a prior feasibility analysis, based on simulation (Elizondo-Noriega et al., 2019). Consequently, failures are not identified as increasing financial risks following implementation. Some claim that it is necessary to integrate this with simulation techniques to model and analyze potential SS benefits before implementation (Elizondo-Noriega et al., 2019; Segura et al., 2019; Ahmed et al., 2019; Abdallah, 2020; Ahmed et al., 2020). Additionally, Cardiel-Ortega et al. (2017) and Ridwan & Noche (2018) add that production systems, like most real systems, are characterized by a systemic, dynamic, and continuous approach, with inherent variability. Thus, a tool that can model these types of complex systems is required.

In this regard, System Dynamics (SD) are an appropriate simulation paradigm to address this need, since it allows for comprehension of the dynamic behavior of complex systems (Alglawe et al., 2019; Elizondo-Noriega et al., 2019; Stadnicka & Litwin, 2019; Adane et al., 2019; Olafsdottir et al., 2019). SD, created by Jay Forrester in the 1950s, is a method with which to solve complex problems using simulation models, which capture the causal interrelationships of a system, and project them as structures of feedback loops (López et al., 2014; Cardiel-Ortega et al, 2017; Mona, 2020). In fact, as Sterman (2000) states, the most complex behaviors, on the systemic level, arise from interactions (feedbacks) between system components, not from the complexity of the components themselves. Likewise, Ahmed et al. (2019) adds that the most valuable aspect of using simulations such as SDs in SS projects is their ability to intervene in the system to be improved using virtual representations of the processes taking place. This reduces the risk of failures and eliminates the need to use real production systems to test hypotheses, as testing these on the real system often requires production halts or rate reductions.

Cardiel-Ortega et al. (2017) state that the integration of SS (DMAIC) and SD is relevant, as this allows for change pattern observation, rather than static images, and permits the capture of the main interrelationships that cause a given problem. This leads to new insight into what could be done. Likewise, Ahmed et al.(2019) add that the most valuable aspect of using simulations such as SD in SS projects is their ability to intervene in the system to improve them, using a virtual representation of the processes taking place, thus reducing the risk of failures, as well as eliminating the need to use real production systems to test hypotheses, as testing real systems often requires halting or reducing production rates (Segura et al., 2019; Ahmed et al., 2019; Ahmed et al., 2019; Ahmed et al., 2020). Then, through the development of simulation models, what-if scenarios, hypotheses, and policies can be tested, without affecting production systems. These models can help find the root causes of defects by forcing a better understanding of the overall system, reducing waste, by testing new work procedures in safe virtual environments, or designing and testing new technologies to estimate costs, financial results, and customer impact (Ahmed et al., 2019).

However, despite the pertinence of SD to the improvement of SS projects, and the fact that several organizations have employed this, there is a group of publications that use SD modeling specifically to study the impact of SS projects within firms, and specifically, in the reduction of process variability (Ridwan & Noche, 2018; Elizondo-Noriega et al., 2019). This is so, since, as stated by Ahmed et al. (2019), SD is predominantly used in the public and private sectors for policy analysis and design, so its application to manufacturing process improvement should be further investigated. In relation to this, Ahmed et al. (2020) conducted a systematic literature review on SS and simulation technologies, and found that further research is necessary in the use of simulation techniques applied to the SS DMAIC methodology.

In order to fill the identified knowledge gap, the present article presents the development and application of a model, which integrates two approaches to improve product quality: six sigma, use of the DMAIC cycle, and System Dynamics (SD). The model uses five phases of the DMAIC cycle, applying the quality-loss function and the hierarchical analytical process in the define stage, system dynamics in the measurement, analysis, and improvement stages, and finally, multivariate statistical control in the control stage. Model validation was carried out in the electrolytic tin plating process, in a pilot company from the metalworking sector in Colombia. The main problem identified in the company under study was an increase in client loss, due to non-delivery, and a 10% decrease in profits, associated with poor quality costs in 2019. The results, obtained by applying the model in the company under study, were reduction of variability in coating thickness, reprocess decreases, reductions in the costs of poor quality owing to thickness, and an increase in profits.

The article is structured as follows: 1) Literature review, 2) Research methodology, 3) Analysis of results, 4) Discussion of results, 5) Theoretical and practical implications, 6) Conclusions, and 7) Limitations and future research.

2. Literature review

2.1. Six sigma

The six sigma methodology is recognized as a business strategy, based on process improvement introduced by Motorola in 1980. This resulted in increased quality, profitability, and competitive advantages (Ridwan & Noche, 2018; Kiatcharoenpol& Seeluang, 2019; De Mattos et al., 2019; Abdallah, 2020; Ahmed et al., 2020; Qayyum et al., 2021; Ketabforoush & Aziz,2021; Ahmad Ansari, 2022). The definition of six sigma can be given from different perspectives: as a methodology for process improvement, through the minimization of variability and reduction of defects, errors, or failures to a rate close to zero, in hopes that the processes meet or exceed customer expectations and requirements (De Carvalho et al., 2014; Essawy et al., 2019; Vergara & Lopez, 2019; Kiatcharoenpo l& Seeluang, 2019; Ahmed et al., 2019; Qayyum et al.,2021).

To address the above, SS uses a disciplined, structured, systematic approach, which is applied to projects, is statistically founded, and supported in the five (5) phases, identified as DMAIC (Define, Measure, Analyze, Improve, Control) described below (Ridwan & Noche, 2018; Essawy et al., 2019; Vergara & López, 2019; Kiatcharoenpol & Seeluang, 2019; Ahmed et al., 2020; Uluskan, 2020; Dagmar & Tarigan, 2021; Qayyum et al.,2021):

- Define: The problem is defined, CTQs are understood, identified, and collected, in relation to customer expectations.
- Measure: CTQs are studied, and the current process performance is measured by establishing the data collection plan, so as to determine defects and associated metrics.
- Analyze: The process is analyzed to establish the root causes of variations and defects that determine critical behavior with which the CTQs identify problems in products or processes, with the current strategy.
- Improve: Design and implementation of process adjustments to eliminate the root issues of the causes of variation, thus improving CTQ performance.
- Control: Empirical verification of project results and control of adjustments and improvements made to the process, so that improvements are sustainable.

As a metric, the "sigma level" reflects a company's ability to manufacture a product or provide a service within prescribed specification limits, i.e. with minimum variability (Kim & Han, 2012; Kiatcharoenpol & Seeluang, 2019; Dagmar & Tarigan, 2021). In this regard, Kim & Han (2012) add that the focus on defect rates and explicit recognition of the correlation between the number of product defects, high operating costs, and level of customer satisfaction makes six sigma unique among other process improvement initiatives.

Traditionally, the statistical techniques used in six sigma have been brainstorming, Value Process Mapping (VSM), process capability, Quality Function Deployment (QFD) and univariate control charts (Stadnicka & Litwin, 2019; Ketabforoush & Aziz, 2021). However, several authors have stated that six sigma must be updated with new powerful tools, as the traditional ones have tended toward the obsolete in today's dynamic environment (Cardiel-Ortega et al., 2017; Abdallah, 2020; Palací-López et al., 2020, Uluskan, 2020). The Quality Loss Function (QLF) designed by Taguchi, which highlights the economic consequences of deviating from target values (Freiesleben, 2008; Cano et al., 2012; Budaj & Hrnciar, 2016) is an effective tool to by which to determine the costs of poor quality in six sigma projects (Trujillo et al., 2015; Uluskan, 2020). Likewise, multivariate process control models, such as Hotelling's T, and generate better results in quality control with multiple characteristics (Trujillo et al., 2015; Haanchumpol et al., 2020).

Due to its relevance and applicability, SS has been used in many fields and sectors, such as supply chain management, optimizing finished goods inventories in multiple nodes of the distribution network (Kumar et al., 2011), logistics and ecommerce (Abdallah, 2020), port logistics (Ridwan & Noche, 2018), financial and administrative processes, to decrease cash flow deficits and working capital control (Sanchez-Rebull et al., 2020), smart city management (Qayyum et al., 2021), the oil & gas sector (De Mattos et al., 2019), and the construction sector (Ketabforoush & Aziz, 2021). Especially, in the manufacturing sector, it has been used for variability reduction in the food industry (Hardy et al.2021), chemical sector (Palací-López et al., 2020), metalworking in tool manufacturing (Kumar & Sosnoski, 2009; Dagmar & Tarigan, 2021), the home appliance industry (Essawy et al., 2019), and in refrigerator construction (Uluskan, 2020), wood panel manufacturing (Hardy et al., 2021), the textile sector (Cardiel-Ortega et al., 2017), automotive sector (Elizondo-Noriega et al.,2019), non-metallic minerals and plastics (Kiatcharoenpol & Seeluang, 2019), micro-milling operations (Garcia-Lopez et al., 2015), and additive manufacturing (Yang et al., 2020).

2.2. System dynamics

System dynamics is a simulation paradigm developed by Dr. Jay W. Forrester in the 1950s, at the Massachusetts Institute of Technology, to help corporate managers improve their understandings of complex industrial processes (Ridwan & Night, 2018; Ahmed et al., 2019; Ahmed et al., 2020). It is used especially to simulate process flows (Butt, 2020). This simulation technique is used to understand the nonlinear behavior of complex systems, over a period of time, using time delays, feedback loops, causality relationships, and stocks where entities accumulate and flows that define the movement from one stock to another (Ahmed et al., 2019; Ahmed et al., 2020; Mona, 2020; Adane et al., 2019; Stadnicka & Litwin, 2019). Irfani et al., (2019) add that SD frames trade-offs in time and space associated with various alternative scenarios, in order to understand the way in which the accumulation and depletion of strategic assets are affected by various policy levers, and determine the ways in which performance drivers affect final outcomes.

SD responds to system thought, applied to industrial processes as complex systems, such that, system thought can generate a conceptual model developed to describe the real system, so that the entire system can be known (Ridwan & Noche, 2018; Ahmed et al., 2019). SD then offers different advantages, as it is able to solve process-centered problems, provide a set of tools with which to understand a system with variables that are difficult to measure, helps to understand causal relationships between variables, delays, and feedback loop effects qualitatively (Ahmed et al., 2020), and permits the observation of the behavior of complex systems, as a function of time change (Sterman, 2000; Ridwan & Noche, 2018).

So far, several studies have applied SD modeling, such as implementation in complex projects that facilitate strategic management (Olafsdottir et al., 2019), the modeling and simulation of interconnected level sets, flows and decision variables that adjust in pseudo-continuous time (Stadnicka & Litwin, 2019), understanding a phenomenon in addition to envisioning powerful and cohesive solutions to solve different system problems in a short to medium-length period (Saryazdi & Ghavidel, 2018), lean supply chain, manufacturing productivity and cost management (Ridwan & Noche, 2018; Irfani et al., 2019; Segura et al., 2019; Ahmed et al., 2020), logistics performance measurement and supply chain systems (Irfani et al., 2019), and the simulation of future scenarios in the lithography (Kamath & Rodrigues, 2020), automotive (Mona, 2020; Adane et al., 2019), construction (Chinda et al., 2020; Olafsdottir et al., 2019), and manufacturing sectors (Stadnicka & Litwin, 2019; Dutta & Ashtekar, 2017).

2.3. Knowledge gap identification: models that integrate six sigma and system dynamics

Despite the importance of SD integration in SS for variability reduction, studies that have addressed this aspect remain limited. To identify studies that address the above, a literature review was conducted, using the Scopus and Web of Science databases, using the following keywords: "system dynamic*", "manufactur*", and "Six Sigma", in the range between 1996-2021. Appendix A shows the results obtained from the literature review. In accordance with the literature review, 73 relevant articles addressing six sigma and/or system dynamics were reviewed. A total of 24 studies addressed only system dynamics, 43 applied only six sigma, only one article addressed the quality loss function in six sigma, and one article addressed multivariate statistical control in six sigma. Similarly, just five articles addressed both SD and SS (Cardiel-Ortega et al., 2017; Ridwan & Noche,2018; Elizondo-Noriega et al., 2019; Ahmed et al., 2019; Ahmed et al., 2020).

Cardiel-Ortega et al. (2017) used SD and the DMAIC cycle in a textile company in Mexico. However, this study does not use Taguchi's quality loss function to identify CTQs in the define phase, nor multivariate statistical control in the control phase. Likewise, they use sigma level and process capability as variability measures. Ridwan & Noche (2018) designed a performance metrics model to improve port quality, using system dynamics. However, they do not use the DMAIC cycle, quality loss function, or multivariate statistical control. Elizondo-Noriega et al. (2019) propose a holistic SD archetype, based on a simulation model, to assess the financial viability of a SS project. However, they do not combine SD with the DMAIC cycle. Ahmed et al. (2020) conducted a systematic literature review on six sigma and simulation technologies, including SD, and found that additional research was required in the use of such techniques applied to the DMAIC methodology. Ahmed et al. (2019) compared the forecasting and visualization capabilities of three simulation paradigms, including SD, to identify their suitability and rigor in eliminating bottlenecks in a Lean Six Sigma (LSS) project, in a Light Emitting Diode (LED) factory. However, they did not combine SD with the DMAIC cycle, the use of the quality loss function, or multivariate process control.

In accordance with the above, the need to develop models that integrate SS and SD approaches, and simultaneously address advanced statistical tools, such as the Taguchi quality loss function and multivariate statistical process control (Hotelling) for variability reduction (in terms of CTQ vs. target value deviation) is identified as a knowledge gap.

3. Research methodology

The integration between six sigma and system dynamics is used to improve product quality by reducing industrial processes variability. The constructed SD model is related to Sterman (2000), and consists of the conceptualization, formulation, validation and simulation of scenarios, while the six sigma methodology is applied using the DMAIC cycle (Abdallah, 2020; Hardy et al., 2021). SD integration and the six sigma model were applied to reduce process variability, in terms of the deviation of CTQs from their target value. Likewise, a case study approach was adopted to conduct this study, in order to validate the proposed model.

The company under study forms part of the metal-mechanic sector in Colombia, and is dedicated to the electrolytic coating of metal parts (tin plating). In the past two years, the company has increased its continuous improvement projects, in order to increase both its market share and profits. This is due to the fact that, in 2019, the commercial and production team identified significant client loss and a 10% decrease in profits. The main cause identified for this situation was failure to deliver to customers, due to the increase in reprocesses, owing to the poor quality of the coatings, as these exhibited CTQ deviation with respect to values required by customers.

To address the identified issue, a model that integrated SS and SD was implemented, for the reduction of variability in the electrolytic tin plating process, as well as to increase profits, due to savings in poor-quality costs. The proposed model is shown in Figure 1. This has been structured into five stages (define, measure, analyze, improve, control) and a set of steps. The data used in the present study was obtained through customer interviews and historical production data, from 2017 to 2019, regarding the tin plating process. A brief explanation of the methodology is set out below.

Stage 1. Definition: Identification of the critical to quality characteristics (CTQ)
Step 1. Analytic Hierarchical Process

The Analytic Hierarchical Process (AHP) is a multi-criteria correlation approach that illustrates the hierarchy of a system, and assigns weights to a group of components or variables (Saaty,1990). The selection of the critical to quality characteristics (CTQ) will occur through the AHP approach, combining three analysis perspectives: the Taguchi quality loss function, company criteria, and customer criteria.

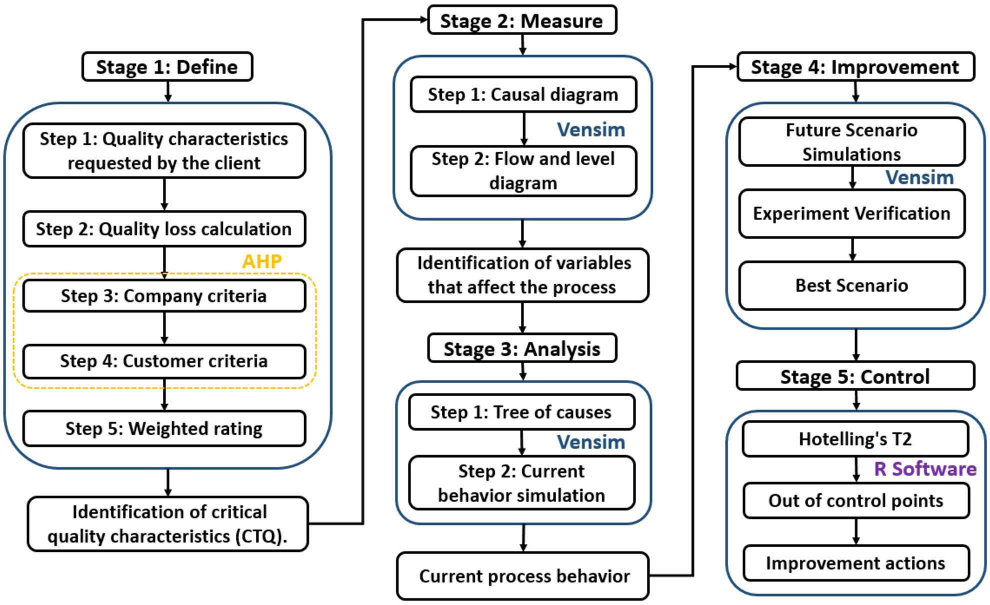

Figure 1. Proposed Model

According to the study by Haider & Lee (2012) the steps to apply the AHP are as follows:

1). Define the objective: what you want to achieve (prioritize) with the analysis.

2). Define the criteria: characteristics that will define whether the objective is met or not. In this case, they will be the critical to quality characteristics (CTQs) that will arise from product characteristics.

3). Establish clients: person, company, function, entity, or participant that will evaluate the criteria for the objective to be achieved.

4). Create the importance matrix: which must be completed by each client.

5). Add the values of each column to a resultant (w1r = w1/w1 + w2/w1 + w3/w1 +… + wn/w1). A row can be included at the end of the array to place these values.

6). Divide each weight by the total sum of its column ((w1/w1)/w1r = w11, (w2/w1)/w1r = w21, (w3/w1)/w1r = w31,…, (wn/w1)/w1r = wn1). These values can be substituted into a new matrix, so as not to lose sight of the order of the process.

7). Add the previous results by row (w11 + w12 + w13 +… + w1n = w1f). A new column can be included at the end of the array to place these values.

8). Calculate the average of the elements in each row (P1 = w1f/n, P2 = w2f/n, P3 = w3f/n,…, Pn = wnf/n). Where P will be the final importance weights for each criterion and n is the number of criteria to be evaluated. It should be noted that the highest rating will be given to the quality characteristic that has generated the highest percentage of participation in accordance with the AHP approach. To evaluate the congruence of the judgments, AHP allows for the calculation of the Consistency Ratio (CR) using the formula CR = CI/RI, where CI is the consistency index and RI is the average random value for the consistency index (Saaty, 1990). The Consistency Index (CI) can be calculated with the formula CI = (λmax - n)/(n - 1), where n is the number of criteria to evaluate and λmax is the maximum self-value of the importance matrix AHP and the weights of importance of each criterion. To achieve an accepted congruence in the method, it is proposed that the CR result be less than 0.1, otherwise the judgments made in the AHP importance matrix should be reviewed (Saaty, 1990).

Step 2. Quality loss function

Quality is defined as the loss created by the product to society from the moment it is delivered for use (Taguchi et al., 2005), better known as the quality loss function. The Taguchi quality loss function can be calculated using Equation (1) (Budaj & Hrnciar, 2016):

$$L = k * (X - T)^2$$
$$k = A * \Delta^2 \quad (1)$$

Where,

L = Total money loss (incremental loss).

k = Proportion of cost, where A represents the cost of a change by the value Δ.

T = Target value of the monitored characteristic (CTQ).

X = Current value of the monitored characteristic (CTQ).

Cano et al. (2012) propose a simpler use of the formula: variable k (cost proportion) can be determined by the expression k = Lo/Δ, where:

Lo = is the cost of poor quality per individual item ($/und).

Δ = is the tolerance of the process, or tolerance of the measured characteristic (und).

Step 3. Company and client criteria

According to Trujillo et al. (2015), given the typical particularities of each industry, it is important to consult company criteria and experience, in order to identify preferences regarding the characteristics considered critical, given their knowledge of the market. This occurs similarly with clients, who can generate a totally different viewpoint towards evaluation criteria, due to their market preferences. En este paso se aplicará la metodología AHP.

Step 4. Weighted rating

With the previous definitions, Table 1 was created. The first column identifies the quality characteristic evaluated. "P" columns (P1, P2, and P3) are the results of the previous analysis, which are given in money, in the case of the quality loss function, and in the rating of client and company. The weighting is the same for each perspective (33.33%) in accordance with the recommendations of Trujillo et al., (2015). “C” columns (C1, C2, and C3) are the weight or rating resulting from the AHP approach, by quality characteristic of the perspective analyzed. The last column is the total weighted rating for each characteristic, which can be calculated using the formula below:

$$Ptn = P1 * C1n + P2 * P2n * C2n + P3 * P3n * C3n \quad (2)$$

Table 1. Quality characteristic qualification matrix

Quality characteristic	Perspectives						Weighted rating (Pt)
	Quality loss function		Company criterion		Customer criterion		
	P1 (33.33%)	C1	P2 (33.33%)	C2	P3 (33.33%)	C3	
Feature 1	P_{11}	C_{11}	P_{21}	C_{21}	P_{31}	C_{31}	P_{t1}
Feature 2	P_{12}	C_{12}	P_{22}	C_{22}	P_{32}	C_{32}	P_{t2}
…	…	…	…	…	…	…	…
Feature n	P_{1n}	C_{1n}	P_{2n}	C_{2n}	P_{3n}	C_{3n}	P_{tn}

Stage 2. Measurement: the identification of variables that affect the process

In system dynamics, as a first step, the problem must be clearly identified and the study objectives described precisely, so as to generate an initial perception of the "elements" related to the problem posed, hypothetical relationships between them, and historical behavior (García, 2017). Thus, the objective of this model is to simulate the impact generated by reprocessing, due to poor quality, on company profits. The system is defined using those critical variables identified in the previous stage, and those that generate a direct relationship therewith. The causal diagram is a tool that collects key elements from the system and the relationships therebetween (García, 2017).

The Vensim software serves to improve the performance of real systems. It has an interaction window that includes all necessary elements for the determination of those relationships, equations, graphs, and loops necessary to simulate the causal diagram.

Each type of data (variables) contains, in its programming, the ability to enter values and equations linked to the causal diagram, which causes it to function, as determined by the process. With the previous information, variables (quality characteristics) that will impact the system dynamics model must be identified and connected through positive and negative relationships, in order to create the necessary feedback loops. This first model will be called "the causal diagram" and only shows the relationship between the variables analyzed in the system. Once the causal diagram is complete, it will be simulated in the Vensim software, in order to determine the type of variable or data, in addition to generating the internal equation that will manage the behavior of each one. This last step will be called "the flow and level diagram", which will simulate the behavior of the current process under analysis.

Stage 3. Analysis: current process behavior

Vensim boasts analysis tools that may be used to show the information and behavior of one or a number of variables in the model, and these may be viewed through text, tables, diagrams, or graphs (Vensim, 2020). This tool is also used to improve decisions anywhere detail and dynamics problems exist, in other words, everywhere, through simulation, data analysis, and the comparison of results (Vensim, 2020). The software allows data tables to be imported into different formats (Excel), so that they may be analyzed and compared, using other methods. Once it is determined that the flow and level diagram is complete, the system will be simulated, and through the different analysis tools, the behavior of each of the variables and the impact generated over time will be analyzed. It is recommended that the cause tree be used to determine the most influential variables in the model, followed by an analysis of graphs and tables, by variable.

Stage 4. Implementation (improvement): simulation of future scenarios

Once the most influential variables in the model have been identified (tree of causes), the data will be recorded in Vensim, where data may be modified in real time, so as to analyze the new system behaviors. It can also generate the simulation and variation of the unit quantity of each variable, to see new results. The only variables that can be modified are those identified as "constant", as the others allow for variation over time.

Control variable identification will help to focus on those that directly impact the system, and these will be the objective to improve and generate new scenarios for system dynamics. Applying the above, new information should be added that portrays the different scenarios proposed. It is recommended that the above be recorded as "Future value 1, 2, 3, etc.". These new scenarios will help to create the different improvement actions that should be applied to the process, such that simulated results may be obtained in system dynamics.

Stage 5. Control

At this stage, a multivariate control, using the Hotelling graph, is proposed. This model is applied to two or more process outputs, which can be correlated and are graphed from the calculation of the T2 statistic, which relates the behavior of their means, variances, and the covariance therebetween, in order to obtain a Hotelling control chart (Hotelling, 1947). The T2 statistic is calculated using Equation (3).

$$T2 = (x - \bar{x})' S^{-1} (x - \bar{x}) \tag{3}$$

Where x is the vector of samples, $\bar{x}$ is the vector of means, and S is the matrix of variances and covariances.

Following the recommendations of Trujillo et al. (2015), to obtain greater precision in control limits, the beta distribution will be used in accordance with the Equation (4).

$$UCL = \frac{(m-1)^2}{m} \beta_{\alpha, p/2, (m-p-1)/2} \text{ and } LCL = 0 \tag{4}$$

Where UCL and LCL represent the upper and lower control limits respectively, p is the number of quality characteristics, and m the sample size. After applying the above, a graph will be obtained that will demonstrate whether or not quality characteristics are under control, allowing them to be identified and provided the respective feedback in the cycle to define new improvement actions.

4. Results

Stage 1. Define: identification of critical to quality characteristics (CTQ)

The procedure was applied in a company from the metalworking sector in Colombia. Products coated with tin were selected for being highly profitable. However, quality problems were identified in the process, when applying the steps of this stage, the results were as follows:

Step 1. Quality characteristics requested by the client

Table 2 lists the quality characteristics of the tinned product, in which the thickness, adherence, color, stains, and/or blisters are found with their respective unit of measure, lower and upper limit plus the target value. This information was determined from the client's requirements, in accordance with the information provided by the company.

Step 2. Quality loss calculation

To calculate the loss of quality, the Taguchi function equation (1) was applied to the characteristics mentioned in Table 2, where the total cost/unit, maximum accepted tolerance, objective value, and loss of quality were calculated. Table 3 shows the results and identifies that the two most important quality characteristics, in accordance with loss of quality, are adhesion and thickness.

Table 2. Quality characteristics requested by the client

Quality features	Specifications			
	Unit of measurement	Lower limit (LL)	Upper limit (UL)	Objetive value
Thickness	µm	8	12	8.5
Adherence	%	0	20	10
Color	Level	1	5	40
Spots and/or blisters	un	0	3	0

Table 3. Quality loss coefficient

Quality features	Loss function parameters			
	Total cost/Unit (L0)	Maximum tolerance accepted (Δ)	Target value (T)	Loss of current quality (S)
Thickness	$4,564.50	0.5	8.5	$36,516.00
Adherence	$42,800.00	10	10	$38,520.00
Color	$81,000.00	1	4	$0.00
Spots and/or blisters	$81,000.00	3	0	$27,000.00

Table 3 shows that, according to the quality loss coefficient, thickness and adhesion are product characteristics that generate the greatest economic losses, in the event of product defects, and are therefore the most important.

Step 3. Company criteria

For the company's criteria, the AHP methodology was applied for the four quality characteristics.

Table 4 shows the final result of the application of the AHP methodology with the company's criteria, obtaining a consistency ratio of 0.094 (Cr <0.1). This indicates that the evaluation is accepted and within process limits. In addition to the above, it is confirmed that the two most important characteristics, in accordance with company criteria, are thickness and that the product does not present stains or blisters.

Step 4. Customer criteria

For client criteria, the assessment of the four quality characteristics was requested from the three main clients of the company studied.

Table 5 shows the final result, on application the AHP methodology with the client's criteria, obtaining a consistency ratio of 0.092 (Cr <0.1). This indicates that the evaluation is accepted and within process limits. In addition to the above, it is confirmed that the two most important characteristics, in accordance with client criteria, are thickness and good adhesion.

Step 5. Weighted rating

For the weighted qualification, the previous data was taken, and Equation 2 was applied to identify the most important quality characteristic, as illustrated in Table 6.

The ratings (C1, C2 and C3) were given on a scale of 1 to 4, where one was the characteristic that generated the least impact and four was that which generated the most impact in the process, where adherence was the most important in the quality loss function (resulted in a greater loss of money) and thickness was the most important to the company and client both (according to the AHP weight). According to Table 6, the most important quality characteristic is thickness, with a score of 2.41, followed by adherence, with 1.68, thirdly, spots and/or blisters, with 1.09, and finally, color, with 0.36.

Table 4. Company AHP consistency ratio

	Thickness	Adherence	Color	Spots and/or blisters	Characteristic weight	Matrix product	Weight division
Thickness	1	5	7	3	0.5209	2.3506	4.5124
Adherence	1/5	1	3	1/5	0.1010	0.4141	4.1003
Color	1/7	1/3	1	1/9	0.0476	0.1924	4.0418
Spots and/or blisters	1/3	5	9	1	0.3305	1.4375	4.3495
							4.2510

Table 5. Customer AHP consistency ratio

	Thickness	Adherence	Color	Spots and/or blisters	Characteristic weight	Matrix product	Weight division
Thickness	1	3	7	5	0.5401	2.3850	4.4161
Adherence	1/3	1	7	3	0.2746	1.1995	4.3684
Color	1/7	1/7	1	1/5	0.0472	0.1912	4.0496
Spots and/or blisters	1/5	1/3	5	1	0.1381	0.5738	4.1541
							4.2470

Table 6. Critical quality characteristic selection

Quality characteristic	Perspectives						Weighted rating (Pt)
	Quality loss function		Company criterion		Customer criterion		
	P1 (33.33%)	C1	P2 (33.33%)	C2	P3 (33.33%)	C3	
Thickness	$36,516.00	3	0.5209	4	0.5401	4	2.41
Adherence	$38,520.00	4	0.1010	2	0.2746	3	1.68
Color	$0.00	1	0.0476	1	0.0472	1	0.36
Spots and/or blisters	$27,000.00	2	0.3305	3	0.1381	2	1.09

Stage 2. Measure: identification of variables that affect the process

Step 1. Causal diagram

According to the previous stage, thickness and adhesion were determined to be the most important critical quality characteristics in the coating process. To identify the variables that affected the process, including quality characteristics, the causal diagram was created with Vensim simulation software.

According to the causal diagram in Figure 2, there are four loops that have a positive and direct impact on accumulated company profit. If a loop is improved, both sales and profit will increase. The loops are listed below.

1) Education and training: focused on improving staff (Kaizen) through training and motivation to achieve operational excellence and customer satisfaction.
2) Automation and efficiency: aimed at improving technology and processes related to mixing tanks to improve adherence, color, and surface of the final product.
3) Advanced technology: which includes the improvement of current rectifiers to decrease, not only the unnecessary electrical energy, but also product immersion time, which impacts thickness.
4) Poor quality Cost: refers to the costs associated with producing the final product with poor quality, which directly impacts unit prices.

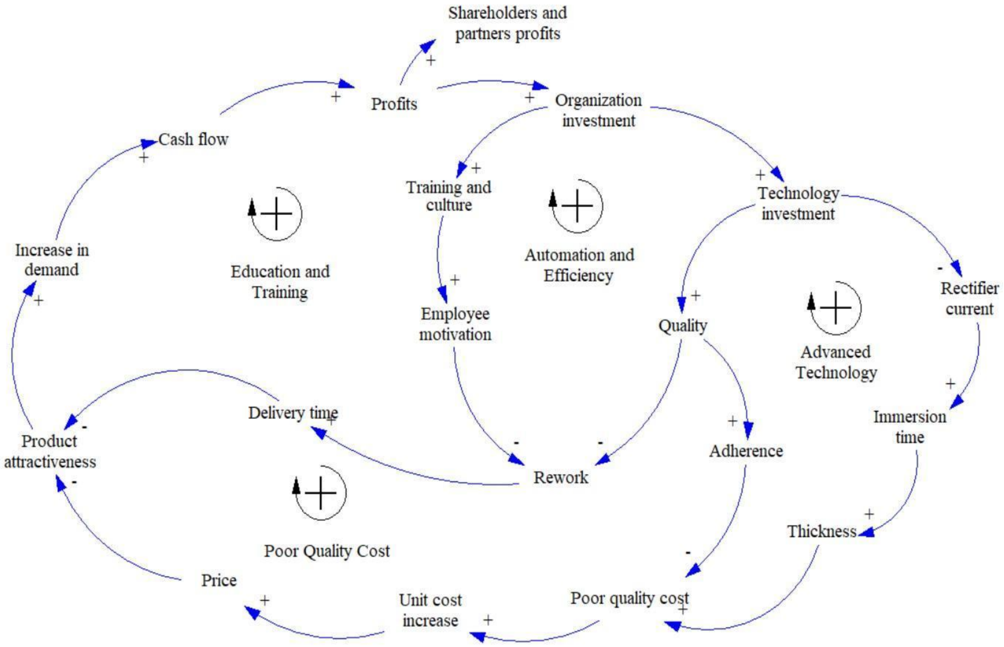

Figure 2. Tin coating causal diagram

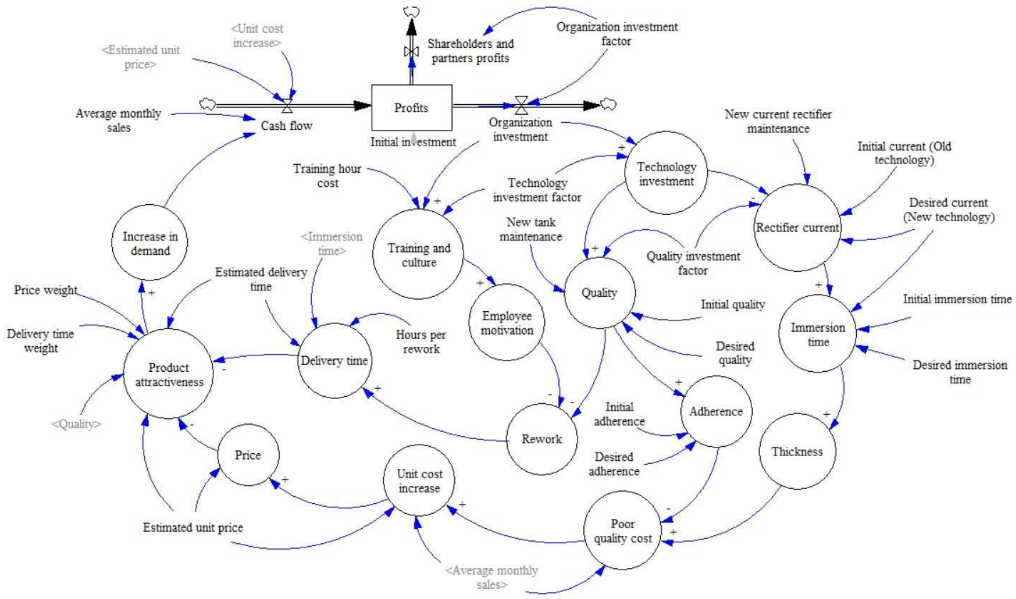

Figure 3. Flow and level diagram

Step 2. Flow and level diagram

Once the above information was recognized and verified, the flow and level diagram was generated, where the constant auxiliary variables that directly affected each auxiliary variable were taken into account. The result is shown in Figure 3.

The equations of each auxiliary, flow, or level variable have, in their internal programming, the equation that manages their behavior over time. The equations that generate the behavior of the process are included within the system. These equations must be created from historical behavior, forecasts, or mathematical modeling for each type of variable.

Stage 3. Analysis: current process behavior

Step 1. Tree of causes

After reviewing the flow diagrams, levels, and equations, Figure 4 was made, where control variables were identified as: profit, product attractiveness, quality, employee motivation, and reprocessing, cost of poor quality, thickness, and adherence, to determine whether or not the system generated stability over time, and as indicators of improvement for the next stage.

Step 2. Current behavior simulation

Once the control variables were defined, the current behavior of the system was simulated, where the main characteristic was that all of the profit was distributed to the shareholders, but no investment was generated in the organization, whether for new projects or improvements, as shown in Figure 5.

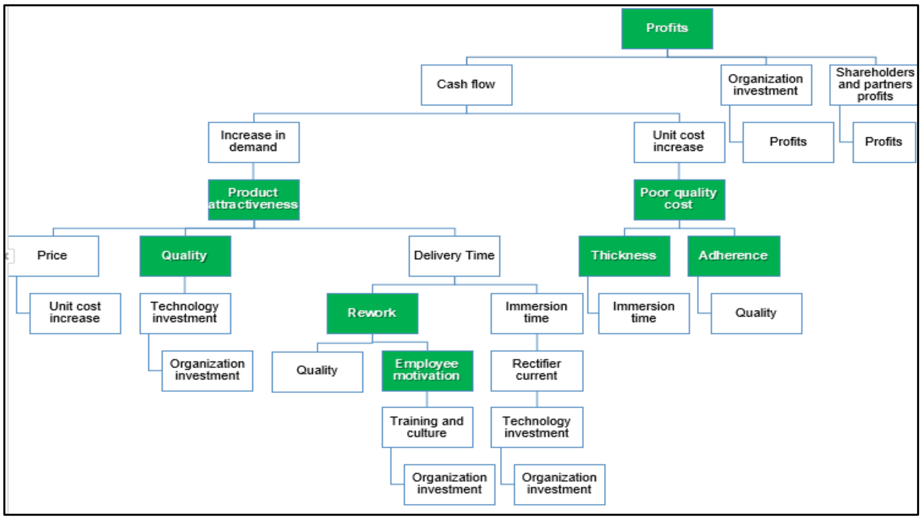

Figure 4. Tree of causes

Figure 6 shows that if the company continues as it does at present, its average earnings will total approximately COP 27 million, per month, with a decreasing trend over time, because the attractiveness of the product will remain at a 3.1 average (where 1 is the least attractive and 5 the most). It also shows indications toward decline, or customer loss, in the near future. Compliance with client quality requirements will remain at an average of 86%, much lower than the current goal of 93%, thus causing both thickness and adhesion to remain at 10 microns and 12% detachment, respectively. This promotes poor quality costs of 8.5 million COP per month, due to the variability in these characteristics. Reprocessing will be necessary for approximately 13 tinned drums per month, due to non-compliance, both in terms of quality requirements and due to low employee motivation, which results in human error. This, in turn, arises due to lack of incentives, training and motivation in company quality culture.

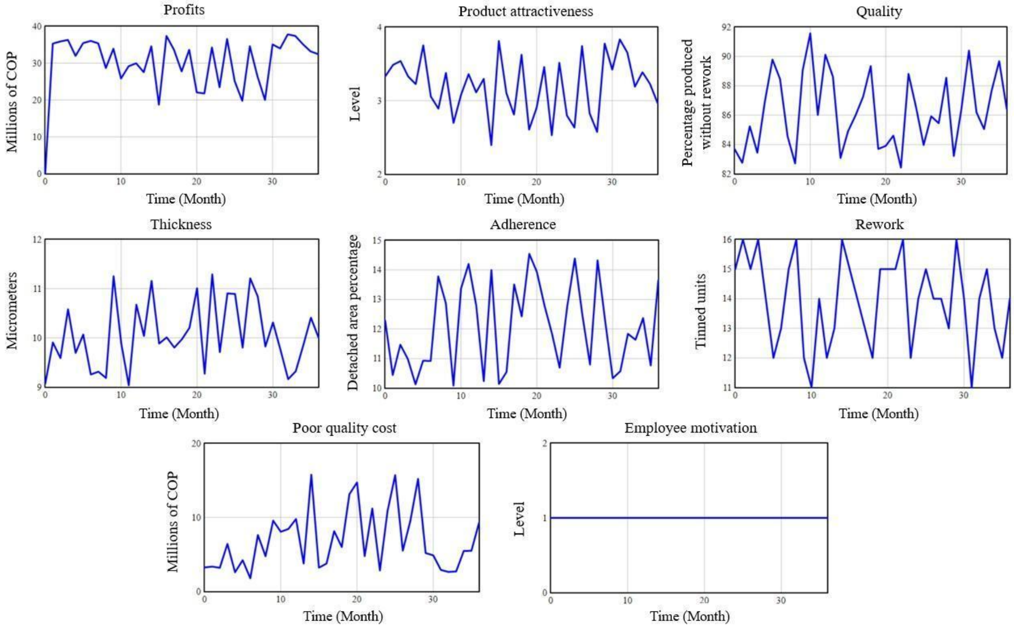

Figure 5. Current process behavior

This simulation offers an unfavorable outlook for the company, and provides instructions for the creation of improvement actions that would reduce the costs of poor quality and increase the profitability of the tinning process through investment in new technology, industrial reconversion, quality culture, and new tools that allow employees to play better roles, with respect to their functions and the achievement of business objectives.

Stage 4. Implementation (improvement): future scenario simulation

The different possible scenarios will show the validity of the hypotheses to be verified, without the need to directly impact the process. These scenarios will serve to verify whether improvement ideas, with respect to new technologies, industrial reconversion, or education, result in increased profits, less reworking, higher quality, less costs of poor quality, or enhanced employee motivation. To generate the scenarios, the constants that directly affect the behavior of the control variables were modified, and those variables that could not vary for reasons inherent to the process were identified, so as to not affect the functioning of system dynamics.

In the simulation, for the weight of the price and the delivery time, the qualification given by the main client of the study company was used, which were 45% and 30% respectively. According to the formula applied to the system auxiliary variable, the quality will have a 100% complement weight of the group, or, 25%. Therefore, the only three constants to modify were the investment factors in the organization, technology, and quality.

The initial investment for the project must be 60 million pesos, in order to generate the machines, tools, and supplies necessary for the development. These improvements include the technological reconversion of mixing tanks, current rectifiers, and operational excellence. Table 7 shows proposed future scenarios.

Table 7. Future scenarios

Variable	Type	Units	Current	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6
Gain	Lvl.	MP.	27	26	26	33	30	35	33
Product appeal	Aux.	Lvl.	3.1	3.1	3.1	3.4	3.3	3.5	3.8
Cost of poor quality	Aux.	MP.	8.5	8.3	8.1	4.5	7.5	4	7
Quality	Aux.	%	86	86	86	86	95	86	95
Reproce-sses	Aux.	Brrl.	13	12	10	13	9	6	4
Adherence	Aux.	%	12	12	12	12	7	12	7
Thickness	Aux.	µm	10	10	10	8.2	10	8.2	10
Employee motivation	Aux.	Lvl.	1	2	3	1	1	5	4.5
Investment factor in the organization	Cnst.	%	0	25	65	58	58	58	65
Technology investment factor	Cnst.	%	N/A	80	80	100	100	65	68
Investment factor in quality	Cnst.	%	N/A	50	50	0	100	0	100
Weight price	Cnst.		45	45	45	45	45	45	45
Weight delivery time	Cnst.		30	30	30	30	30	30	30
Initial investment	Cnst.	MP	0	-60	-60	-60	-60	-60	-60
INCREASE (+) / DECREASE (-) OF PARAMETERS									
Gain		%	-	-3.70	-3.70	22.22	11.11	29.63	22.22
Product appeal		Lvl.	-	0	0	0.3	0.2	0.4	0.7
Cost of poor quality		%	-	-2.35	-4.71	-47.06	-11.76	-52.94	-17.65
Quality		%	-	0.00	0.00	0.00	10.47	0.00	10.47
Reprocesses		%	-	-7.69	-23.08	0.00	-30.77	-53.85	-69.23
Adherence		%	-	0.00	0.00	0.00	-41.67	0.00	-41.67
Thickness		%	-	0.00	0.00	-18.00	0.00	-18.00	0.00
Employee motivation		Lvl.	-	1	2	0	0	4	3.5
								Best Scenario	

Notes: Lvl = Level, Aux = Auxiliar, Cnst = Constant, MP = Millions of COP, Brrl = Barrel, N/A = Doesn´t apply.

In accordance with proposed scenarios, the best scenario was revealed to be number 5. For Scenario 5, it is inferred that it is more profitable to improve current rectifiers than mixing tanks, but remains clear that the low level of employee education and training directly influences the amount of reprocessing necessary. With the above, a balance point is sought between operational excellence and investment in technology, generating the following parameters: 58% in investment in the organization, 65% in investment in technology, and 35% investment in operational excellence, in addition to 100% in investment in current rectifiers.

In order to carry out the implementation of this project in the future, the following is necessary:

1) Initial investment for the purchase of new current rectifiers: 60 million pesos.

2) 58% reinvestment of profits in the company.

3) Of the investment in the company, 65% must go to maintenance and improvement of the current rectifier process, and 35% to training in operational excellence.

4) 40 hours per month minimum in training and Kaizen events for process improvement and problem analysis.

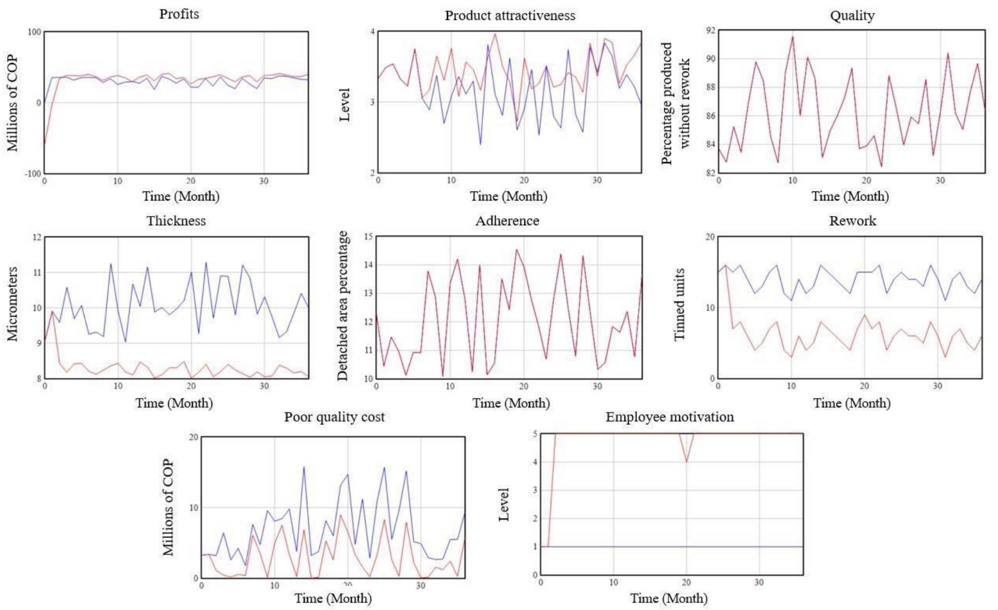

Figure 6. Future process behavior

Figure 6 shows new process behavior, in accordance with the parameters of Scenario 5. When implemented, it will increase average monthly company profits to 35 million COP, with increasing behavior over time, due to the increase in product attractiveness, at a 3.5, thanks to the decrease in the poor quality costs, which decrease by 4.5 million COP per month, approaching the range of appropriate thickness (8.2 microns), as well as lower reprocessing numbers (seven less per month, on average) thanks to greater employee motivation. Although compliance with the quality requirements remains as it was before (86%), as does adherence (12%), the favorable results are obvious with the improvement of current rectifiers and the implementation of a better-quality culture, which generates an improvement forecast for the company and the tin plating process.

The main benefits of implementing this project are:

✓ A 29% increase in monthly company profits.

✓ A 53% reduction in poor quality costs, due to excess coating thickness.

✓ A decrease of 1.8 microns, on average, of coating thickness (variability reduction)

✓ A 54% reduction in reprocessing, due to human error.

✓ Increased employee motivation, through operational excellence.

✓ A more attractive product on the market.

Stage 5. Control

Once the project was completed, a simultaneous control of critical quality characteristics (thickness and adhesion) was carried out, so that they would remain within the control limits, and the cost of poor quality would not be directly affected. Notwithstanding, the multivariate control process (Hotelling) was used to detect critical values outside of the accepted limits. Observations occurred monthly (unit of time). The multivariate control chart was made using R software. The code used works with the "qcc" library, which has the tools and formulas necessary to determine Hotelling's T2.

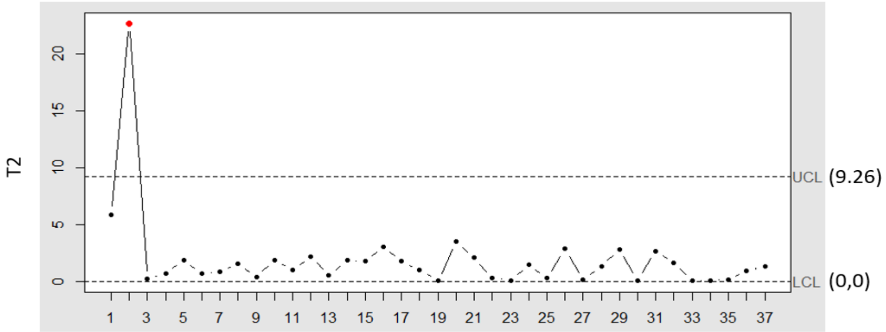

Figure 7. Hotelling multivariate control chart (T2)

Figure 7 illustrates the Hotelling multivariate control chart (T2), in which an out-of-control point is seen, that obeys Observation 2, which was created during the first month of project implementation, while all the other observations are within control. The above occurs since it is the month of projected adjustments, where the equilibrium point has not yet been achieved. After reaching this, however, everything returns to the normal parameters of the process. Therefore, this point may be considered under control, and is maintained for the following months, giving an indication that the project to be implemented will be under control, in accordance with Hotelling and the defined critical quality characteristics.

5. Discussion

Several studies have addressed both Six Sigma and SD approaches for variability reduction. However, in the literature review conducted, both of these, together with other advanced statistical tools, such as QLF and multivariate control, reduced variability in complex processes such as electrolytic coating of tin plating. The proposed model, through the integration of these two approaches, permitted the achievement of the following results: 1) the identification of critical quality characteristics, 2) identification of the most representative variables associated with the cost of non-quality, sales, and company profit, 3) control variables in the system were determined to simulate the current process behavior and identify improvement actions, and 4) simulation of the most optimal scenario and control tool. As a fundamental effect, there was a significant reduction in variability, represented by a decrease of 1.8 microns, on average, in the coating thickness, which generated a 54% reduction in reprocessing, due to human error, a 53% decrease in poor quality costs, and a 29% increase in the company's monthly profits.

The results obtained show the high-performance level achieved in the improvement of product quality and the significant reduction of variability, as compared to other studies such as Garcia-

Lopez et al. (2015) who decreased surface roughness (<0.5 μm) in the micro-milling process. Likewise, Kumar & Sosnoski (2009) decreased the average deformation in wear tools by 35%. Dagmar & Tarigan (2021) reduced defects in the welding of steel material by 6.6%, Essawy et al. (2019) reduced defect rate by 1.13% in the home appliance manufacturing process, Kiatcharoenpol & Seeluang (2019) reduced 8.38% of deformation defects in plastic, Mishra & Rane (2019) reduced defects in iron casting by 99%, Vignesh et al. (2019) reduced defects in automotive joint welds by 99%, De Carvalho et al. (2014) reduced the rate of defective seats in the automotive sector by 69%, and Mishra & Sharma (2014) reduced defects occurring in the paint production supply chain by 9.12%.

Studies that impacted production costs were also found, such as Essawy et al. (2019), who reduced scrap costs by 12%, Vergara & Lopez (2019) who saved 27.7 million COP per year in a graphic production company, Ridwan & Noche (2018) who decreased the cost of internal failure in a seaport by 55.52%, and Hilmola (2006) who increased profits by 21.4% in foreign exchange management in production purchases. These results provide an indication of possible results of the application of this model to decrease costs and increase profits.

6. Theoretical and practical implications

This study presents several contributions to the literature. First, it is one of the few studies that have explored the integration of SD and SS for quality improvement in complex industrial processes. Second, despite the fact that other authors have used SS and SD in process improvement, they have been applied independently, in most cases, so there is still very little research regarding the benefits of their integration in variability reduction (Segura et al., 2019; Ahmed et al., 2019; Ahmed et al., 2020). Third, this study includes two advanced quality tools, the Taguchi quality loss function and multivariate statistical control. Fourth, although it is based on a case study, it serves as an example of the empirical analysis of a real company through the application of SS and SD integration as a prospective tool for continuous process improvement (Segura et al., 2019).

The present investigation also presents several practical implications: first, six sigma through the application of the DMAIC cycle, with SD integration, is a powerful tool with which to simulate improvement projects prior to implementation. Likewise, the model can guide management in the determination of the best scenario with which to make investments in the process, and thus obtain results that benefit companies, in terms of both profits and product quality. Additionally, within the framework of Industry 4.0 and digital transformation, the integration of SS with advanced simulation techniques such as DS can improve manufacturing and the R&D capabilities (Butt, 2020) of emerging countries, such as Colombia. Therefore, the present study is a reference for manufacturing companies seeking continuous quality improvement and business competitiveness.

7. Conclusions

Six sigma is a process improvement methodology that works via variability reduction, based on the DMAIC cycle. Likewise, SD is a simulation paradigm used to model causal relationships in complex processes. Although there is evidence of the benefits of both approaches in the improvement of organizational performance, and especially quality improvement, their integration has rarely been addressed for the reduction of variability in complex industrial processes. In this regard, several authors have proposed the need to integrate the DMAIC cycle with advanced simulation techniques that allow for modeling all of the factors and underlying causal relationships of complex processes systemically, as well as to perform feasibility analysis through scenarios of the proposed improvements, before their implementation.

To fill this gap, a hybrid model that integrates the six-sigma approach, using the DMAIC cycle and System Dynamics (SD) was proposed to reduce process variability. The study then proposes a model that integrates SD in the analysis, measurement and improvement phases for the DMAIC cycle, as well as the Taguchi quality loss function, in the define phase, and multivariate statistical control, in the control phase. The model was validated in an electrolytic tin plating process in a Colombian company from the metal-mechanic sector.

The model allowed for the identification of important quality characteristics for the client and study company, where variables significant to the process were characterized, and control variables were defined, so as to then simulate the current procedure and identify improvement actions with future scenarios oriented toward the benefit of the company. The simulation generated a positive forecast for implementation of the proposed model, yielding the possibility of a significant reduction in variability, represented by a decrease of 1.8 microns, on average, in coating thickness, a 54% reduction in reprocessing, a 53% decrease in poor quality costs, and a 29% increase in the company's monthly profits.

8. Limitations on future research

The present study had several limitations. One of these derives from the composition of the groups interviewed to select critical process characteristics. These were formed by bringing together mainly experts from the company under study and the company's best customers. It is likely that a broader and more diverse approach, with experts from other companies would show possibilities and improvements in the evaluation of this model that were not detected in the groups used.

As future lines of research, the proposed model and its indicators should be validated and tested in other industrial sectors to confirm and validate their benefits. Likewise, since simulation techniques is an Industry 4.0 technology, and has gained relevance in recent years, this investigation should be explored in greater detail in future work, combining other technologies, such as Big Data and cyber-physical systems for real-time process data collection. Likewise, the model could be extended to use other multivariate statistical techniques to improve results, as could new simulation methods and recent innovative tools in six sigma.

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Appendix A

Author	Type of research	Sector	SD	SS	QLF	MSPC	Improved variability?	How much?	Improved financial returns?	How much?
Alexander et al. (2021)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Dagmar & Tarigan (2021)	Case study	Steel construction	No	Yes	No	No	SI	6,60%	No	N/A
Hardy et al. (2021)	Case study	Wood	No	Yes	No	No	No	N/A	No	N/A
Ketabforoush & Aziz (2021)	Case study	Construction	No	Yes	No	No	Si	The S/N ratio was improved by 15.62 dB.	No	N/A
Makwana & Patange (2021)	Literature Review	General	No	Yes	No	No	No	N/A	No	N/A
Qayyum et al. (2021)	Research	Smart city management	No	Yes	No	No	No	N/A	No	N/A
Abdallah (2020)	Case study	Logistic & e-commerce	No	Yes	No	No	No	N/A	No	N/A
Ahmed et al. (2020)	Investigación	Electric	Yes	Yes	No	No	No	No	No	No
Butt (2020)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Chinda et al. (2020)	Literature Review	Construction	Yes	No	No	No	No	N/A	No	N/A
Galli (2020)	Investigación	N/A	No	Yes	No	No	No	N/A	No	N/A
Kamath & Rodrigues (2020)	Case study	Prints, lithography	Yes	No	No	No	No	N/A	Yes	unit costs decrease by up to 50%
Lizarelli & Alliprandini (2020)	Case study	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Mona (2020)	Case study	Automotive	Yes	No	No	No	No	N/A	No	N/A
Palací-López et al. (2020)	Case study	Chemical	No	Yes	No	Si	No	N/A	No	N/A
Sá et al. (2020)	Research	N/A	No	Yes	No	No	No	N/A	No	N/A
Singh & Singh (2020)	Research	Manufacturing	No	Yes	No	No	No	NA	No	Na
Uluskan (2020)	Case study	Refrigerators	No	Yes	Si	No	No	N/A	Yes	N/A
Vinodh et al. (2020)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Yang et al. (2020)	Case study	Additive Manufacturing	No	Yes	No	No	Yes	No dice	Yes	N/A
Adane et al. (2019)	Case study	Automotive	Yes	No	No	No	No	N/A	Yes	Decrease of between 5% and 23% of unit cost depending on the scenario to be chosen
Ahmed et al. (2019)	Literature Review	General	Yes	Yes	No	No	No	No	No	No
Alglawe et al. (2019)	Case study	Automotive	Yes	No	No	No	No	N/A	Customer growth	N/A
Costa et al. (2019)	Research	Food	No	Yes	No	No	No	N/A	No	N/A
De Mattos et al. (2019)	Review	Oil & Gas	No	Yes	No	No	Yes	N/A	Yes	N/A
Elizondo-Noriega et al. (2019)	Research	Automotive	Yes	Yes	No	No	No	N/A	No	N/A

Author	Type of research	Sector	SD	SS	QLF	MSPC	Improved variability?	How much?	Improved financial returns?	How much?
Essawy et al. (2019)	Case study	Appliances	No	Yes	No	No	Yes	Defect rate reduced from 1.18% to 0.05%.	Reduced cost of defective parts and normal scrap metal costs.	12%
Irfani et al. (2019)	Research	Logistics/maritime transport	Yes	No	No	No	No	N/A	No	N/A
Kiatcharoenpol & Seeluang (2019)	Case study	Non-metallic minerals and plastics	No	Yes	No	No	Si	Reduction from 10.94% to 2.56% of deformation defects	No	N/A
Li et al. (2019)	Research	General	No	Yes	No	No	No	N/A	No	N/A
Mishra & Rane (2019)	Case study	Non-metallic minerals and plastics	No	Yes	No	No	Si	99%	No	N/A
Olafsdottir et al. (2019)	General study	Construction	Yes	No	No	No	No	N/A	SI	N/A
Oleghe & Salonitis (2019)	Case study	General	Yes	No	No	No	No	N/A	No	N/A
Sánchez-Rebull et al. (2020)	Research	Food	No	Yes	No	No	Si	Increase sigma level to 4.2	Yes	49,000 euros in savings per year.
Stadnicka & Litwin (2019)	Case study	Manufacturing	Yes	No	No	No	No	N/A	No	N/A
Segura et al. (2019)	Research	Manufacturing	Yes	No	No	No	No	No	No	No
Veena & Prabhushankar (2019)	Literature Review	Manufacturing	No	Yes	No	No	No	N/a	No	N/A
Vergara & López (2019)	Research	Graphic arts	No	Yes	No	No	Yes	Improved process capacity from 1.5 to 2.68	Yes	Savings of approximately $27,760,199 million pesos.
Vignesh et al. (2019)	Case study	Automotive	No	Yes	No	No	Yes	99%	No	N/A
Ridwan & Noche (2018)	Research	Port	Yes	Yes	No	No	Yes	Cpk can be dramatically increased by 39.71 and 39.56 percent.	Yes	COPQ can be reduced by 27.91%.
Saryazdi & Ghavidel (2018)	Case study	Wires and cable	Yes	No	No	No	No	N/A	Yes	N/A
Tokgöz et al. (2018)	Case study	Aircraft	Yes	No	No	No	No	N/A	No	N/A
Basios & Loucopoulos (2017)	Research	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Cardiel-Ortega et al. (2017)	Research	Textil	Yes	Yes	No	No	Yes	0,6	No	N/A
Dutta & Ashtekar (2017)	Case study	Metal Mechanic	Yes	No	No	No	No	N/A	No	N/A
Gallo et al. (2016)	Research and Literature Review	Supply chain and remanufacture	Yes	No	No	No	No	N/A	Yes	Sales increase by up to 100% in the scope of the simulation, but profits decrease by €90,000 due to product redesign costs.

Author	Type of research	Sector	SD	SS	QLF	MSPC	Improved variability?	How much?	Improved financial returns?	How much?
Naeem et al. (2016)	Research	Metal Mechanics	No	Yes	No	No	Yes	The sigma level of the manufacturing process is improved to 4.01 from 3.58	No	N/A
García et al. (2015)	Research	Metal Mechanics	No	Yes	No	No	Yes	Average surface roughness was reduced (<0.5 μm)	No	N/A
Colledani et al. (2014)	Conceptual	General	Yes	No	No	No	No	N/A	No	N/A
De Carvalho et al. (2014)	Case study	Automotive	No	Yes	No	No	Yes	69% of defects, sigma level from 2.06 to 3.32	Yes	89.000 US /month
Mishra & Sharma (2014)	Research	General	No	Yes	No	No	Yes	Nivel sigma de 1.71 a 2.38. DMPO de 422,000 a 198,250. % de defectos se redujo de 15.44% a 6.32%	No	N/A
Reosekar & Pohekar (2014)	Literature Review	General	No	Yes	No	No	No	N/A	No	N/A
Khataie & Bulgak (2013)	Case study	Manufacturing	Yes	No	No	No	No	N/A	Yes	N/A
Shanmugaraja et al. (2013)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Zhang et al. (2013)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Kim & Han (2012)	Case study	Construction	No	Yes	No	No	No	N/A	No	N/A
Senthilkumar et al. (2012)	Case study	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Kumar et al. (2011)	Case study	Supply chain	No	Yes	No	No	No	N/A	No	N/A
Sadraoui & Ghorbel (2011)	Case study	Furniture	No	Yes	No	No	No	N/A	No	N/A
Zuashkiani et al. (2011)	Literature Review	Manufacturing	Yes	No	No	No	No	N/A	Yes	N/A
Größler (2010)	Research	Manufacturing	Yes	No	No	No	No	N/A	Yes	Increase in total performance of approximately 33%.
Salah et al. (2010)	Literature Review	Manufacturing	No	Yes	No	No	No	N/A	No	N/A
Kumar & Sosnoski (2009)	Case study	Metal Mechanic	No	Yes	No	No	Yes	Reduction of mean deformation from 0.0043 to 0.0028	Yes	Savings of US$ 10562.6 per year
Vella et al. (2009)	Case study	Construction	No	Yes	No	No	No	N/A	No	N/A
Hilmola (2006)	Conceptual	Manufacturing	Yes	No	No	No	No	N/A	Yes	21.4% increase in earnings and 57% decrease in WIP
Rajamanoharan & Collier (2006)	Case study	Services	No	Yes	No	No	No	N/A	No	N/A
Rue (2006)	Case study	Nanoelectric Components	Yes	No	No	No	Yes	N/A	Yes	N/A
Tong et al. (2004)	Case study	Printed circuit boards	No	Yes	No	No	No	N/A	Yes	Nearly 40% reduction in cost of quality
Visawan & Tannock (2004)	Case study	Automotive	Yes	No	No	No	Yes	N/A	Yes	N/A
Jambekar (2000)	Conceptual	Manufacturing	Yes	No	No	No	No	N/A	No	N/A
Mandal et al. (1998)	Literature Review	Manufacturing	Yes	No	No	No	No	N/A	SI	No dice
Bennett & Kerr (1996)	Conceptual	Manufacturing and services	Yes	No	No	No	No	N/A	No	N/A

Notes: SD=System Dynamics, SS=Six Sigma, QLF=Quality Loss Function, MSCP: Multivariate Statistical Control Process