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Robustness of a Metal Finishing Process Using the Taguchi Method Following the Lean-Sigma Approach

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Abstract

The design of experiments technique and its variants are used in the industry to improve production processes. This article briefly demonstrates the usefulness of Taguchi's design of experiments in the manufacturing sector and combines it with a Lean-Sigma approach to solve quality problems. To evaluate the efficiency of the methodology, a metal-coating process was selected to reduce the variation caused by noise factors in the thickness of the coating layer. Similarly, the aim was to approximate the average thickness of the coating to the specifications required by the client. The complete system consists of an electrochemical process, in which the metal parts are subjected to changes in their chemical and physical properties. The process consists of ten steps: degreaser wash, rinse, deep wash, a second rinse, acid neutralization, rinsing, coating, rinsing, dipping in ink, and sealing. Employing the approach proposed in this research, the mean and variation in thickness were resolved over seven weeks, improving the CPK level of the process from an initial value of 0.2 to 2.5, representing a reduction from 20% rework to 0%.

Keywords
Lean Sigma, Taguchi, Sigma Level, Problem Solving

1. Introduction
Since the beginning of the 19th century, when economic, technological, and social transformations called the first Industrial Revolution ended, the manufacturing industry has been an essential part of the development and growth of many countries worldwide. Undoubtedly, the industrial revolution is a watershed for automated systems and mass production to begin to influence the generation of small and large-scale products (Mahla et al., 2022; Sanjeevannavar et al., 2022).

By the 19th century, industry was concerned with finding ways to produce in quantity, giving little or no importance to quality. This production lasted until the end of the 19th century when the first ideas focusing on quality improvement began to emerge (Heidari-Rarani et al., 2022). By the 1980s, a firm concept of quality in processes and services was already in place, and different certifications and quality evaluation methods began to emerge, as well as techniques dedicated to process optimization and improvement. Thus, it is necessary to qualify and quantify the quality of a product or service (Hisam et al., 2024).

According to Lokesh et al. (2022), a tool that allows for the improvement of both products and processes such that the goods produced are best suited to market demands is the design of experiments, the pioneer of which is Ronalld A. Fisher, a mathematician who first applied it to the agricultural sector in 1919 (Chen et al., 2022). An experiment is a test or trial; therefore, a design of experiments is a test or series of tests in which deliberate changes are induced in the input variables of a product or process, better known as controllable factors. Thus, it is possible to observe and identify the effects of these factors on the output variable, better known as the response variable (Priyanga & Muthadhi, 2023). The Taguchi method, developed by Dr. Genichi Taguchi, is a robust design of experiments approach for improving product quality and reducing manufacturing costs (Reddy et al., 2024). It uses orthogonal arrays to organize and test parameters that affect process performance efficiently, minimizing the number of experiments required (Amadane & Mounir, 2022). Initially applied in manufacturing, this method has been extended to other fields, including education, where it can improve classroom quality by identifying controllable factors and mitigating the effects of uncontrollable variables (Bai et al., 2022).

Taguchi's methodology has been instrumental in improving the quality of products and processes in various industries. His approach revolves mainly around robust design, which aims to minimize variation and improve performance through systematic experimentation (Patel et al., 2021). The applications of this method and the results are presented below.

A prominent case is the optimization of dye removal processes by electro-oxidation, as detailed by Hasanzadeh et al. (2023). Their study employed the Taguchi method to determine the optimal parameters for dye removal. Researchers can conduct a minimum number of experiments using an orthogonal array design while effectively identifying the significant factors influencing dye removal. This application underscores the method's ability to improve process efficiency and reduce experimental costs, a distinctive feature of Taguchi's approach.

Another significant application of this method is illustrated in the work of (Chen, Biswas, Ubando, et al., 2023), in which risk analysis was integrated with Taguchi's robust design principles to optimize design parameters in manufacturing. This case study demonstrates how the Taguchi method can systematically reduce the variation in design variables, thereby improving performance consistency. The authors highlighted that by employing orthogonal matrices, they could effectively explore multiple design parameters simultaneously, leading to near-optimal settings that improved both yield and profitability. This integration of risk analysis with Taguchi's techniques exemplifies the versatility of his methodologies in addressing complex manufacturing challenges.

Another compelling example was presented by Vates et al. (2021), who discussed the Taguchi method as a robust design tool in various manufacturing contexts. This study emphasizes the systematic application of the design of experiments to minimize expected losses and improve product quality. The Taguchi method facilitates a structured approach to quality improvement by identifying the optimal design parameters that are essential in competitive manufacturing environments. This case illustrates how Taguchi's principles can improve the product design and process reliability.

In summary, the Taguchi method is a powerful tool for optimizing processes and improving the quality of various applications. The reviewed cases highlight its effectiveness in reducing variation, minimizing costs, and improving the overall performance in manufacturing and other fields. On the other hand, this approach has not been employed, or there is at least no evidence that it is used with a focus on troubleshooting manufacturing processes and its effect on short-term sigma level variation.

The objective of this research is to demonstrate the usefulness of Dr. Taguchi's experimental design in the manufacturing sector and combine it with a lean–sigma approach to solve the problem in a short period by determining the effect on the variation of sigma levels in the short term, demonstrating the effectiveness of the literature in terms of improving quality performance. For this purpose, a metal coating process is selected, which attempts to reduce the variation caused by noise factors in the thickness of the coating layer. Similarly, the aim was to approximate the average coating thickness to the required specifications. The complete system consists of an electrochemical process in which the metal parts are subjected to changes in their chemical and physical properties. The process consists of ten steps: degreaser wash, rinse, deep wash, a second rinse, acid neutralization, rinsing, coating, rinsing, rinsing, dipping in ink, and sealing.

Following this introduction, section two includes the methodology of this research. Section three discusses the results, section four presents the conclusions and section five presents some limitations and future research.

2. Methodology

The proposed methodology is based on Dr. Genichi Taguchi's robust experiment design using a Lean-Sigma approach. Table 1 shows a block diagram of the steps of this methodology, which aims to reduce the variation in the response variable and approximate it to its target value, taking into consideration the noise factors that influence the process.

Table 1. Phases and steps of the proposed methodology

Identify and Measure the Problem	**Root Cause Analysis**	**Develop a solution**	**Verify Solution**	**Control Plan**
1. Define the variable	3. Identify noise factors	5. Experimentation and data collection	7. Confirmation run	8. Documentation of results
2. Define the ideal function	4. Identify controllable factors	6. Data analysis		

2.1. Define the variable

As part of the proposed methodology's first step, quality and scrap reports are reviewed to determine which is the main contributor negatively impacting quality. Following the recommendations of Chen, Biswas, Kwon, et al. (2023), the process characteristic that compromises safety, quality and deliveries is prioritized as inclusion criteria. Preferably, it is a feature that is critical to the part's functionality and reduces its reliability and part lifetime (Prabhu et al., 2024). Wheeler et al. (2018) stated that a control chart or a process capability analysis can be used to estimate the process dppm's levels.

2.2. Defining the ideal function

Once the response variable is identified, engineering or customer drawings are consulted, as well as all the necessary documentation, such as the Bill of Materials (BOM), quotations, and standards. Information was obtained on the target value, low limit, high limit, units, and cost per piece.

2.3. Identify noise factors

Based on the experience of the work team of mechanical, electrical, quality, and manufacturing designers in similar processes, the factors that affect the response variable and cannot be controlled or not desired to be controlled due to high cost to control during the production process.

During this step, it is suggested to convene a brainstorming session with all those involved in different processes and at different levels (technician, engineer, superintendent, etc.), which suggests that everyone provides at least one noise factor that they consider to affect the process and records it; at the end, a nominal group technique method is performed, which consists of everyone giving a weighting to three factors, and at the end select the ones with the highest score. According to Elumalai et al. (2022), at least one factor with 3 levels should be selected as a noise factor. Also, it is important to analyze the historical information available and do a Gemba walk to the process to gather information and confirm the noise factors do really affect the response variable.

2.4. Identify controllable factors

In this step, the considerations of the process engineering team and the experience of the operating personnel are considered as a basis to select the factors and levels that most affect the response variable in the search for the target value. As mentioned in the previous step, it is necessary to brainstorm with the entire team to provide information that includes different viewpoints. Once brainstorming was performed, the factors were weighted to select those with the highest score. According to Engler et al. (2024), selecting at least three controllable factors at two levels is suggested for realizing a robust design using Dr. Taguchi's approach. Historical reports could support ensuring that the controllable factors have an effect over the response variable.

2.5. Experimentation and data collection

Following Taguchi's approach, the internal and external matrices are generated using the controllable factors and noise factors identified in the previous step. Table 2 lists the experimental matrix used for data collection.

Table 2. Experimental matrix using Dr. Taguchi's approach

					Noise Factor 1	**External Matrix**			
					Noise Factor 2				
					...				
Run Number	**Processing Time**	**Sealing Time**	**Powder Mixture**	**Powder Temperature**	**Noise Factor N**		**S/N**	**StDev**	**Mean**
1	**Internal Matrix**					**Data**			
2									
3									
4									
5									
6									
7									
8									

2.6. Data analysis

The S/N column of Table 2, Signal/Noise, represents the ability of each combination of controllable factor levels to mitigate the effects of noise factors on the response variable, measured in decibels. The data obtained from the experimental run were analyzed using Formulas 1a and 1b to generate the S/N column in Table 2.
The StDev column in Table 2 lists the standard deviation of the data obtained in each experimental run. Similarly, the Mean column records the mean of each combination of controllable factor levels.

$$\frac{S}{N} = -10Log_{10}\left(\frac{\sum_{j=1}^{n}\frac{1}{Y_{ij}^{2}}}{n}\right) \qquad \text{Bigger is better} \qquad (1a)$$

$$\frac{S}{N} = 10Log_{10}\left(\frac{\bar{y}^{2}}{s^{2}}\right) \qquad \text{Nominal is better} \qquad (1b)$$

The levels of each controllable factor are selected according to the purpose of the application. To increase the S/N ratio, the levels of factors with the highest S/N ratio were selected. If the aim was to decrease the standard deviation, the levels of the factors with the lowest standard deviations were selected. Finally, if the purpose is to approximate the response variable to a target value, the levels of the factors closest to that target value are selected.

2.7. Confirmation run

With the controllable factors operating at the levels selected by the data analysis, a random number of test specimens was generated for a confirmation run. During the confirmation run, variations in the levels of the noise factors were applied to corroborate that the selected levels of the controllable factors are robust to the effects of the controllable factors on the response variable.

Considering the error to be detected, the number of specimens for the confirmation run was obtained using Equation 3 based on the standard deviation calculated using Equation 2.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n-1}} \qquad (2)$$

Where:
$\bar{x} = Media\ de\ los\ datos$
$\sigma = Desviación\ Estándar$
$n =$ Número de probetas temporal

$$N = \left(\frac{Z_{\frac{\alpha}{2}} * \sigma}{e}\right)^2 \qquad (3)$$

Where:

$N = Número\ de\ probetas$
$Z_{\frac{\alpha}{2}} = Abscisa\ de\ la\ curva\ normal$
$\sigma = Desviación\ Estándar$
$e = Error\ máximo\ permitido$
If the number of samples was less than the number of specimens in the confirmation run, it was considered a reliable sample for statistical calculations and hypothesis testing.

2.8. Documentation of results

Once the factors and levels are identified and validated through the confirmation run, the work team document the information updating all the documentation including: the process sheets, including the recommended levels, work instructions, and process control plans, PFMEA if applicable, etc.

3. Results and Discussion

3.1. Identify the response variable

The team met in a brainstorming session with the participation of quality, engineering, maintenance, production, and management personnel to identify the response variable for the problem's solution, using historical quality, planning and production reports. During previous weeks, high levels of rework have been reported due to insufficient thickness in the metal parts, and previous reports indicated an approximate rework of 30% of the parts, resulting mainly over resources applied to the process, negatively impacting the cost; on the other hand, deliveries to sister plants were delayed, causing line stoppages.

After exhaustive analysis and considering the safety and quality considerations made by the team, the decision was made to use the thickness of the paint applied to the metal as the response variable for this project, this based on the experience of the work team but mostly based on the quality reports and complaints received recently. Once the response variable was identified, measurements were taken to observe the behavior and estimate the size of the problem. For this, we used the reports of the quality inspectors, which contain measurements of the thickness made with a properly calibrated device, taking a total sample of 30 days, taking 10 daily measurements, following the recommendation of the current literature to use at least 30 data points and use subgroups to approximate the data to a normal distribution, following the central limit theorem.

Figure 1 shows a capability analysis of the data, where it can be observed that the data are totally biased towards the lower limit, having several measurements outside the customer's specification. It is important to mention that the CPK and CPM metrics are outside the minimum recommended values according to international standards, where it is recommended to have at least a CPK value of 2 for critical products of the automotive industry.

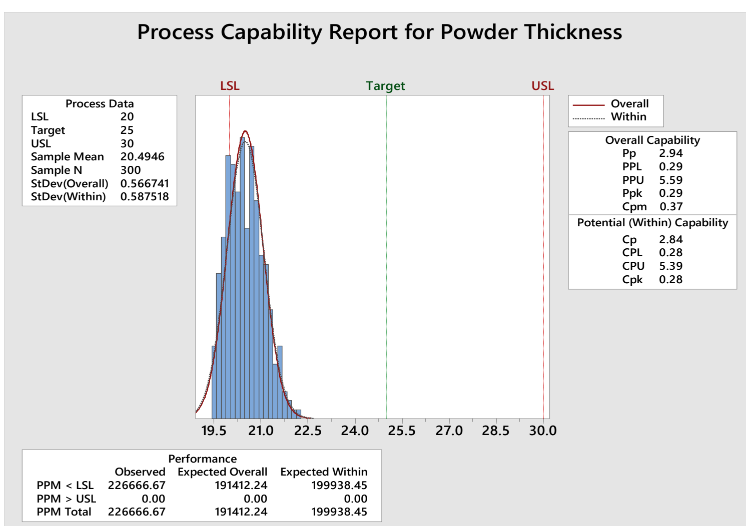

Figure 1. CPK analysis of the data under initial conditions

3.2. Defining the ideal function
Once the response variable is identified, the drawings and standards are reviewed to identify the product specifications, and the data are recorded in Table 3.

Table 3. Response variable specifications

Response Variable	Target Value	Low Limit	High Limit	Units	Cost per piece
Paint Coat Thickness	25	20	30	Microns	2.88 dlls

3.3. Identify noise factors
The team gathered members of the product and process design team to determine which noise factors were integrated into the design of experiments. After a brainstorming session and consensus, it was determined that the most influential factor was the temperature. Noise is considered because it is not desirable to control the temperature during the production runs because it increases the time of model change, directly affecting the efficiency of the process; therefore, it is desirable to determine the combination of factors that make the process robust. Table 4 lists the tempered noise factor and three selected levels.

Table 4. Noise factor and its levels

Noise Factors	Levels		
	Level 1	Level 2	Level 3
Temperature	40 C	60 C	80 C

3.4. Identify controllable factors
With the help of production, quality, group leader, maintenance, and manufacturing personnel, the setup process sheets were analyzed to determine the controllable factors and their respective levels that most influence the response variable, in this case, the paint thickness. After a lengthy brainstorming session, the team determined that only four of the 12 parameters had a considerable influence on the response variable. Table 5 lists these factors and their respective levels.

Table 5. Controllable factors and their respective levels.

Controllable Factors	Level 1	Level 2
Processing Time	5 min	10 min
Sealing Time	1 min	10 min
Powder Blend	25%/75%	35%/65%
Dust Temperature	15 C	23 C

3.5. Experimentation and data collection
With the controllable and noise factors identified and selected, the orthogonal matrix was constructed using the Minitab software, and an L8 orthogonal array consisting of eight runs was used, as shown in Table 6. Subsequently, the production time was requested to plan for the execution of the experiment, and the data were collected and recorded, as shown in Table 6. The corresponding calculations were performed and recorded in the same table using the S/N, standard deviation, and average formulas.

Table 6. Orthogonal Matrix L8

Run Number	Processing Time	Sealing Time	Powder Mixture	Powder Temp.	Noise Factor Temp.	Noise 1 40 C	Noise 2 60 C	Noise 3 80 C	S/N	StDev	Mean
1	5	1	25	15		21	25.8	21	18.23	2.77	22.6
2	5	1	35	23		28.8	21.6	25.2	16.9	3.6	25.2
3	5	10	25	23		29.4	22.8	18.5	12.65	5.49	23.57
4	5	10	35	15		21.6	25.2	22.2	21.53	1.93	23
5	10	1	25	23		27	21.6	14.8	10.77	6.11	21.13
6	10	1	35	15		33.4	33.1	30	24.65	1.88	32.17
7	10	10	25	15		32.5	29.4	36.2	19.65	3.4	32.7
8	10	10	35	23		28.5	14.2	20.4	9.5	7.02	20.93

3.6. Data analysis

The team decided that the objective of the experimental design was to center the process, that is, to bring the average of the response variable closer to the target value of 25 established in the client's specification. Therefore, using the Minitab software, the standard deviations were calculated for each level of each controllable factor; the results are presented in Table 7, please note that using the Taguchi's approach, the values in yellow are the lowest values since the minimization of standard deviation was chosen, thus the values in yellow would be the level for each of the factors that most contribute to reduce the standard deviation.

Table 7. Standard deviations of the levels of each factor.

Answer: Standard Deviation				
Level	**Processing Time**	**Sealing Time**	**Powder Blend**	**Dust Temperature**
1	3.448	3.592	4.445	2.497
2	4.604	4.46	3.607	5.555

Once the standard deviations were calculated and the objective was to approach the nominal value of the specification, Taguchi's method was used. This method established that the level of each factor with the lowest standard deviation should be selected. The levels selected based on this recommendation are listed in Table 8.

Table 8. Selection of recommended levels for controllable factors.

Controllable Factors	**Level**
Processing Time	5 min
Sealing Time	1 min
Powder Blend	35%/65%
Dust Temperature	15 C

3.7. Confirmation run

After selecting the controllable factors, a confirmation run was performed, which consisted of the following steps. First, the recommended levels were placed in the manufacturing process, and then an initial run of ten parts was performed, during which changes were made to the noise factor to ensure that the recommended levels were not affected when the noise factor was present. Once the parts were produced, five measurements were taken for each part and the average paint layer was calculated.

Next, sample size calculation was performed to demonstrate that 10 was statistically sufficient. The sample size is seven, which is less than the number of samples collected, so it is concluded that the number of samples is sufficient. We continued collecting data and recalculating CPK and CPM. Figure 2 shows the comparison of before and after, where it can be seen that the process moves from the lower limit to the nominal specification; on the other hand, CPK increases from 0.281 to 2.550. This means that with the levels of the proposed controllable factors, it is possible to reduce the rework and have a focused process with zero parts per million defects in the long term.

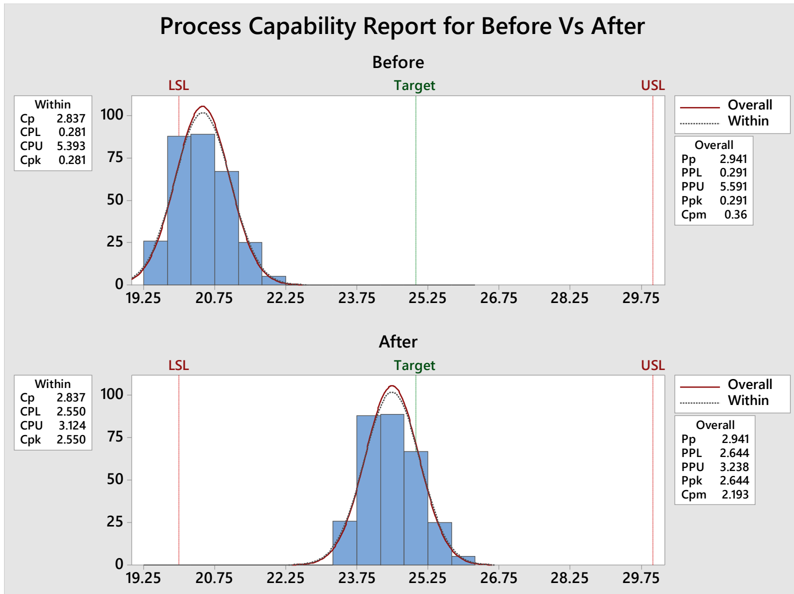

Figure 2. Comparison of CPK levels before and after treatment.

3.8. Documentation of results

Finally, the control plan documents, and parameter sheets were updated, and the optimum operating levels were published, as listed in Table 8. Additionally, kaizen events were scheduled to train personnel for various shifts, and control charts were implemented to monitor the response variable.

Table 8. Recommended levels of controllable factors

Controllable Factors	Recommended Operating Level
Processing Time	5 min
Sealing Time	1 min
Powder Blend	35%/65%
Dust Temperature	15 C

4. Conclusion

During the last few decades, one of the main problems faced by the manufacturing industry is the increase in rework, adding activities that do not add value, and the only thing they do is to increase manufacturing costs and also have repercussions in the failure to deliver on time. This is caused by variations in manufacturing processes owing to noise factors. For this purpose, companies have opted to use the design of experiments to reduce process variation. However, there are several techniques; the method proposed by Dr. Taguchi has proved to be effective in strengthening processes to noise factors that cannot be controlled or do not want to control because of the implications of doing so. However, the traditional approach of these methods is oriented towards the medium term, causing the company to continue losing and increasing its costs for months. Therefore, in this work, we propose the use of Dr. Taguchi's method with a lean sigma approach, which implies orienting it to the solution of short-term problems. This allows solving the problem in a matter of weeks, providing results at lean speed without leaving aside the primary objective, which is to reduce the variation in the processes.

Evidence shows that the powder metal coating process, the case used for this application, produces defective parts that are outside the specification limits. Having initially a CPK of 0.281, which implies approximately 200,000 parts per million defects, by identifying the controllable and noise factors, the team employs a Robust Design proposed by Dr.

Taguchi, in which, using an L8 orthogonal array, it is possible to reduce the variation and focus the process, increasing the CPK to a value of 2.550, having as a final resulting in zero parts per million defects. These results are achieved in seven weeks, as opposed to the traditional approach, which takes approximately six months or more.

The novelty and scientific contribution of this research is the combination of the Taguchi Method and the Lean Sigma approach which is focused on problem solving in a short period of time. Literature reports the use of Taguchi method based on the traditional method which takes months to complete, having an increase of wastage thus cost increases due to scrap and reworks. The case study shows that in a period of 4 weeks the problem was solved, having a positive impact on delivery time and quality levels. The cost reduction comparison in both approaches is around $900,000, taking into consideration the solution of the problem from 8 months in the traditional approach compared to 4 weeks with the proposed approach. It can be noted that the Lean Sigma approach has a direct and positive impact on the economic sustainability of the manufacturing industry.

Therefore, it can be concluded that the lean sigma approach has proven to be a positive contribution to companies since the results are in a matter of weeks. This allows deliveries to be met on time, quality levels, and costs. It also has a positive environmental impact by reducing the use of chemicals during rework or the disposal of metal parts contaminated with chemicals.

5. Limitations and Future Research

Some of the limitations and implications of the proposed method are that historical information on the response variable must be available, dependable, and can be validated. Otherwise, it would imply an increase in the time required to provide a solution by a matter of weeks. However, it is necessary to have accurate and calibrated equipment to avoid measurement errors during the initial data collection. Another limitation of this approach is that continuous improvement projects as the proposed in this research is a must that are leaded by a black belt at least, because quality and engineering tools knowledge is needed to guide the team throughout the entire process of the project, also it is important to involve the operational into the work team to ensure they provide ideas, the people that operate the machine or the process have more knowledge and in most of the times they have better ideas that could contribute positively to improve or solve the problem.

This approach can be applied to any manufacturing sector around the world, the literature shows evidence how the Taguchi method can be used in sectors such as: automotive, medical, electronics, powder coating, metals and molding.

For future research, it is recommended to investigate Dr. Taguchi's method and the effect that the measurement system has on the reduction of variation in the short and long term since the current research work is concluding based on the short-term sigma level and not in the long term, which theoretically according to Mikel Harry is 1.5 sigmas, it is necessary to confirm that the improvement obtained is maintained in the long term instead of assuming the current theoretical value.

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Biographies

Omar Celis Gracia received the BS and master's degrees in industrial engineering from the Universidad Autonoma of Ciudad Juarez, Mexico, in 2014 and 2016, respectively. He is a full-time doctoral student at the Advanced Engineering Sciences Program at the Universidad Autónoma of Ciudad Juarez, Mexico. Omar works as a Quality and Continuous Improvement Superintendent at Keytronic with over 10 years of demonstrated experience in the electronic and metal industry. He is also a graduate teacher at the Instituto Superior Lymer, with eight years of experience. His main research areas are related to improving key performance indicators in the maquiladora industry using the Lean Six Sigma approach.

Fabiola Hermosillo Villalobos received a master's degree in industrial engineering from the Universidad Autonoma de Ciudad Juarez, Mexico, in 2017. She is a full-time advanced engineering science doctoral student at the Universidad Autonoma de Ciudad Juarez. Fabiola works as a Manufacturing Engineer in Keytronic, with over five years of experience. Her research areas include lean manufacturing and simulations to improve manufacturing processes.

Jorge Luis García Alcaraz is a full-time researcher at the Department of Industrial Engineering at the Universidad Autónoma de Ciudad Juárez. He received an MSc in Industrial Engineering from the Instituto Tecnológico de Colima (Mexico), a Ph.D. in Industrial Engineering from Instituto Tecnológico de Ciudad Juárez (Mexico), a Ph.D. in Innovation in Product Engineering and Industrial Process from University of La Rioja (Spain), a Ph.D. in Sciences and Industrial Technologies from the Public University of Navarre (Spain), a Ph.D. in Mechanical Engineering from University of Zaragoza (Spain) and a Postdoc in Manufacturing Process from University of La Rioja (Spain). His main research areas are multi-criteria decision making and techniques applied to lean manufacturing, production processes, and supply chain modeling. He is a founding member of the Mexican Society of Operational Research and an active Mexican Academy of Industrial Engineering member. He is a national researcher recognized by the National Council of Science and Technology of Mexico (CONACYT) as Level III.

Francisco Javier Estrada Orantes is a professor of Quality Engineering, Lean Manufacturing, and Applied Statistics at Universidad Autonoma de Ciudad Juarez. He is also the director of the E-FACTOR GROUP, a consulting firm based in El Paso, TX. He supported industrial organizations in quality and manufacturing systems in the southwest region. Dr. Estrada earned a BS degree in Industrial and Chemical Engineering from the Instituto Tecnologico de Durango, a master's degree in Industrial Engineering, and a Ph.D. in Engineering and Environmental Science from The University of Texas at El Paso. He is currently an active senior member of the ASQ and IISE.