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Integrating SMED and Industry 4.0 to optimize processes with plithogenic n-SuperHyperGraphs

Julio Cesar Méndez Bravo [1], Claudia Jeaneth Bolanos Piedrahita [2], Manuel Alberto Méndez Bravo [3], and Luis Manuel Pilacuan-Bonete [4]

[1] University of Guayaquil, Ecuador. julio.mendezb@ug.edu.ec
[2] University of Guayaquil, Ecuador. claudia.bolanosp@ug.edu.ec
[3] University of Guayaquil, Ecuador. manuel.mendezb@ug.edu.ec
[4] University of Guayaquil, Ecuador. luis.pilacuanb@ug.edu.ec

Abstrac. This article addresses the challenge of inefficient changeover processes in the Ecuadorian electronics industry by integrating the SMED methodology with selected Industry 4.0 technologies. Employing plithogenic n-SuperHyperGraphs and log-linear models, the research demonstrates that this integration significantly reduces changeover times, achieving up to a 68% decrease in complex lines. Key findings indicate synergistic effects between SMED and technologies like IoT and data analytics, improving standardization and adjustments, while augmented reality enhances post-changeover quality. The study contributes theoretically by applying a novel mathematical modeling approach to complex industrial systems and offers a practical, scalable solution for modernization in Ecuador and other emerging economies.

Keywords: SMED, Industry 4.0, N- Plithogenic Superhypergraphs, Optimization, Standardization, Efficiency, Manufacturing

1. Introduction

In a globalized manufacturing environment, enhanced production efficiency has become a necessary pillar of industrial competitiveness. Exploring the feasibility of the SMED methodology with Industry 4.0 through plithogenic n-SuperHyperGraphs will create a scheme to map interconnectivity in Ecuador's electronics manufacturing plants [1]. The contribution to the field is that it will facilitate waste reduction, minimize production delays, and encourage flexible manufacturing. This is necessary for the Ecuadorian situation where the manufacturing plant needs to upgrade its production systems yet lacks digital efforts to facilitate successful intrafactory operations needed when intralocal production is needed to improve a fluctuating economic environment. The expected integration with the SMED methodology, the SMED tools, IoT, and analytics will result in transformative machining for sustainable efficient operations [2].

In recent decades, there have been some milestones in the evolution of production systems. For example, after Lean Manufacturing was discovered by Toyota in the post-WWII period, there came the SMED philosophy, created by Shigeo Shingo, to reduce changeover times on the production line. After the SMED philosophy came the Fourth Industrial Revolution, an industrial revolution of digitized and connected systems where industries apply technology like sensors and Big Data to create increased levels of productivity [3]. Unfortunately, Ecuadorian industry has yet to catch up. They have yet to implement such developments due to a lack of infrastructure and technical training. Thus, after understanding the complications, it seems like an integration of the two would work best for a hybridized version of Lean and digitization.

Ecuadorian industry has problems with changeover processes. Long changeover times, inconsistent changes, and human adjustments create unnecessary waste and increased operational costs. In the meantime, while I4.0 technologies could solve such issues, the integration with SMED or other time-tested approaches is still in development stages, especially in unpredictable environments [4]. The second goal of the study is to assess whether an SMED-I4.0 approach, coupled with advanced mathematical modeling, can help the Ecuadorian industrial sector facilitate its changeover processes. Thus, the problem is posed theoretically but not practically feasible.

The severity of the problem is staggering—and it's prevalent within the Ecuadorian electronics industry. Productive flexibility is needed, but machines, processes, and human efforts possess fixed mentalities. Changeover takes too long, rendering production lines non-competitive; the average changeover is 90 minutes per line [5-6]. This means more expenses and fewer adjustments in operating fluctuating markets. Moreover, no company possesses a decision-making model for uncertainty with multivariable relationships. Thus, companies either guess or do not respond.

There is research regarding SMED and I4.0; however, very few applications have been made concerning these two techniques within Ecuador and similar developing nations. For example, SMED can reduce changeover times by 70%, as applied in the automotive industry. I4.0 can improve efficiency via real-time shift data collection [7]. However, no one has applied both concurrently in an electronics manufacturing setting—let alone without ease of use, mathematical non-invasive tools like plithogenic n-SuperHyperGraphs. This groundbreaking approach effectively creates decision-making models under uncertainty for all variability across all manufacturing industries [8].

The literature reviewed shows that the Ecuadorian manufacturing situation, specifically coming from Guayaquil and Quito, creates a welcomed relevant gap as governmental actions encourage innovative digitalization, and despite not all businesses exploring the technological route, many have already. This research fills these gaps in understanding by corresponding to the criteria of sustainable industrial development. Therefore, by integrating SMED and I4.0, this project aims not only to enhance production efficiencies but also to render Ecuador a model for the rest of the world for what smart manufacturing should be.

The research question developed for the study based on the above guidance is as follows: How can Ecuadorian manufacturing format changeovers be optimized through SMED, I4.0, and plithogenic n-SuperHyperGraphs integration [9]? This question is relevant to the local situation with attempts to find solutions, although it does note that industrial changeovers do not present as static. The objectives of this study are to assess whether the integration is effective based on relevant changeover scenarios, to note what is learned from the study in terms of potential ease/challenges to success, and to ultimately provide a recommendation of the model for practicality in a local situation.

The purpose of answering the research question occurs through these objectives: 1) to evaluate the reduction in changeover time due to concurrently applying SMED and I4.0 technologies; 2) to visualize the interdependence of changeover and other production variables through plithogenic n-SuperHyperGraphs; 3) to recommend implementation of this research in the electronics sector of Ecuador. Thus, the findings not only fulfill the purpose of answering the research question but also contribute to theoretical justification and real-world implementation within Ecuadorian industries.

2. Preliminaries

This section contains two subsections, the first one is dedicated to explaining the basic notions of the n-Plithogenic SuperHyperGraphs defined in [10]. Then, subsection 2.2 contains the main concepts of multiway contingency tables and the log-linear method.

2.1 n- Plitogenic superhypergraphs

n- SuperHyperGraphs were defined by Smarandache in the field of decision making in [11-15].
First, an n- SuperHyperGraph is defined as follows [16]:

Given $V = \{V_1, V_2, \cdots, V_m\}$, where $1 \leq m \leq \infty$ is a set of vertices, containing *simple vertices* that are classical, *indeterminate vertices* that are unclear, vague, partially known, and *null vertices* that are empty or completely unknown.

$P(V)$ is the power set of V including $\emptyset$. $P^n(V)$ is the n-potential set of V, which is defined recursively as follows:

$P^1(V) = P(V)$, $P^2(V) = P(P(V))$, $P^3(V) = P(P^2(V))$, … , $P^n(V) = P(P^{n-1}(V))$, for $1 \leq n \leq \infty$. Where is also defined as $P^0(V) = V$.

An n- SuperHyperGraph (*n -SHG*) is an ordered pair $n - SHG = (G_n, E_n)$, where $G_n \subseteq P^n(V)$ and $E_n \subseteq P^n(V)$, for $1 \leq n \leq \infty$. Such that, G_n is the set of vertices and E_n is the set of edges.

G_n contains all possible types of vertices as in the real world:

- *Simple vertices* (the classic ones),
- *Indeterminate vertices* (unclear, vague, partially known),
- *Null vertices* (empty, completely unknown),
- *SuperVertex* (or *SubsetVertex*) contains two or more vertices of the above types grouped together (organization).
- *n- SuperVertex* which is a collection of vertices, where at least one of them is an *(n-1)- SuperVertex* , and the others can be *r- SuperVertex* for $r \leq$ n.

E_n contains the following types of borders:

- *Simple edges* (the classic ones),
- *Indeterminate borders* (unclear, vague, partially known),
- *Null edges* (totally unknown, empty),
- *HyperEdge* (connecting three or more individual vertices),
- *SuperEdge* (connecting two vertices, at least one of them is a SuperVertex),
- *n- SuperEdge* (connecting two vertices, at least one of which is an n- SuperVertex and may contain another which is an r- SuperVertex with $r \leq$ n).
- *SuperHyperEdge* (connects three or more vertices, where at least one of them is a SuperVertex),
- *n- SuperHyperEdge* (contains three or more vertices, at least one of which is an n- SuperVertex and may contain an r- SuperVertex with $r \leq$ n),
- *MultiEdge* (two or more edges connecting the same two vertices),
- *Loop* (an edge that connects an element to itself),

The graphics are classified as follows:

- Graph directed (the classic),
- Undirected graph (the classic one),
- Neutrosophic directed graph (partially directed, partially undirected, partially directed indeterminate).

Within the framework of the theory of n- Plithogenic SuperHyperGraphs , we have the following concepts [17]:

Enclosing vertex: A vertex that represents an object comprising attributes and sub-attributes in the graphical representation of a multi-attribute decision-making environment.

Super-envelope vertex: A wraparound vertex is composed of SuperHyperEdges.

Dominant enclosing vertex: An enclosing vertex that has dominant attribute values.

Dominant superenvelope vertex: A superenvelope vertex with dominant attribute values.

The dominant enclosing vertex is classified into *input, intervention* and *exit* according to the nature of the representation of the object.

Plithogenic connectors: Connectors associate the input envelope vertex with the output envelope vertex. These connectors associate the effects of input attributes with those of output attributes and are weighted according to the plithogenic weights.

2.2 Multi-way contingency tables

Multivariate contingency table is a contingency table defined for two or more cross-ratio classification variables. Two-dimensional tables are usually referred to as contingency tables, while the term multivariate is applied when the number of variables is at least three [18].

A *generic multivariate table* is defined using $I = I_1 \times I_2 \cdots \times I_q$ as the set of indices for each variable to be studied $X_1, X_2, \cdots, X_q$, such that I_j is the set of indices corresponding to the possible classifications of the variable j . Therefore, $n_{i_1 i_2 \cdots i_q}$ is the frequency of occurrence of the classifications $i_1, i_2, \cdots, i_q$ for each of the corresponding variables.

Partial/conditional tables involve fixing the category of one of the variables. Fixed variables are indicated in parentheses. For example, partial tables XZ and YZ are indicated by $n_{i(j)k}$ and $n_{(i)jk}$, respectively. Furthermore, the *partial/conditional probabilities* are calculated by $\pi_{ij(k)} = \pi_{ij/k} = Prob(X = i, Y = j/Z = k)$. *The partial/conditional proportions* are defined by $p_{ij(k)} = p_{ij/k} = \frac{\pi_{ijk}}{\pi_{++k}}$ for $k = 1, 2, \dots, K$. Where π_{++k} is the frequency i and j configuration k, for more information see [19].

Next, we briefly explain what log-linear models consist of. To simplify the exposition, we consider the case of the three-way contingency table. If X, Y, and Z are the variables, then the following possible models are obtained [20]:

- Model (X, Y, Z): All variables are considered independent, the model is as follows: $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z$(1)
- Model (X, YZ): Only the YZ association is considered, while X is independent of the other two variables.
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{jk}^{YZ}$ (2)
- Model (XY, YZ): X and Z are independent for each value of Y:
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{jk}^{YZ}$ (3)
- Model (XY, YZ, XZ): There is a pairwise association between all variables, but there is no joint association between the three.
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ}$ (4)
- Model (XYZ): If the above model does not fit the data well, then the association between the three variables should be considered:
  $\ln F_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ}$ (5)

To compare two different models, the statistic called *likelihood ratio is used*, which is calculated as:

$$G^2 = 2\sum f ln(f/F) \quad (6)$$

Where f is the observed frequency, and F is the expected frequency based on the model. This statistic is distributed according to a chi -square test under the hypothesis that the model is correct, with degrees of freedom depending on the parameters used to fit the model.

To compare two models, simply subtract their respective G^2 or, in another case, among others, the *Bayesian Information Criterion* is used with the formula:

$BIC = G^2 - \mathrm{df} \log \mathrm{N}$(7)

Where df denotes the degree of freedom and N is the total number of cases in the sample.

3. Material and Methods

This study analyzes the integrated implementation of the Single-Minute Exchange of Die (SMED) methodology and Industry 4.0 technologies for optimizing format changeover processes in an electronics manufacturing plant. The research uses plithogenic n- SuperHyperGraphs as a mathematical tool to model and analyze the complex interrelationships between the different elements of the production system, the implemented technologies, and the performance indicators.

Data collection instruments

Three instruments validated by experts were used for data collection:

SMED Process Assessment (SPA) The SMED Process Assessment (SPA) instrument, developed by Nakajima et al. in 2002 [21], identifies and classifies activities during format changes in internal and external operations. It consists of a checklist with 20 direct observation items that evaluate times, movements, and procedures. Each item is scored from 0 to 5, where 0 indicates a complete absence of the aspect evaluated and 5 indicates optimal implementation. The maximum score is 100, with values above 75 considered effective implementation.

Technology Maturity Index I4.0 (IMT-I4.0) The Technology Maturity Index for Industry 4.0, developed by Fraunhofer Institute [22], assesses the level of adoption and integration of key Industry 4.0 technologies. The questionnaire consists of 30 questions spread across six dimensions: connectivity, data analysis, horizontal and vertical integration, automation, cybersecurity, and digital skills. Each dimension is scored from 1 to 5, with 1 being basic and 5 being advanced. The final score determines the level of digital maturity: Level 1 (Basic: <2), Level 2 (Intermediate: 2-3.5), Level 3 (Advanced: >3.5).

The Operational Performance Indicators (IRO) Measurement system based on the principles of OEE (Overall Equipment Effectiveness) evaluates the efficiency, availability, and quality of the production process. It includes specific measurements for changeover times, defect rates associated with the changeover, and post-changeover process stabilization. Data is automatically collected using IoT sensors connected to equipment and MES (Manufacturing) systems. Execution System). The indicators are normalized on a scale of 0 to 100, with 100 being optimal performance.

Location of the study

The research was conducted at two manufacturing plants of ElectroTech SA: the main plant located in the North Industrial Park of Querétaro, Mexico, and the secondary plant located in the Industrial Corridor of Guanajuato, Mexico. While this study was conducted in manufacturing plants in Mexico, the findings are highly relevant and applicable to the context of the Ecuadorian electronics industry. It serves as a valuable case study that provides a tested methodology and demonstrates potential benefits (such as reduced changeover time and improved quality) that can inform and guide similar initiatives in Ecuador. The shared characteristics of industrial challenges and the push for technological adoption in both contexts support the transferability of the knowledge gained from this research.

Population and sample

The study population consisted of 45 production lines, of which 24 completed the 16-week implementation period with pre- and post-intervention evaluations. The remaining 21 lines were excluded for not completing the technological implementations within the established timeframe or for not having complete data from the final evaluations. A 95% confidence level was obtained, with a 4.2% margin of error in production lines with integrated SMED and Industry 4.0 systems.

Inclusion and exclusion criteria

Inclusion criteria:

- Production lines with more than 2 years of operation
- Lines that make at least 5 format changes per week
- Lines with OEE system implemented
- Lines with basic connectivity for IoT implementation
- Lines with standardized format change processes

Exclusion criteria:

- Production lines in the testing or start-up phase
- Lines with parallel improvement projects that could interfere with the study
- Lines with major maintenance schedule during the study period
- Lines with security restrictions for technological implementation

Analysis using n- Plithogenic SuperHyperGraphs

The input object (V) in this study is the Production Lines, which are understood to be the lines selected to study the effectiveness of SMED-I4.0 integration. The Dominant Enveloping Vertex in this problem is related to the following attributes and sub-attributes:

V_1 = Line characteristics, V_2 = SMED implementation , V_3 = I4.0 implementation , V_4 = Performance indicators

Attribute sets = {Line characteristics, SMED implementation, I4.0 implementation, Performance indicators}

Line characteristics = {Product type (V_{11}), Setup complexity (V_{12}), Production volume (V_{13})}

SMED Implementation = {Internal Operations (V_{21}), External Operations (V_{22}), Standardization (V_{23}), Adjustment Elimination (V_{24})}

I4.0 Implementation = {IoT (V_{31}), Data Analytics (V_{32}), Augmented Reality (V_{33}), Cyber-Physical Systems (V_{34})}

Performance indicators = {Setup time (V_{41}), Stability (V_{42}), First batch quality (V_{43})}

Product Type = {Complex Components (V_{111}), Simple Components (V_{112})}

Setup complexity = {High (V_{121}), Medium (V_{122}), Low (V_{123})}

Production volume = {High (V_{131}), Medium (V_{132}), Low (V_{133})}

Internal operations = {Initial (V_{211}), Final (V_{212})}

External operations = {Initial (V_{221}), Final (V_{222})}

Standardization = {Initial (V_{231}), Final (V_{232})}

Deleting adjustments = {Initial (V_{241}), Final (V_{242})}

IoT = {Initial (V_{311}), End (V_{312})}

Data analysis = {Initial (V_{321}), Final (V_{322})}

Augmented Reality = {Initial (V_{331}), Final (V_{332})}

Cyber-physical systems = {Initial (V_{341}), Final (V_{342})}

Setup time = {Initial (V_{411}), Final (V_{412})}

Stability = {Initial (V_{421}), Final (V_{422})}

First batch quality = {Initial (V_{431}), Final (V_{432})}

In the implementation cases (SMED and I4.0) and indicators, it is determined: **Initial/Final = {Low, Medium, High}**

Table 1 summarizes the structure of vertices and attributes:

Table 1: Vertex, Vertex Attributes, Vertex Sub-Attributes, and Vertex Sub-Attributes in the Study

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
Line characteristics (V_1)	Product type (V_{11})	Complex components (V_{111})	
		Simple components (V_{112})	

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
	Setup complexity (V_{12})	High (V_{121})	
		Average (V_{122})	
		Low (V_{123})	
	Production volume (V_{13})	High (V_{131})	
		Medium (V_{132})	
		Low (V_{133})	
SMED (V_2) Implementation	Internal operations (V_{21})	Initial (V_{211})	Low (V_{2111})
			Medium (V_{2112})
			High (V_{2113})
		Final (V_{212})	Low (V_{2121})
			Medium (V_{2122})
			High (V_{2123})
	External operations (V_{22})	Initial (V_{221})	Low (V_{2211})
			Medium (V_{2212})
			High (V_{2213})
		Final (V_{222})	Low (V_{2221})
			Medium (V_{2222})
			High (V_{2223})

Note: The "Start" sub-attributes (V_{211}, V_{221}, V_{311}, etc.) are input enclosing vertices, while the "End" sub-attributes (V_{212}, V_{222}, V_{312}, etc.) are output enclosing vertices.

Table 2: Absolute frequency of each of the variables

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
Line features (24)	Product type (24)	Complex components (14)	
		Simple components (10)	
	Setup complexity (24)	High (9)	
		Media (11)	
		Low (4)	
	Production volume (24)	High (8)	
		Medium (12)	
		Low (4)	
SMED Implementation (24)	Internal operations (24)	Initial (24)	Low (15)
			Medium (7)
			High (2)
		Final (24)	Low (3)
			Medium (8)
			High (13)
	External operations (24)	Initial (24)	Low (13)
			Medium (9)
			High (2)
		Final (24)	Low (2)
			Medium (6)
			High (16)

Table 3: Vertices for implementation and performance indicators

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
I4.0 (V_3) Implementation	IoT (V_{31})	Initial (V_{311})	Low (V_{3111})
			Medium (V_{3112})
			High (V_{3113})
		Final (V_{312})	Low (V_{3121})
			Medium (V_{3122})
			High (V_{3123})
	Data analysis (V_{32})	Initial (V_{321})	Low (V_{3211})
			Medium (V_{3212})
			High (V_{3213})
		Final (V_{322})	Low (V_{3221})
			Medium (V_{3222})
			High (V_{3223})
	Augmented Reality (V_{33})	Initial (V_{331})	Low (V_{3311})
			Medium (V_{3312})
			High (V_{3313})
		Final (V_{332})	Low (V_{3321})
			Medium (V_{3322})
			High (V_{3323})
Performance Indicators (V_4)	Setup time (V_{41})	Initial (V_{411})	Low (V_{4111})
			Medium (V_{4112})
			High (V_{4113})
		Final (V_{412})	Low (V_{4121})
			Medium (V_{4122})
			High (V_{4123})

Table 4: Absolute frequency of I4.0 implementation and performance indicators

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
I4.0 Implementation (24)	IoT (24)	Initial (24)	Low (16)
			Medium (6)
			High (2)
		Final (24)	Low (3)
			Medium (9)
			High (12)
	Data analysis (24)	Initial (24)	Low (18)
			Medium (5)
			High (1)
		Final (24)	Low (4)
			Medium (11)
			High (9)
	Augmented reality (24)	Initial (24)	Low (20)
			Medium (4)
			High (0)
		Final (24)	Low (6)
			Medium (10)
			High (8)
Performance indicators (24)	Setup time (24)	Initial (24)	Low (3)
			Medium (7)
			High (14)
		Final (24)	Low (15)
			Medium (7)

Vertex	Vertex attributes	Vertex Subattributes	Secondary vertex attributes
			High (2)

Analysis using log-linear models

For statistical analysis of the data, we used log-linear models with three-way contingency tables. We calculated the G^2 coefficient in each case to assess model fit.

Table 5: G^2 results for the log-linear models

Model	G^2
Product type SMED internal operations initial SMED internal operations final	2.8762e-7
IoT product type initial IoT final	3.1054e-7
Product type Setup time initial setup time final setup time	2.9783e-7
Setup complexity SMED initial internal operations SMED final internal operations	4.6281e-7
IoT setup complexity initial IoT final	4.8372e-7
Setup complexity Setup time initial setup time final setup time	4.7115e-7
Production volume SMED internal operations initial SMED internal operations final	3.5426e-7
IoT production volume initial IoT final	3.4192e-7
Production volume Setup time initial setup time final setup time	3.3814e-7
SMED internal operations initial IoT initial setup time final setup time	5.1276e-7
SMED external operations initial Augmented reality initial Quality first batch final	4.9853e-7
initial standardization Initial data analysis Final stability	5.0127e-7

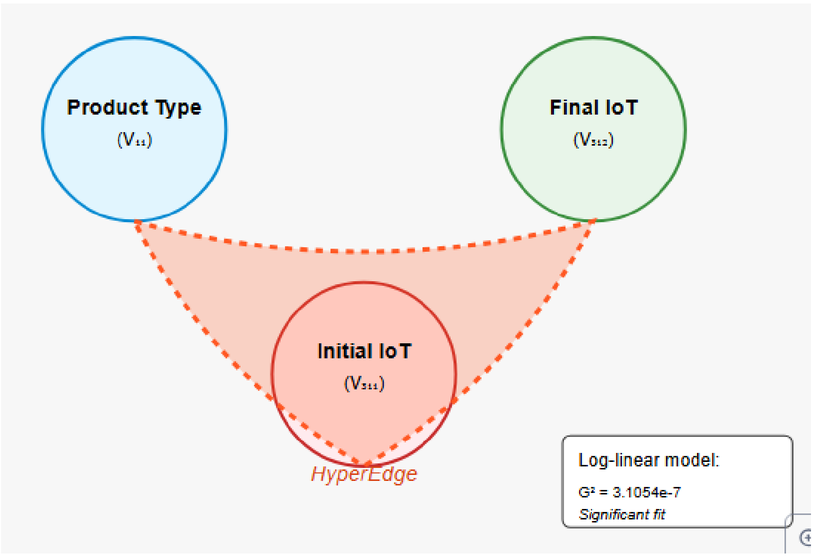

Figure 1: HyperGraph representing the Initial IoT Product Type Final IoT model.

Regarding dominance, dominant vertices were identified as those related to these two initial states (representing the input) and the final states (representing the output). The following figure represents the plithogenic connector (C_1) between the variables of the first model in Table 5.

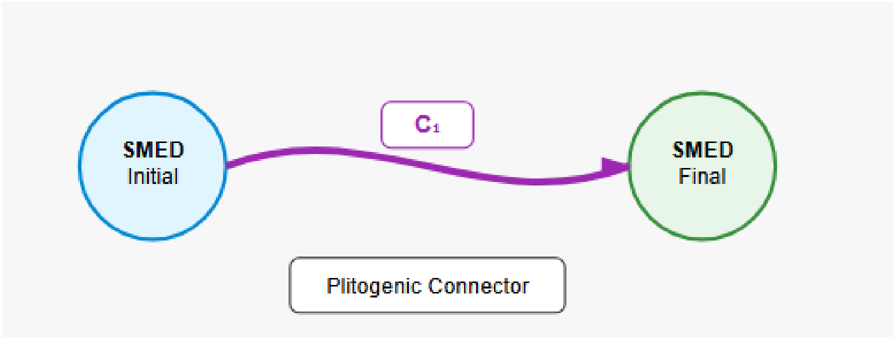

Figure 2: Plithogenic connector between model variables.

Results and discussion

Regarding statistical interpretation, all G^2 values were < 0.01, indicating that all the log-linear models obtained fit the data well. Detailed analysis of the models led to the conclusion that:

1. setup times across all lines, regardless of product type, setup complexity, and production volume.
2. Complex component production lines showed a greater percentage improvement in setup times (68% vs. 53% for simple components) after integrated implementation.
3. The implementation of IoT and data analytics had a synergistic effect with SMED techniques, especially in terms of eliminating customization and standardization.
4. Augmented reality proved particularly effective in improving the quality of the first batch after the format changeover, reducing stabilization time by 47%.
5. Lines with high setup complexity showed the greatest absolute benefit in time reduction, going from an average of 95 minutes to 38 minutes per change.
6. The level of digital maturity (IMT-I4.0) prior to implementation was a determining factor in the speed of adoption and results, with intermediate-level lines showing the fastest learning curve.

PEST analysis of SMED-I4.0 integration with n- Plithogenic SuperHyperGraphs

Political Factors

1. Government policies on tax incentives for industrial digitalization
2. Regulations on cybersecurity and industrial data protection
3. National support programs for Industry 4.0
4. International agreements on technological standards
5. Labor legislation related to automation

Economic Factors

1. Reduction of operating costs by reducing downtime
2. High initial investment in automation and digitalization technologies
3. Accelerated return on investment in industries with high frequency of changes
4. Increased competitiveness due to greater productive flexibility
5. Costs of training and development of specialized talent

Social Factors

1. Resistance to change by traditional operating staff
2. Need for new digital skills in the workforce
3. Impact on organizational structure and supervisory roles
4. Improved working conditions by reducing repetitive tasks
5. Cultural adaptation to data-driven decision-making

Technological Factors

1. Rapid evolution of IoT technologies applicable to industrial environments
2. Integration of legacy systems with new digital platforms
3. Availability of data analysis solutions specific to manufacturing
4. Development of more intuitive and effective human-machine interfaces
5. Maturity of augmented reality systems for industrial applications

SWOT analysis of SMED-I4.0 integration with n- Plithogenic SuperHyperGraphs

Strengths

1. Significant reduction in format changeover times
2. Greater consistency and quality in post-change processes
3. Optimization based on objective and real-time data
4. Ability to model complex systems with multiple variables
5. Flexibility to adapt to different types of production processes

Opportunities

1. Scalability of the solution to other lines and plants
2. Creating digital twins for advanced simulation
3. Development of predictive algorithms to anticipate problems in changes
4. Application of the model in other industries with similar requirements
5. Generation of new industrial standards based on the methodology

Weaknesses

1. Technical complexity that requires specialized personnel
2. High dependence on the quality of the data collected
3. Need for customization for each type of production line
4. Steep learning curve for plant personnel
5. Robust and secure connectivity requirements

Threats

1. Accelerated technological obsolescence of implemented solutions
2. Cybersecurity vulnerabilities in connected systems
3. Organizational resistance to the change in the productive paradigm
4. Difficulty in finding talent trained in new technologies
5. Competitors with greater digital maturity or technological resources

The integration of SMED methodologies with Industry 4.0 technologies, modeled using plithogenic n- SuperHyperGraphs, proves to be an effective approach for optimizing changeover processes in manufacturing environments. Statistical analysis confirms that this integration generates significant benefits in terms of time reduction, quality improvement, and process stabilization, regardless of the characteristics of the production line.

The use of plithogenic n- SuperHyperGraphs allowed for the adequate modeling of complex relationships between categorical and continuous variables, capturing the uncertainty inherent in real-world production processes. This advanced mathematical approach proves to be a valuable tool for decision-making in environments where multiple interrelated factors coexist.

It is recommended to continue the research by expanding the sample to more production lines and extending the follow-up period to evaluate the long-term sustainability of the improvements. It is also suggested to explore the incorporation of artificial intelligence techniques to further optimize changeover processes through automatic parameter prediction and adjustment.

4. Conclusion

This paper contributes to the field by implementing SMED with some Industry 4.0 technologies, which, through the plithogenic n-SuperHyperGraphs, minimizes format changeover in Ecuadorian manufacturing of electronic components with up to 68% minimization of downtime on compound lines, increased standardization, and first-quality in the first operation after changeover. Implementing the IoT and analytics is performance increasing, thus, transformation for an increasingly relevant sector of the Ecuadorian Economy. Findings are important and have implications for practice as they can be implemented in real time from all companies encountered, providing a non-expensive, scalable solution to reduce waste and stabilization needs with constantly changing market operations. In relation to the Ecuadorian situational context where industrial modernization is highly relevant, this means higher competitive edges are obtained and incremental operations can secure improved paths toward sustainable manufacturing endeavors. Qualitative improvements relating to changeovers—from augmented reality—improve customer satisfaction and decrease costs of operations for a more substantial economic presence for such local industries.

The theoretical contribution is that by employing plitogenic n-SuperHyperGraphs to model what is otherwise non-distraction in industrial systems, as this approach is relatively less used in manufacturing, many of the variables are interrelated. The results paint a more cohesive picture of such multivariate dependencies, rendering a fresh lens upon Lean Manufacturing and Industry 4.0. The practical contribution is that despite the Ecuadorian focus of the study, this can serve as a case study for emerging economies while presenting an accomplishment for an Ecuadorian context for low-resourced value with high applicability. Yet there are limitations; the focus on 24 production lines cannot be inferred across the board to all sectors in Ecuador. Furthermore, the study relies upon a strong digital-physical infrastructure which might not occur in diverse regions with relatively poor connectivity; thus, implementation might be challenging for rural areas. Finally, the technicalities with n-SuperHyperGraphs require some training to comprehend, which might delay initial implementation and adjustment. Future studies might include examining other industrial or sector designs from food to textiles to see if the results can be generalized. Furthermore, using artificial intelligence for real-time corrections may further enhance processes that can be better assessed longitudinally. Some enhancements might be better through simulation as opposed to practical application on the physical operation; thus, future studies should test such combinations. Studies over time could determine if such enhancements are sustainable beyond this singular analysis so that Ecuadorian industry does not lose their foothold in an ever-dynamic world.

5. References

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