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Statistical method using Principal Component Analysis to determine high variability parameters affecting the balancing of an assembly line

Hillali Y.[1,2], Zegrari M.[1], Alfathi N.[3], Chafik S.[2], Tabaa M.[2]

[1] *Laboratory of Complex Cyber Physical Systems (LCCPS), ENSAM Casablanca, University Hassan 2, Morocco*
[2] *Pluridisciplinary Laboratory of Research and Innovation (LPRI), EMSI Casablanca, Morocco*
[3] *Laboratory Intelligent Systems and Applications (LSIA), EMSI Tanger, Morocco*

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Modern assembly lines face numerous challenges when it comes to satisfying client expectations. The challenges discussed include increasing customization demands, maintaining quality standards, managing lead times, addressing sustainability concerns, and effectively utilizing advanced technologies. This challenges impact assembly lines efficiency and effectiveness in other word balancing of the line. This research aims to identify the essential components that significantly influence the balance of assembly lines. To achieve this objective, a novel approach is proposed using a 3D matrix interpretation and statistical method, Principal Component Analysis (PCA). The research leverages the MATLAB tool to analyze the interactions between various parameters and identify highly changeable factors that impact assembly line balance. By employing this methodology, the study aims to provide valuable insights into identifying the parameters of an assembly line balancing and enhancing overall operational efficiency. The finding of this approach, reveal a significant influence of altering the piloting parameters on assembly line balancing. This result underscores the importance of dynamically balancing the assembly line to achieve optimal performance.

Keywords: *3D matrix; principal component analysis; dynamic balancing; high variability parameters.*

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1. Introduction

The manufacturing industry is undergoing rapid changes in response to shifting market demands and technological advancements. One of the most prominent trends in modern production is the concept of mass customization, wherein firms alter product specifications to accommodate varying customer demands and production volumes [1]. To remain competitive in this increasingly digital and volatile environment, businesses must successfully forecast, adapt to, and cope with external changes in the market [2]. Mass customization is essential in meeting the diversified and personalized requirements of modern consumers, which include shorter product life cycles, customized product configurations, and high production flexibility. The symbiotic relationship between mass customization and Industry 4.0 manifests in a transformative impact on assembly line dynamics within the manufacturing domain. Mass customization, characterized by the tailored production of goods to meet individualized customer demands, converges with Industry 4.0 encompassing digital technologies such as the Internet of Things, artificial intelligence, and automation [3]. This convergence substantiates a paradigm shift in assembly line processes. The assembly line, infused with Industry 4.0 technologies, gains unparalleled flexibility and adaptability. Swift reconfiguration capabilities enable seamless accommodation of diverse product variations without compromising efficiency. The integration of big data analytic empowers data-driven decision-making, facilitating optimization and continual improvement across assembly line stages [4].

Real-time monitoring and control mechanisms, facilitated by IoT devices, mitigate errors and elevate overall operational efficiency. The impact of Industry 4.0 and mass customization on the assembly line is characterized by a dynamic re-balancing act [5].

Achieving and maintaining the balance amidst the evolving landscape of customization, data-driven insights, human-machine collaboration, and supply chain intricacies emerges as a central challenge and opportunity in the contemporary manufacturing paradigm [6].

2. State of art

2.1. Assembly line balancing

Assembly lines are one of the most important industrial manufacturing implementations. In today competitive globe, assembly lines can handle the massive expansion in customer expectations and product range for the production sector [7]. Assembly lines are flow-focused production processes, that manufacturers use them for producing large numbers of items. The components of products are assembled using material handling equipment such as conveyor belts [8]. Tasks must be allotted to a group of sequentially linked stations while taking precedence connections into consideration. Different performance metrics are taken into account such as cycle duration and station count in the assembly line balance problem (ALBP) [9]. The Assembly Line Balancing Problem (ALBP) is a large family of problems that investigates the optimum approach to distribute tasks to workstations in order to optimize an efficiency criterion. These assembly lines are straight (conventional) and U-shaped (U-type) [10]. The primary challenge lies in maintaining the stability of an assembly lines balance, which is often compromised due to the dynamic nature of factors affecting the balancing process, such as the implementation of mass customization techniques [11]. In the scientific literature, researchers have extensively investigated the parameters that contribute to balancing variability in various systems [12–14]. These parameters, which directly influence the balancing status, have been classified into two distinct set of parameters: Y_i and X_{ij} in this paper. Class Y_i represents the parameters that directly cause variability, while Class X_{ij} corresponds to the root parameters that decompose the parameters Y_i, further elucidating the underlying factors affecting balancing. To provide a visual representation of the parameters and their relationship with balancing, Figure 1 has been included. This figure presents a comprehensive compilation of the different parameters mentioned in the scientific literature, categorizing them based on their direct link with balancing. By organizing these parameters into distinct classes, researchers can gain a better understanding of the factors contributing to balancing variability and explore potential avenues for optimization and control.

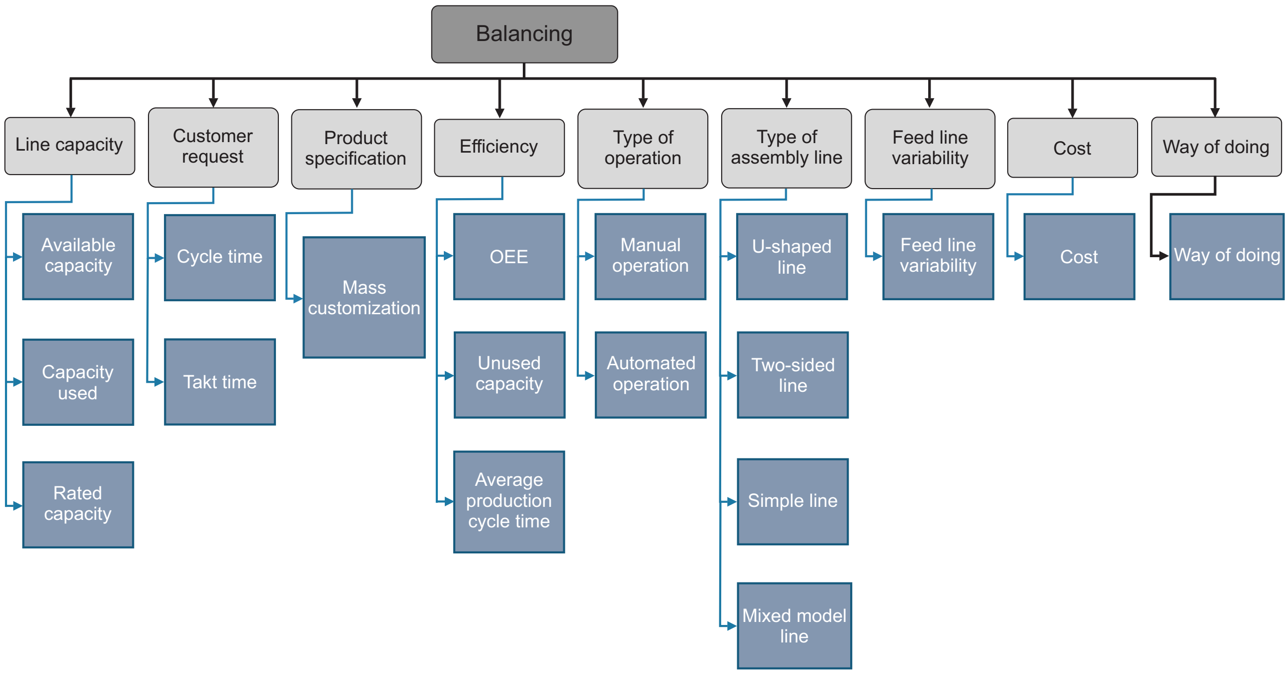

Fig. 1. Parameters impacting the balance of assembly line.

2.2. Principal component analysis (PCA)

In today competitive industrial landscape, manufacturers strive to optimize their processes, enhance product quality, and improve overall operational efficiency. Principal Component Analysis (PCA) has emerged as a powerful tool for analyzing and interpreting multivariate data, making it particularly relevant in the industrial domain. PCA is a statistical technique used for dimensionality reduction and feature extraction. It aims to transform a high-dimensional dataset into a lower-dimensional space while retaining the maximum amount of information. By capturing the most significant variations within the data, PCA helps to identify underlying patterns, correlations, and influential factors that may not be apparent in the original dataset [15]. In the industrial context, PCA offers valuable insights for various applications, ranging from quality control and fault detection to process optimization and product design (see Table 1).

Table 1. Application of PCA in production lines.

Applications of PCA in Manufacturing Assembly Lines	Use case and problematics treated
Quality Control and Fault Detection	Use of PCA for anomaly detection and process monitoring
	Real-time quality assessment and decision-making
Process Optimization and Performance Improvement	PCA-based analysis of process variables and key performance indicators
	Identification of influential factors and optimization targets
	Statistical modeling and prediction of manufacturing performance
Product Design and Development	PCA for feature selection and dimension reduction in product design
	Identification of critical design parameters and their impact on performance
	Evaluation and optimization of product configurations

Assembly lines must be adaptable, effective, and capable of handling a wide range of commodities and variations. To do this, it is critical to determine the important parameters that have a substantial influence on productivity before implementing new balancing in assembly lines [16]. This may include characteristics such as operator skill levels [17], feeder line variability [18], and other parameters that might impact manufacturing line balancing variability. The primary objective of this research is to build a 3D matrix representation to develop a comprehensive of the link between the balancing parameter and the other parameters. The next step is to examine the interrelationships among parameters to comprehend how changes in specific parameters can affect the balance of an assembly line. By conducting statistical methods Principal Component Analysis (PCA), we seek to identify the key parameters that exert the most significant influence on assembly line balance. This knowledge can prove instrumental in determining which parameters require careful monitoring and control to ensure a stable production process [19]. Furthermore, the findings from this study can offer valuable insights into the design and optimization of assembly lines, potentially leading to enhanced efficiency and productivity. The rest of this paper is organized as follows. Section 2 displays the proposed solution to the unpredictability of assembly line balance. Section 3 includes a pilot study to determine the practicality of the proposed technique. Section 4 summarizes the findings and suggests future research subjects.

3. Methodology

3.1. 3D Matrix representation

To better understand the unpredictable nature of Y balancing parameters, we note:

— Y represent Efficiency of Balancing.
— Y_i represents parameters that cause variability of the general parameter Y.
— $Y = F(Y_i)$: Y can be expressed as a function of Y_i.

The objective is to build a representation to identify the sources of variability in the balancing. To do this, we can use the relation Y represent efficiency of balancing of a production line. The fluctuation of the balancing parameter Y is due to several parameters Y_i, where Y_i denotes the source that influence the variability of the general parameter Y. So, we have proposed a representation that demonstrates the relationship between Y (efficiency of balancing) and Y_i (the variables that cause the fluctuation of the parameter Y). We observe:

— Y represent the general parameter of balancing.
— Y_i is the set of variables that affect Y where $i \in [1, n]$.

Table 2. Application of PCA in production lines.

Y	Y_1	Y_2	Y_3	$\dots$	Y_n

Table 3. Application of PCA in production lines.

Y	Y_1	Y_2	Y_3	$\dots$	Y_n
	X_{11}	X_{21}	X_{31}		.
	X_{12}	X_{22}	X_{32}		.
	X_{13}	X_{23}	X_{33}		.
	.	.	.		.
	.	.	.		.
	.	.	.		.
	.	.	.		.
	.	.	.		.
	X_{1j}	X_{2j}	X_{3j}		X_{nm}

The following example illustrates the relationship between the parameter Y_i and the general parameter of balancing Y, we suppose that: Y = efficiency of balancing and Y_1 = Takt time. The next step consists to define the parameter X_{ij}, such that X_{ij} are the root parameters that compose each parameter Y_i, where $i \in [1, n]$ and $j \in [1, m]$. So that, the variability of X_{ij} causes the variability of the general parameter Y. Now, we are able to construct a simple representation using the parameter X_{ij} as follow:

— Y = efficiency of balancing.
— Y_1 = Takt time.
— X_{11} = Customer request.

Let us consider V_{ijk}, ($i \in [1, n]$, $j \in [1, m]$ and $k \in [1, t]$) that represents the possible values for the parameter V_{ij}. To summarize, in below the parameters used in the 3D matrix representation:

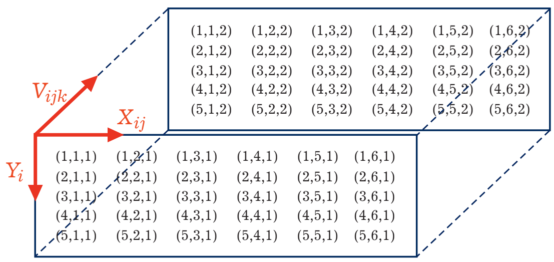

Fig. 2. 3D Matrix representation.

— Y = Efficiency of balancing.
— Y_i = Parameters that cause variability for the general parameter Y where $i \in [1, n]$.
— X_{ij} = the root parameters that decompose the parameters Y_i where and $j \in [1, m]$.
— V_{ijk} = represents the possible values for the sub parameters X_{ij} where $i \in [1, n]$, $j \in [1, m]$ and $k \in [1, t]$.

3.2. Principal component analysis (PCA)

The utilization of Principal Component Analysis (PCA) enables the identification of parameters with high variability that impact assembly line balancing [20]. PCA is a statistical technique that reduces the dimensionality of data while retaining essential information. In the context of our study on assembly line balancing, PCA can be applied to determine the parameters that contribute the most to the observed variance of the efficiency of balancing Y. By employing PCA, we can extract principal components from the 3D matrix representation. By examining the loadings or weights assigned to each variable on the different principal components, we can identify the parameters that exhibit high variability and have a significant impact on assembly line balancing [21]. This allows us to concentrate efforts on monitoring and controlling these parameters to maintain a stable balance throughout the production process. The application of Principal Component Analysis (PCA) facilitates the identification of parameters with high variability that have a significant impact on assembly line balancing. This approach provides an effective method for determining the key factors to monitor and control in order to maintain a balanced and optimized assembly line.

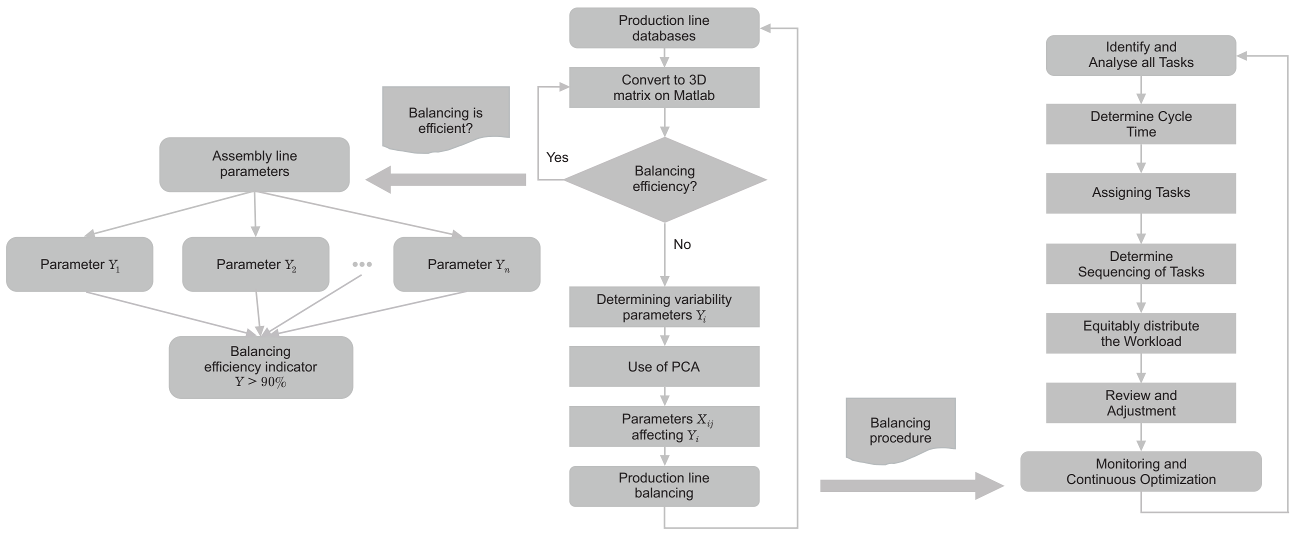

Fig. 3. Dynamic balancing procedure.

The balancing procedure delineates a structured sequence of actions for the seamless integration of the proposed approach aimed at efficiently realigning the production line. This methodology offers a conventional set of instructions for the operationalization of line balancing, concurrently streamlining the process through the utilization of a 3D matrix and graphical representations employing MATLAB. The primary objective is to establish a standardized protocol for the optimization of assembly line balancing through the employment of this procedural framework.

4. Application

4.1. Assembly line balancing

In accordance with the established methodology, we shall now apply it to an industrial case within the automotive sector. Initially, we have collated a comprehensive database comprising information that is specific to the manufacturing line employed. This assembly line consists of a total of 29 manual stations, as illustrated in Figure 4 below.

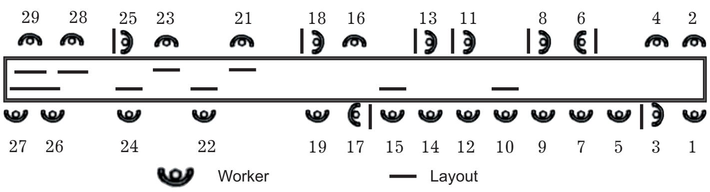

Fig. 4. Assembly line.

Balancing an assembly line is a crucial process to maximize production and minimize costs. The key steps to balancing an assembly line are as follows for more information [14, 15]:

- Data collection: All relevant data about the assembly line, including cycle times, processing times, number of operators, and downtime, must be collected.
- Identifying bottlenecks: Using the collected data, bottlenecks in the line, i.e., steps in the line where the flow is limited, must be identified.
- Determining desired production rate: By determining the desired production rate, the necessary cycle time for each step in the line can be calculated.
- Balancing the line: Using the calculated cycle time for each step in the line, the line can be balanced by adjusting operations and redistributing operators to eliminate bottlenecks.
- Verifying results: It is crucial to verify the results of the line balancing to ensure production goals are met. If adjustments are necessary, they must be made to maintain line balance.
- Monitoring and improving: Regular monitoring of line performance is essential to detect potential problems and make improvements to maintain optimal production.

Our chrono analysis and variability study revealed that some stations were overburdened, leading to obstructions in the assembly process. Therefore, balancing the assembly line becomes necessary. Figure 5 below provides a visual representation of this balance.

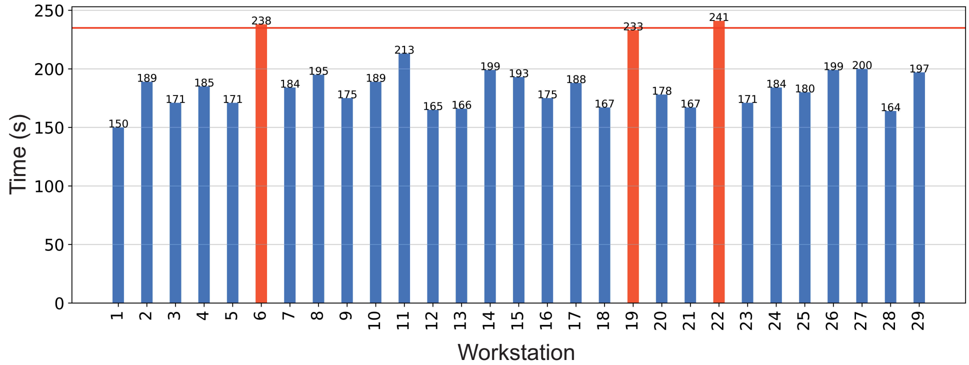

Fig. 5. Variability graph before balancing.

Through the use of one of the available balancing algorithms, as reported in the references [22–24], we have implemented the largest candidate rule algorithm to reallocate tasks and operations among each workstation, aiming to balance the assembly line. Following the application of the algorithm, we have analyzed the variability graph of the workstations and concluded that the line is now balanced, as all workstations exhibit an equivalent workload, as depicted in the figure below. By using the formula (1) below, we calculated the balancing efficiency indicator to properly measure the quality of balancing used:

$$Y_b = T_w c/(m \cdot T_s). \tag{1}$$

We note:

— Y_b: Balancing efficiency indicator;
— T_{wc}: Work content time;
— m: number of workstations;
— T_s: the duration of the slowest station.

After implementing the largest candidate rule algorithm [19], we found that our line is well-balanced, with a calculated balancing efficiency indicator of 97%. Drawing from the assembly lines variability graph, it is discernible that the line is deemed balanced, given that each stations workload appears to be equitably distributed.

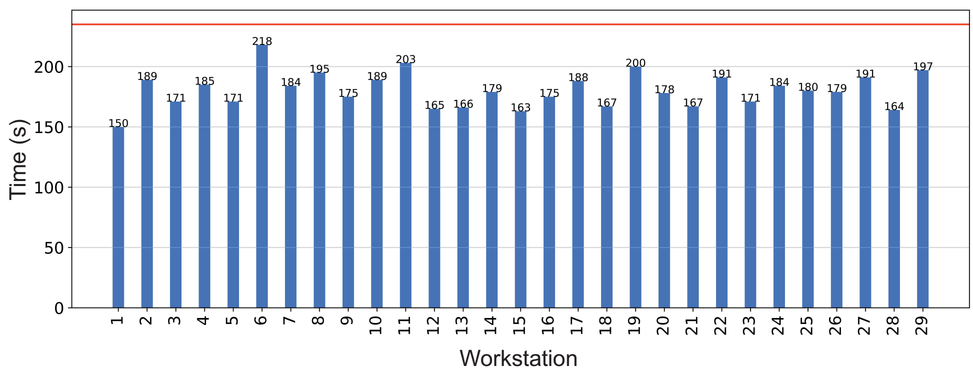

Fig. 6. Variability graph after balancing.

4.2. 3D Matrix representation

We will apply the methodology described in the preceding section to an industrial situation in the automotive industry. First, we have assembled a database with details particular to the manufacturing line in use. In fact, this corporation employs an assembly line with 29 manual stations [24]. Database used contains a set of parameters, or Y_i, that are automatically taken into account while piloting the production line. Parameter Y_i and X_{ij}: Y_i: Efficiency

— X_{11}: Cadence: Number of conforming bundles made per time.
— X_{12}: Range time: fixed index which expresses the duration of a cycle of assembly until the final control;
— X_{13}: Staff: number of staff present;
— X_{14}: Working hours;
— Y_2: The time allocated to manufacture a beam;
— X_{21}: Shift time bottleneck;
— X_{22}: Shift time;
— Y_3: Takt time:
— X_{31}: Production time;
— X_{32}: Daily demand;
— Y_4: Product specification:
— X_{41}: Routing time;
— X_{42}: LAD frequency (product rotation frequency).

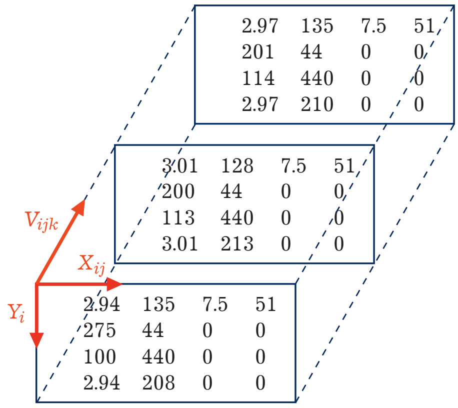

Fig. 7. 3D Matrix representation.

4.3. Principal component analysis (PCA)

The application of the statistical method (PCA) with use of Matlab tool in this case, including the results found. The relation between the parameters Y_i was evaluated as shown in Figure 8.

The relative contributions of the variables are as follows: Y_1 – 66.5732%, Y_2 – 32.9541%, Y_3 – 0.47268%, Y_4 – 0%.

The analysis reveals that Y_4 has an extremely negligible contribution of 3.214% to the observed variability, indicating that it has virtually no impact on the balance of the assembly line. Y_3 demonstrates a modest contribution of 0.47268%, suggesting a minor influence on the overall balance. However, Y_2 exhibits a notable contribution of 32.9541%, indicating its significant effect on the assembly lines balance. Y_1 emerges as the most influential factor, accounting for 66.5732% of the observed variability, thus playing a critical role in determining the overall balance. These results emphasize the importance of closely monitoring and controlling Y_1 to maintain a stable and optimized assembly line. Y_2 should also be considered as it significantly impacts the balance and warrants attention in the optimization process. In contrast, Y_3 and Y_4 can be deemed less critical in terms of their contributions. In order to determine the root parameter causing variability in Y_1, which subsequently impacts the balancing indicator, we now proceed to examine the sub-parameters of Y_1. The analysis of the sub-parameters aims to identify the primary factor responsible for the observed variability in Y_1. By investigating the relationship between the sub-parameters of Y_1 and their impact on Y_1's variability, we can uncover the root parameter that influences the balancing indicator.

The relative contributions of the variables are as follows: X_{11} – 99.9912%, X_{12} – 0.0087739%, X_{13} – 0%, Y_{14} – 0%.

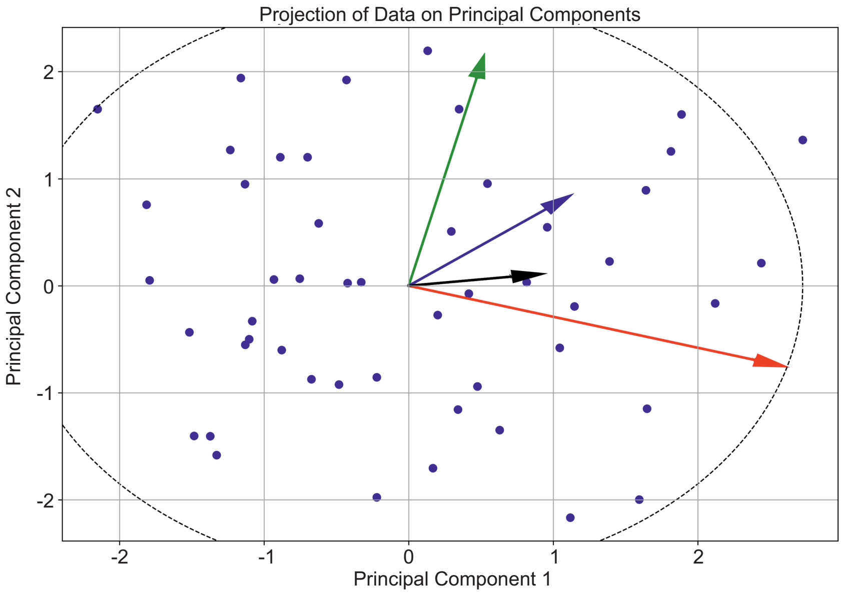

Fig. 8. PCA analysis of the parameters Y_i.

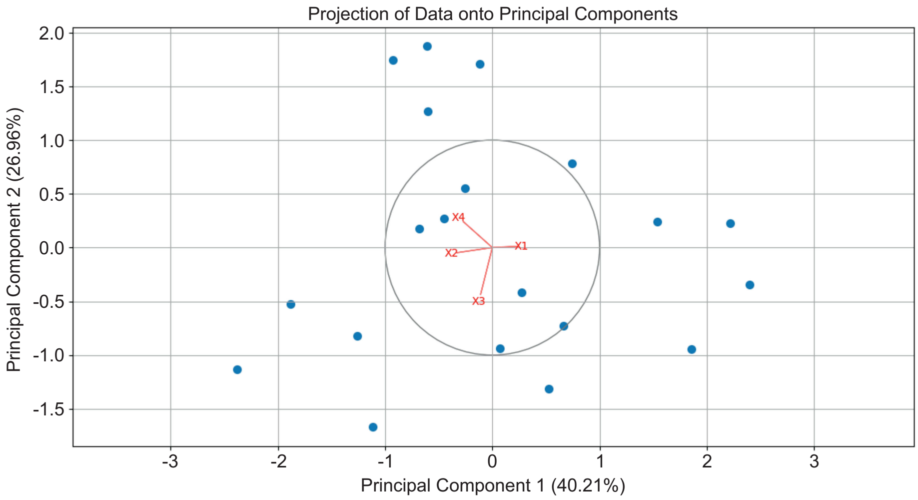

Fig. 9. PCA analysis of the parameters X_{1j}.

The results indicate that X_{13} and X_{14} have no significant contribution to the observed variability. X_{12} demonstrates a minimal contribution of 0.0087739%. However, X_{11} stands out as the dominant factor, accounting for 99.9912% of the observed variability. These findings suggest that X_{11} plays a crucial role in influencing the overall balance and performance of the system under study. It is essential to closely monitor and control X_{11} to maintain a stable and optimized assembly line.

4.4. Results interpretation

The results shown in the application section gives us a clear visibility of parameters impacting assembly line balancing, and therefore causing variability in balancing, hence dynamic balancing. The primary objective of employing Principal Component Analysis (PCA) is to reduce the dimensionality of a database while elucidating the relationships between parameters Y_i and X_{ij} through linear combinations of the original variables for each principal component. This analysis also provides insights into the relative contributions of the variables, as indicated by the proportion of variance explained by each parameter. From the PCA results, we can infer the correlations among the parameters and identify those Y_1 and X_{11} parameters with substantial variability that significantly influence the balance of the assembly line. To assess the implications of the outcomes derived from the PCA method, we conducted a parameter variation analysis on those exhibiting notable variability, as depicted in the subsequent figure.

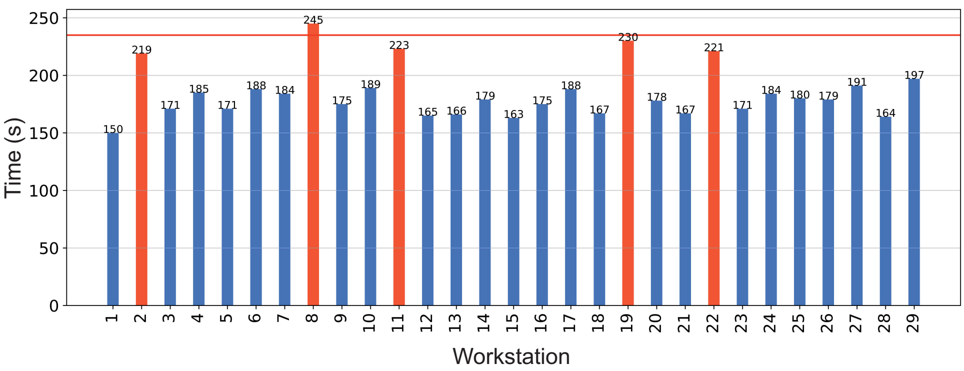

Fig. 10. Variability graph after varying X_{11}.

The variability chart depicted in Figure reveals the conspicuous existence of five prominent bottlenecks located at specific workstations within the analyzed assembly line. These bottlenecks have been precisely identified as Workstations 2, 6, 11, 19, and 22. The exploration of parameter variability was conducted in accordance with the PCA X_{11} methodology.

5. Conclusion and future work

In this paper, we studied the variability of parameters that impact the balancing of an assembly line. In order to ensure dynamic balancing, assembly lines need to be adaptable and responsive to changing control settings, particularly with the increasing demand for customized products. To achieve this, it is essential to identify the critical elements with high variability that directly influence the balance of the assembly line using statistical method PCA with interpretation in MATLAB tool. These elements play a significant role in maintaining balanced variability. However, if not appropriately controlled, they can lead to instability in the balance.

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Статистичний метод із застосуванням аналізу основних компонентів для визначення параметрів високої варіабельності, що впливають на балансування складальної лінії

Хілалі Ю.[1,2], Зеграрі М.[1], Алфаті Н.[3], Чафік С.[2], Табаа М.[2]

[1] *Лабораторія складних кіберфізичних систем (LCCPS), ENSAM Касабланка, Університет Хасана 2, Марокко*
[2] *Багатодисциплінарна лабораторія досліджень та інновацій (LPRI), EMSI Касабланка, Марокко*
[3] *Лабораторія інтелектуальних систем і додатків (LSIA), EMSI Танжер, Марокко*

Сучасні складальні лінії стикаються з численними проблемами, коли справа стосується задоволення очікувань клієнтів. Проблеми, які обговорювалися, включають підвищення вимог до персоналізації, підтримку стандартів якості, управління часом виконання робіт, вирішення проблем сталого розвитку та ефективне використання передових технологій. Це ставить під сумнів ефективність складальних ліній і результативність, іншими словами, балансування лінії. Це дослідження спрямоване на виявлення основних компонентів, які суттєво впливають на збалансованість складальних ліній. Для досягнення цієї мети пропонується новий підхід із використанням 3D-матричної інтерпретації та статистичного методу, аналізу головних компонентів (PCA). Дослідження використовує інструмент MATLAB для аналізу взаємодії між різними параметрами та виявлення факторів, які сильно змінюються, що впливають на баланс складальної лінії. Використовуючи цю методологію, дослідження має на меті надати цінну інформацію щодо визначення параметрів конвеєрного балансування та підвищення загальної ефективності роботи. У результаті цей підхід виявив значний вплив зміни параметрів пілотування на балансування складальної лінії. Цей результат підкреслює важливість динамічного балансування складальної лінії для досягнення оптимальної продуктивності.

Ключові слова: *3D матриця; аналіз головних компонентів; динамічне балансування; висока варіабельність параметрів.*