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Monte Carlo-Based Assessment of Machine Flexibility in Group-Configured Part-Feeding Systems

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Abstract

Modern high-mix, low-volume manufacturing faces significant downtime during setup changes in part-feeding systems, yet no quantitative model currently exists that links group-based reconfiguration strategies to a measurable flexibility index under stochastic batch-size conditions. This study therefore aims to develop and experimentally validate a probabilistic mathematical model for assessing machine flexibility when a group-based reconfiguration approach is applied to part-feeding systems. The methodology combines Monte Carlo simulation to model random batch-size distributions with physical validation using a rotary orienting device across eight distinct sleeve types. Simulation results indicate that the proposed strategy reduces setup labor by 51-61% in systems handling 100 different part types. When fewer than one-third of parts require reconfiguration, the machine flexibility index reaches 0.088 ± 0.014, meeting established thresholds for high system flexibility. Experimental tests confirm that a uniform group-level adjustment maintains operational efficiency deviations within 3-5% across varying part geometries. The primary novelty of this work lies in introducing a confidence-bounded flexibility coefficient that explicitly incorporates auxiliary loading subsystems, which are consistently overlooked in existing deterministic approaches. This provides a practical, data-driven tool for production planning that enhances responsiveness without sacrificing throughput or increasing system complexity.

Keywords:

Production Process;

Reconfiguration;

Probabilistic Model;

Cost Reduction;

Monte Carlo Method;

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1- Introduction

Modern mechanical manufacturing is characterized by high product variety and frequent order changes, driven by customer demands for customized specifications and the widespread shift toward low-inventory production strategies [1, 2]. Most production facilities therefore operate in high-mix, low-volume environments, where the ability to respond rapidly to varying part types and batch sizes is a fundamental competitive requirement [3]. In such settings, production systems must be simultaneously flexible and efficient, a combination that is difficult to achieve in practice. In high-mix production, regular equipment reconfiguration is unavoidable when switching from one part type to another. These changeovers lead to machine downtime, reducing the efficiency of production resources and increasing product costs. The reconfiguration of part-feeding systems responsible for delivering workpieces to machines is particularly time-consuming, yet it remains one of the least studied sources of production inefficiency. Traditional approaches that rely on individual setup for each part type result in excessive system complexity and significant time losses [1].

The core challenge lies in the fact that reducing changeover time for transport and feeding systems is often achieved through increased technical complexity, which is not always efficient. The potential of a group-based reconfiguration strategy, where similar operations are grouped to minimize the number of full changeovers, has been insufficiently

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explored. Furthermore, there is a lack of mathematical models capable of predicting the impact of group-based setups on production system flexibility under varying batch sizes [4, 5]. Recent studies show that assessing the level of production flexibility remains a pressing and unresolved challenge in industrial engineering, particularly in the context of high-mix production. The literature indicates that the reconfigurability of production systems makes it impossible to assess flexibility using static parameters; consequently, a multidimensional framework that accounts for operational variability has been proposed. Their findings underscore the need for dynamic models [6].

Furthermore, contemporary literature increasingly focuses on the contribution of auxiliary subsystems to overall production efficiency. Operations involving the processing and feeding of workpieces can account for a disproportionately large share of time, which does not add value, yet they are rarely modeled with the same rigor as the main processing operations [7]. Similarly, it can be seen that the logic of group configuration used in auxiliary systems yields significant gains in terms of changeover efficiency, without requiring capital-intensive modifications [8]. This highlights the relevance of reconfiguring the loading system as a key lever for increasing flexibility.

This study aims to develop a mathematical model for assessing the flexibility of a production system when applying a group-based reconfiguration approach to part feeding systems. The model will support informed decisions on part grouping parameters and enable the prediction of how group setups affect production efficiency. This, in turn, will help minimize equipment downtime, reduce labor requirements for changeovers, and improve the utilization of production capacity while maintaining the required level of system flexibility in response to changing customer demands.

Monte Carlo-based probabilistic modeling is employed to achieve this. The findings are expected to justify the use of group-based reconfiguration in production planning and pre-production engineering, both for traditional and additive manufacturing. The proposed approach is anticipated to reduce time and material costs associated with equipment changeovers and enhance overall resource efficiency.

The paper is structured as follows. Section 2 reviews current approaches to improving production system flexibility, including digital twins, Single-Minute Exchange of Dies (SMED) methods, and group technology, and identifies a gap in the quantitative assessment of the contribution of feeding systems to overall flexibility in high-mix production. Section 3 presents the developed mathematical model for evaluating machine flexibility while considering the stochastic nature of batch sizes, describes the experimental procedure using vibratory bowl feeders with eight bushing types, and justifies the choice of the Monte Carlo method for numerical simulation. Section 4 provides quantitative results on the relationship between machine flexibility and the proportion of parts requiring reconfiguration under varying batch sizes, along with experimental validation of group-based reconfiguration without significant efficiency loss. Section 5 compares the results with existing studies on production system flexibility, highlights the novelty of the proposed approach, and demonstrates its advantages over deterministic assessment methods. Section 6 concludes with key findings on the practical applicability of the model for optimizing feeding systems and production planning.

This work addresses a research gap related to the development of a method for analyzing equipment utilization in the context of setup work and managing workpiece composition variations. The primary contributions of this study are as follows:

- The development of a stochastic mathematical model that explicitly accounts for the probabilistic nature of batch sizes and random order distributions represents a significant advancement over traditional deterministic approaches. This approach allows for more accurate prediction of system behavior under conditions of high heterogeneity and low production volumes.
- A novel equipment flexibility index has been developed for the purpose of evaluating the effectiveness of strategies, with a particular focus on changes in product batches.
- During the course of the study, the proposed model was subjected to experimental testing, in which physical components were employed, thereby substantiating the hypothesis that the generalized configuration enhances operational efficiency.

2- Literature Review

Implementing multi-criteria analysis of a production system (PS) in real time under contemporary conditions that require continuous improvement, maintenance, and repairs remains a challenging task [9-11]. In practice, such analysis is typically based on criteria that enable rapid assessment and visualization of the current production status.

In general, a work shift consists of time spent on core operations and time lost due to unplanned interruptions, such as equipment changeovers, breakdowns, delayed resource delivery, and other disruptions. To evaluate production efficiency, the ratio of downtime to total shift time is commonly used. This metric reflects the effective utilization of time and resources and can inform managerial decisions aimed at improving system performance [12].

In high-mix production environments, the digital twin serves as a foundational tool for real-time monitoring and predictive analytics. It functions as a virtual counterpart of physical machines, continuously collecting sensor data, simulating machining operations, and evaluating reconfiguration scenarios without requiring equipment downtime. This approach reduces unplanned idle time by 19-30% and significantly decreases operator errors during tooling setup [13]. However, despite the effectiveness of digital twins in predicting maintenance events, these approaches often ignore the bottlenecks created by supporting systems. Moreover, the high implementation costs and computing resources of digital twins limit their accessibility for small and medium-sized enterprises (SME).

In addition, each digital twin is increasingly integrated with predictive maintenance modules. Through machine learning, these systems analyze historical failure data to forecast when reconfiguration events are likely to coincide with component degradation or accelerated wear. Such predictive capabilities enable dynamic rescheduling of changeovers, reducing unplanned downtime by 40-45% through early detection of degradation indicators. By combining physical and virtual modeling, these systems facilitate the development of adaptive, intelligent manufacturing environments, often referred to as “smart factories” [14].

It should be noted that, compared to alternative approaches, the Single-Minute Exchange of Dies (SMED) methodology demonstrates particularly high effectiveness in enhancing production responsiveness to changing customer requirements. This is achieved through a systematic reduction in changeover time and faster adaptation to variations in part design.

SMED is a structured approach to collective reduction of machine reconfiguration time. It classifies changeover activities into two categories: external (performed while the machine is running) and internal (requiring machine stoppage). By converting internal tasks to external wherever possible, SMED enables continuous production without compromising productivity or increasing downtime. This classification improves a range of quantitative and qualitative performance indicators, including responsiveness to customer demands and production agility. Through detailed time-motion analysis, unnecessary operations can be minimized and the duration of essential tasks progressively reduced. Furthermore, SMED-based evaluation helps identify the bottleneck operation (the single task that most significantly determines the total reconfiguration time), thereby enabling targeted improvements that substantially reduce waste. Since changeover duration directly affects system flexibility, optimizing each operation and streamlining production planning can significantly shorten setup times. In this context, categorizing each operation into internal or external groups and subsequently optimizing them allows for a notable reduction in overall machine reconfiguration time. This, in turn, enhances equipment utilization and increases production output [15-17]. However, the SMED methodology optimizes setup times based on the assumption of static, predictable batch sequences. This approach does not account for the variability in batch sizes typical of multi-product manufacturing SMEs, which can potentially lead to suboptimal batching strategies when demand exhibits stochastic behavior.

Group-based setup involves classifying parts into families based on similarities in manufacturing operations and geometric characteristics. This approach allows the feeding system and associated software to be configured once per group, rather than individually for every part type and dimension, significantly reducing total reconfiguration time. The classification process typically follows a multi-stage procedure: first, parts are clustered hierarchically to determine the optimal number of families; then, multi-criteria optimization is applied, incorporating factors such as tool change intervals, planned batch sizes, and reconfiguration costs [18]. Despite its conceptual appeal, group technology is typically based on static part clustering and lacks quantitative models for assessing how production flexibility changes depending on batch conditions. The classification process, while useful for reducing setup frequency, does not provide explicit metrics for assessing whether the chosen grouping strategy is optimal for a given production scenario.

For example, recent work on stochastic production planning showed that accounting for uncertainty significantly increases the costs of late order fulfillment. Our research extends this principle to the shop floor, where stochastic part sizes significantly affect the efficiency of auxiliary systems [19].

In modern manufacturing, production is predominantly high-mix, with batch sizes for identical parts often varying significantly. This variability directly affects the assessment of production efficiency and necessitates the use of probabilistic modeling to accurately represent system behavior. To evaluate the impact of group-based feeding configurations and batch size variability on machine-level flexibility, the Monte Carlo simulation method is particularly suitable. It enables the generation of stochastic scenarios that reflect real-world uncertainty in part mix and batch volumes, thereby supporting robust flexibility assessment [20].

The literature review reveals a significant gap in the quantitative assessment of the production system flexibility: existing studies focus primarily on machine-level adaptability and the application of digital twins, SMED, and group technology. However, the impact of auxiliary part feeding systems on the overall flexibility of high-mix production remains underexplored. Specifically, there is a lack of mathematical models capable of quantifying and predicting changes in machine flexibility when group-based reconfiguration of feeding systems is applied under stochastic batch-size conditions. Although Monte Carlo simulation has been successfully used in production system analysis, its potential for evaluating group setup strategies under probabilistic production scenarios has not yet been implemented.

This study addresses this gap through an integrated approach that combines a probabilistic model for machine flexibility assessment explicitly incorporating feeding systems, and Monte Carlo simulation to analyze stochastic production scenarios. In contrast to existing deterministic approaches, the proposed model considers batch-size variability and enables the identification of an optimal part grouping strategy that minimizes reconfiguration frequency for vibratory bowl feeders.

This review identifies a significant gap in manufacturing systems research. While digital twins, SMEDs and swarm technologies make a valuable contribution to improving manufacturing flexibility, there is a significant drawback shared by all three. That drawback is the fact that none of these approaches simultaneously considers stochasticity at the machine level. In addition, none of them explicitly focuses on auxiliary feed systems, nor do they provide quantitative predictive metrics for assessing flexibility. This study aims to address these interdependent shortcomings by developing an integrated probabilistic model that combines swarm-based reconfiguration logic with Monte Carlo simulation to predict machine flexibility. The model has been specifically developed for auxiliary feed systems, which are frequently overlooked in flexibility studies despite their considerable impact on overall system performance. The proposed study introduces a quantitative flexibility coefficient and provides experimental validation, thereby providing a cost-effective decision-making tool for optimizing the design of parts feed systems.

The novelty of this study lies in establishing quantitative relationships between group reconfiguration parameters, particularly the proportion of parts requiring setup, and an integrated flexibility indicator for high-mix production systems. This provides a practical, data-driven tool for engineering decisions aimed at optimizing feeding systems without increasing their complexity.

3- Materials and Methods

3-1- Machine Flexibility Coefficient

Conducting online multi-criteria analysis of production conditions under continuous repair and maintenance activities remains a complex task [21-26]. A work shift comprises time spent on core production operations and time lost to unplanned interruptions, such as changeovers, equipment failures, and material shortages. A widely used parameter for assessing operational efficiency is the ratio of downtime to total shift time. This indicator reflects the effective use of available time and serves as a basis for improving productivity through targeted technical or organizational solutions [27].

To specifically evaluate the operational efficiency of a flexible reconfigurable production system, one can employ the machine flexibility coefficient ($K_{F.M.}$), defined by Equation 1:

$$K_{F.M.} = \frac{T_C}{T_M + T_R} \tag{1}$$

where T_C is the total time for reconfiguring systems in the case of organizing the production of a new type and size of parts; T_M is the total machining time spent on production of one part; T_R is the PS recovery period (without reconfiguration); T_M+T_R represents the total cycle time during which the system functioned most efficiently.

Production systems exhibit varying degrees of flexibility. To classify systems with high adaptability, we adopt a threshold based on the coefficient of variation of the machine flexibility coefficient demonstrating enhanced (in this case $K_{F.M.} \leq 0.1$), medium (when $0.1 < K_{F.M.} \leq 0.2$), and low flexibility ($0.2 < K_{F.M.}$). The flexibility coefficient threshold is defined as the ratio of time or labor costs associated with changeovers to total production costs, with the stipulation that these costs be less than 10% of the total. This suggests that the penalty for high product diversity is negligible from an operational perspective, enabling virtually uninterrupted processing despite frequent batch alterations.

The $K_{F.M.} \leq 0.1$ threshold for high flexibility corresponds to widely accepted industrial engineering standards, in which auxiliary and setup work exceeding 10% of the total cycle time is considered economically significant and disruptive to the production process [27]. These thresholds can also be seen in lean manufacturing systems, where a setup-to-production ratio of less than 10% is considered a prerequisite for continuous flow under conditions of high variability. Medium and low thresholds are calculated in a similar manner and reflect gradually increasing reconfiguration loads that require compensatory planning or system redesign.

In practice, $K_{F.M.}$ values indicate how efficiently the overall production cycle will be reconfigured. For example, if $K_{F.M.} = 0.084$, this indicates that the reconfiguration time is approximately 8.4% of the total production cycle time, which indicates that the system spends relatively little time on reconfiguration and is flexible. Conversely, if $K_{F.M.} = 0.162$, this would mean a decrease in productivity, which may require planners to allocate additional buffer time or reduce the variety of part types processed during a single shift.

The corresponding parameter values are referred to as target values.

The analyzed production system comprises two core subsystems:

- A feeding system: vibratory bowl feeders with orientation mechanisms,
- A machining system: spindle-based fixtures.

The total time required to produce a single part includes the following setup and processing components (in seconds):

$$T_{Mi} = t_{MePS1} + (t_{MePS2} + t_{MePS3} + t_{MePS4})N_i \quad (2)$$

where t_{MePS1} is a hook reconfiguration, sec; t_{MePS2} – spindle stopper positioning, sec; t_{MePS3} – replacement of tools and NC program adjustment, sec; t_{MePS4} – spindle stopper repositioning, sec.

In addition to other components, the total setup time T_R includes tool changeover, fixture adjustments, and program reconfiguration. If the reliability of the tools is expressed by a parameter T, the number of interruptions in the production of conditional batches of products of the i-th types and dimensions in the volume N_i can be expressed by the formula $t_{MePS3}N_i/T$. If one interruption is necessary to restore the functionality of a set of tools, it is denoted by a recovery time t_{SS}, then

$$\mathrm{T_{Ri}} = \frac{\mathrm{t_{MePS3}N_i}}{\mathrm{T}}\mathrm{t_{SS}} \quad (3)$$

where, T denotes tool life. The machine flexibility indicator for the i-th part is defined in Equation 4:

$$K_{F.M.i} = \frac{T_{Ci}}{T_{Mi}+T_{Ri}} = \frac{t_{MePS1}+t_{MePS2}+t_{MePS3}+t_{MePS4}}{t_{MePS1}+(t_{MePS2}+t_{MePS3}+t_{MePS4})N_i+\frac{t_{MePS3}N_i}{T}t_{SS}} \quad (4)$$

This indicator can be extended to a sequence of n production batches, comprising N_i parts scheduled for machining for each batch ($i = 1,2,\dots,n$). An integrated flexibility coefficient $K_{F.M.}$ is then computed as a weighted average across all batches in Equation 5:

$$K_{F.M.} = \frac{\sum_{i=1}^{n} K_{F.M.i}N_i}{\sum_{i=1}^{n} N_i} \quad (5)$$

here, n – total number of different types of parts in the production plan.

The value of $K_{F.M.}$ is primarily influenced by two factors: the reconfiguration time of the vibratory bowl feeders and the batch sizes for each part type and dimension.

3-2- Probabilistic Modeling using the Monte Carlo Method

Let the number of semifinished products of the first type and first size category be denoted by the discrete variable N, which lies within the range [$N_{\min}$, $N_{\max}$]:

$$N = \{N_i | N_{min} \le N_i \le N_{max}\} \quad (6)$$

During prospective analysis, it is essential to have specific values representing the quantities of semifinished products across all types and size categories, or alternatively, to establish a rule governing the distribution of these quantities:

$$N_i | P(N_i = \xi), N_{min} \le \xi \le N_{max} \quad (7)$$

When it is necessary to include or exclude the setup time of rotary orienting devices for all i-th parts (regarding whether the i-th part belongs to the next setup group), one should introduce an indicator $K_{C.i}$, which signifies whether a setup is required for the i-th semifinished product type and size category. Here, 1 indicates that a setup is required, whereas 0 indicates that no setup is needed.

Let M denote the set of all semifinished product types and sizes, where $|M| = n$ represents the total number of distinct type-size combinations in the population.

Let D be a subset of M related to the set of parts that do not require equipment reconfiguration during processing. Thus, D comprises all type-size combinations of semifinished products for which setup adjustments of the loading system are unnecessary. Therefore, $D \subseteq M$ reflects the total number of such part variants.

Conversely, the set of semifinished product type-size combinations that do require reconfiguration of loading equipment is as follows: $M \backslash D$.

Any i-th types and dimensions of semifinished products will be part of the set M or D. In this case:

$$K_{C.i} = \begin{cases} 0, i \in D \\ 1, i \in (M \backslash D) \end{cases} \quad (8)$$

The probability of reconfiguring the loading systems, denoted U_C, is expressed as the ratio of the number of semifinished product type-size combinations requiring reconfiguration (i.e., for which $K_{C.i}$ =1) to the total number of type-size combinations of semifinished products:

$$U_C = \frac{|M \backslash D|}{|M|} = \frac{|M \backslash D|}{n} \quad (9)$$

It should also be noted that the quantity of semifinished products N_i follows a uniform distribution:

$$P(N_i = \xi) = \frac{1}{N_{max} - N_{min}}, N_{min} \leq \xi \leq N_{max} \tag{10}$$

The results of the probabilistic simulation of a high-mix manufacturing system, where group-based setup reconfiguration of loading operations is implemented and machine flexibility is to be evaluated, can be represented by the following mathematical model:

$$\begin{gathered} N_i | P(N_i = \xi), N_{\min} \leq \xi \leq N_{\max} \\ T_{Mi} = t_{MePS1} + t_{MePS2} + (t_{MePS3} + t_{MePS4}) N_i \\ T_{Ri} = \frac{t_{MePS4} N_i}{T} t_{SS} \\ T_{Ci} = t_{MePS1} + t_{MePS2} + t_{MePS3} + t_{MePS4} \\ K_{C.i} = \begin{cases} 0, i \in D \\ 1, i \in (M \backslash D) \end{cases} \\ K_{F.M.} = \frac{T_C}{T_M + T_R} \\ K_{F.M.} = \frac{\sum_{i=1}^{n} K_{F.M.i} N_i}{\sum_{i=1}^{n} N_i} \end{gathered} \tag{11}$$

3-3- Model Development for Simulating Loading Operations in High-Mix Manufacturing

The loading of machine tools with semifinished products represents a transformation of each input into an output, a process that must be supported by appropriate mechanisms. Accordingly, the developed multi-input model incorporates the following elements:

- Interdependencies among the fundamental components of the production system.
- Time requirements associated with the operation of these fundamental production components.
- Individual workpieces subject to loading (e.g., ferrules, sleeves).
- Batches of loaded semifinished products comprising 45 to 450 distinct items.
- Qualification level of setup personnel.
- Characteristics of the loaded workpieces.
- Specifications of the loading system itself.

Model decisions were formulated using an integrated methodological approach comprising Monte Carlo simulation, associative evaluation techniques, experimental design principles, and empirical research implementation [28]. The underlying resource infrastructure includes the PS owner, computational hardware, and dedicated loading complexes. The primary outputs of each machine-loading operation are an assessment of the efficiency of group-based setups and actionable recommendations for optimizing setup procedures.

To ensure reproducibility, the following sequence was implemented:

- For a defined set of part types M, a binary vector indicating reconfiguration necessity $K_{C.i}$ is generated based on the target probability Uc.
- The algorithm performs 100 iterations. In each iteration k, random batch sizes Ni are generated for each part type using the discrete uniform distribution on the interval [$N_{\min} \leq N_{\max}$]; the total setup time T_C and total machining time T_M are calculated based on the generated batch sizes and fixed time norms; the instance flexibility coefficient $K^{(k)}_{F.M.}$ is computed for the current iteration.
- The flexibility coefficient of the machine is calculated as the arithmetic mean of 100 iterations, and the 90% confidence interval is calculated using Chebyshev's inequality.

A visual representation of the developed model is provided in Figure 1. The schematic illustrates digitally encoded information flows, depicting their trajectory through successive processing stages as they contribute to the attainment of defined operational objectives.

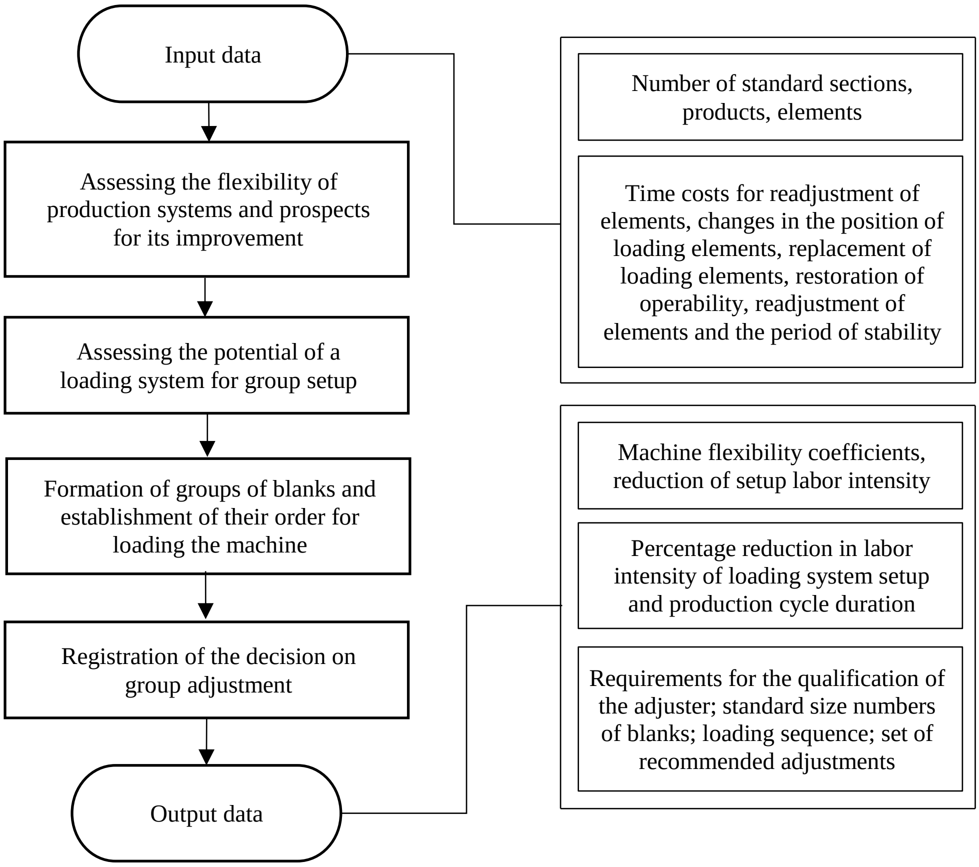

Figure 1. Schematic representation of the model simulating machine loading operations

To validate the developed mathematical model for assessing the flexibility of the production system, an experimental study was conducted using actual manufacturing equipment. The object of investigation was a rotary orienting device, a key component of the loading system in high-mix production. The experimental setup consisted of a rotary orienting device (ROD) equipped with an adjustable feed pawl. The pawl rotation speed was maintained constant at 16 revolutions per minute across all experimental runs to ensure comparability of results between different test series. Eight distinct types and size categories of sleeves were employed as test specimens, with geometric parameters representative of the typical range of parts processed in high-mix production environments. Sleeves were selected as model workpieces because of their widespread use in mechanical engineering practice and their sufficient geometric simplicity, which ensures reproducibility of experimental conditions.

The experimental methodology involved a systematic investigation of how the positioning of the feed pawl relative to the workpiece affects the performance of the rotary orienting device. For each sleeve type, tests were conducted at three different pawl positions relative to the semifinished workpiece. For every combination of sleeve type and pawl position, thirty repeated measurements were performed, providing a sufficient statistical basis to identify consistent operational patterns. The efficiency of the rotary orienting device was quantified by counting the number of correctly oriented semifinished workpieces delivered to the subsequent manufacturing operation per 1,000 pawl revolutions. This indicator enables an objective comparison of device performance across different setup configurations and workpiece types, as it normalizes output with respect to a standardized unit of equipment operating time.

Statistical analysis of the experimental data was performed using Spearman’s rank correlation coefficient, a nonparametric measure that assesses the presence and strength of a monotonic relationship between variables without assuming normality of their distributions. Specifically, correlation dependencies were examined between the performance of the rotary orienting device and the feed pawl positioning for each sleeve type. The computed correlation coefficients were compared against critical values to determine the statistical significance of the observed patterns at a predefined confidence level. The use of Spearman’s nonparametric method was justified by the discrete nature of certain measured variables and the need to ensure robustness of the results against potential outliers in the experimental data.

The selection of 100 iterations was substantiated by a preliminary convergence analysis, which monitored the moving average and standard deviation of $K_{F.M.}$ as the number of iterations increased from 10 to 500. The mean value stabilized within ±0.002 of the final estimate after approximately 60-70 iterations in all tested scenarios, and the width of the 90% Chebyshev confidence interval ceased to decrease significantly after 100 iterations. Consequently, it was determined that 100 iterations would be adequate to obtain stable point estimates and confidence bounds while maintaining computational efficiency suitable for practical engineering analysis prior to production.

Chebyshev's inequality gives wide confidence intervals, which is its main difference from parametric alternatives such as normal approximation or bootstrap resampling. For a sample of 100 iterations, the 90% confidence interval of the normal approximation will be approximately 1.3-1.6 times narrower than the Chebyshev bound given here, while the bootstrap interval will be similar in width to the normal approximation. However, both alternatives require either assumptions about the distribution or a sufficiently large resampling budget to be reliable. Given that the distribution of $K_{F.M.}$ in real production conditions may be asymmetric, the use of Chebyshev's inequality is considered a more appropriate method for conservative engineering decisions. Therefore, the specified confidence intervals should be interpreted as upper limits of uncertainty, and in practice, the intervals are likely to be narrower.

The experimental verification conducted using eight types of bushings and one configuration of a rotary orientation device represents a deliberate design choice aimed at ensuring reproducibility and controlling geometric variability within a manageable range. The model presented is geometry-independent, as it works with setup time norms and batch size parameters that can be changed for any group of parts and any feeding mechanism. For alternative feeding technologies, such as flexible robotic feeders or vision-guided pick-and-place systems, the model remains applicable provided that the changeover time and processing cycle time can be determined.

Model validation was performed by comparing the results of numerical simulations with experimentally obtained data on the operational performance of the rotary orienting device. The comparison focused on several key parameters, including: the relationship between the machine flexibility index and the proportion of workpieces requiring reconfiguration of the loading system, and the impact of batch size on the efficiency of the group-based setup strategy. Particular emphasis was placed on verifying the ability of the model to adequately predict variations in the machine flexibility index under different workpiece-grouping strategies; this capability constitutes the primary practical application of the proposed methodology. The adequacy of the model was assessed using two complementary criteria: the inclusion of experimentally observed values within the confidence intervals predicted by the numerical simulation, and the qualitative alignment between the simulated and empirical trends in the behavior of the investigated performance characteristics. This dual-criteria approach ensured both statistical and practical validity of the model across a range of realistic production scenarios.

4- Results

To determine the influence of reconfiguration characteristics of the rotary orienting device (ROD) on its productivity, a ROD with a circumferential chute length of 400 mm was employed. Sleeves of eight distinct types and size categories were used for orientation trials; their specifications are presented in Figure 2. Additionally, a feed pawl with a pickup segment width d_{cr} of 6 mm was employed. The pawl rotated at a constant speed of 16 revolutions per minute (rpm) in all experimental runs.

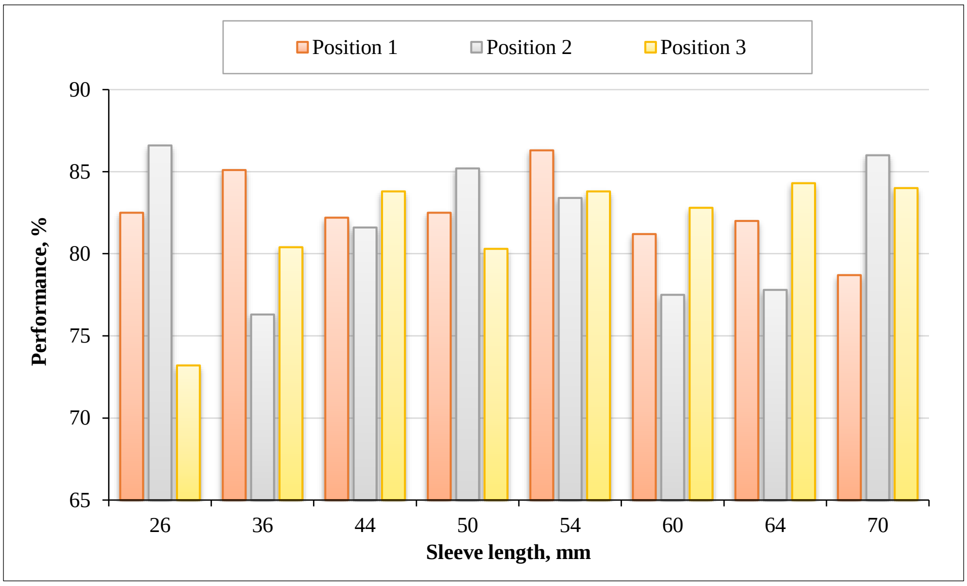

Figure 2. Performance of the rotary orienting device (ROD)

The selection of eight different types of bushings was dictated by the necessity to create a representative sample which would cover a wide range of geometric parameters typical of multi-product manufacturing. These dimensions are sufficient to identify the clusters required to test the group retooling strategy.

Productivity was quantified as the number of correctly oriented semifinished parts delivered per 1,000 pawl revolutions. Three distinct pawl positions were examined:

Position 1: The pawl engaged the sleeve at the bottom of the device, corresponding to the initial phase of workpiece pickup from the bulk feed.

Position 2: The pawl contacted an upper point of the sleeve, simulating a scenario in which the workpiece had already been partially lifted along the orienting chute.

Position 3: The pawl and sleeve were axially aligned, representing the optimal configuration for reliable workpiece engagement and transport.

Figure 2 shows the set of measured values characterizing the operational efficiency of the ROD under these conditions. To analyze the relationship between device performance and the initial pawl position relative to the orientable sleeves, Spearman's rank correlation method was applied.

For the variable pairs R_{ab}-R_{aa}, R_{ab}-R_{at}, and R_{at}-R_{aa}, Spearman's rank correlation coefficients were $r = -0.27$, $r = -0.48$, and $r = 0.13$, respectively.

The list of limiting values is as follows in Equation 4:

$$r_{cr} = \begin{cases} 0.77(\alpha \leq 0.05) \\ 0.88(\alpha \leq 0.01) \end{cases} \tag{4}$$

When individual (dedicated) setup is applied, the average values of the machine flexibility index $K_{F.M.}$ are 0.142 and 0.185 for planned production batches ranging from 200 to 500 workpiece types, respectively. A comparison of the calculated Spearman coefficients with critical values confirms that none of the observed correlations are statistically significant. This finding suggests that, within the range of tested bushing types, there is no constant relationship between position and device performance. From a pragmatic standpoint, this finding underscores the notion that performance is predominantly autonomous of the latch's position within the examined series of components. This observation directly corroborates the efficacy of implementing a unified latch configuration at the group level, a strategy that is applicable across diverse categories of bushings.

A contemporary PS operating as a high-mix facility with a defined level of flexibility is characterized by variability in the quantity of workpieces per batch for the first type and first size category. Moreover, the batch size itself significantly influences the outcomes of PS productivity analysis.

In the numerical experiments, each simulation scenario was repeated at least 100 times, enabling the generation of numerous model realizations encompassing diverse batch compositions and varying numbers of PS reconfigurations. The results of these model runs are presented in Figure 3 as numerical (bar) charts.

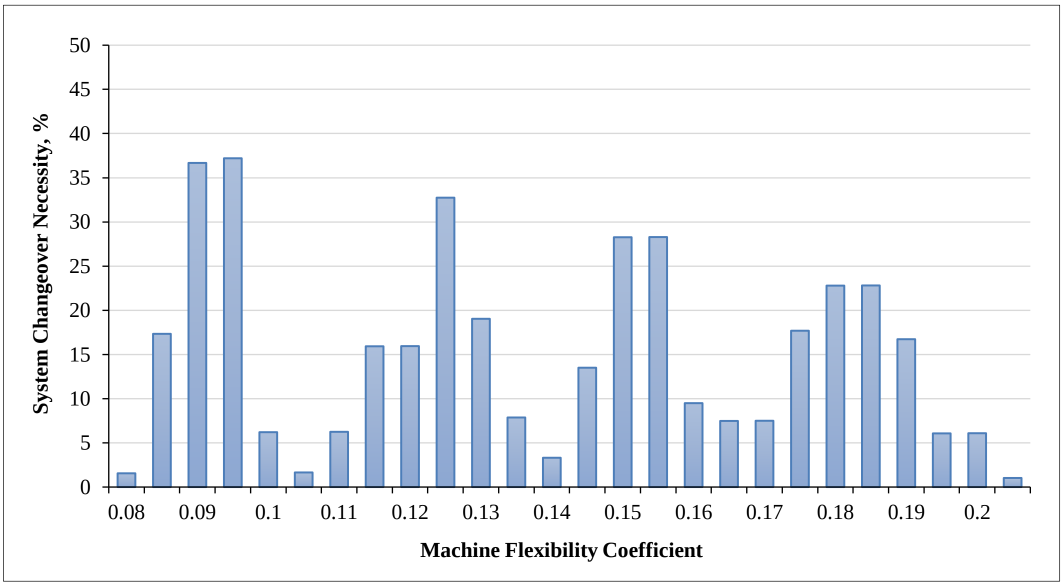

Figure 3. Reconfiguration requirement for loading operations P_C as a determinant of the machine flexibility index $K_{F.M.}$ (Planned batch sizes ranging from 45 to 450 parts)

Evaluation of the numerical diagrams shown in Figure 3 indicates that when $P_C = 0$ ($K_{F.M.} = 0.088 \pm 0.014$), the analyzed PS exhibits increased flexibility. When $P_C = 1/3$ ($K_{F.M.} = 0.120 \pm 0.021$), $P_C = 2/3$ ($K_{F.M.} = 0.151 \pm 0.027$), and $P_C = 1$ ($K_{F.M.} = 0.185 \pm 0.026$), the analyzed PS demonstrates average flexibility.

Table 1 consolidates the simulated machine flexibility index values across all tested reconfiguration scenarios, making the progression explicit.

Table 1. **Simulated K_F.M. values as a function of reconfiguration probability with 90% Chebyshev confidence intervals and corresponding flexibility classifications**

Reconfiguration probability P_C	Mean $K_{F.M.}$	90% Confidence interval
0 (no reconfiguration required)	0.088	±0.014
1/3 (one-third of parts require setup)	0.120	±0.021
2/3 (two-thirds of parts require setup)	0.151	±0.027
1 (all parts require individual setup)	0.185	±0.026
1 (batch sizes 200-500)	0.144	±0.011

The transition from $P_C = 0$ to 1/3 results in an increase in $K_{F.M.}$ of 0.032, representing the most substantial incremental change observed between any two adjacent reconfiguration levels. This finding suggests that the system exhibits a high degree of sensitivity to the introduction of even a modest reconfiguration requirement. This non-linearity suggests that the most efficient approach to optimize group-based setup is to maintain a proportion of parts requiring reconfiguration below one-third, as opposed to reducing it from two-thirds to one-half. Secondly, as the probability of correct classification, or P_C, increases, the confidence interval widens progressively (from ±0.014 at $P_C = 0$ to ±0.027 at $P_C = 2/3$), reflecting growing variability in system behavior as more reconfiguration events interact stochastically with variable batch sizes. This increasing uncertainty at higher reconfiguration rates reinforces the operational risk associated with individual setup strategies. Not only is the mean flexibility index worse, but the system's behavior becomes harder to predict, complicating production scheduling. Thirdly, the narrower confidence interval observed under the constrained batch size range of 200-500 parts (±0.011 compared to ±0.026 at the same $P_C = 1$) confirms that larger and more uniform batch sizes stabilize system performance even when full reconfiguration is required. This suggests that batch consolidation is a viable complementary strategy when group-based setup cannot fully eliminate reconfiguration events.

The results of the model evaluation (values of the machine flexibility index, $K_{F.M.}$) were calculated using Chebyshev's inequality, with a confidence level of 90%, which is a conservative choice justified by the high volatility characteristic of production environments [29, 30]. Figure 4 presents a numerical (bar) chart summarizing the outcomes of the quantitative experiments, which were conducted under initial production system (PS) conditions. In each experimental scenario, every component of the PS was reconfigured to accommodate a new type and size category of semifinished workpieces: $P_C = 1$ (that is $K_{F.M.} = 0.144 \pm 0.011$).

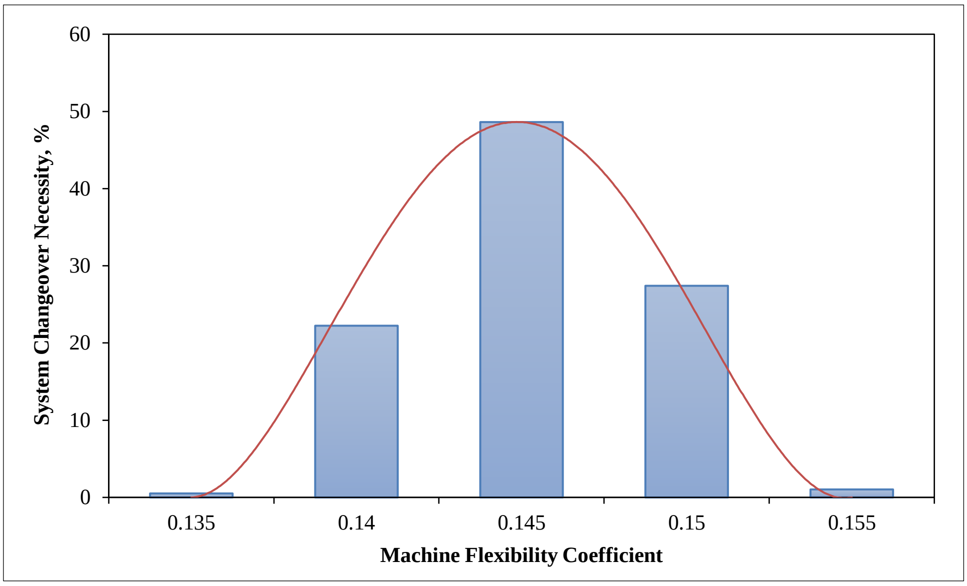

Figure 4. **Reconfiguration requirement for the production system (PS) as a determinant of the machine flexibility index $K_{F.M.}$ for planned batch sizes of 200-500 workpiece types**

The level of labor intensity is defined by the setup time required to prepare the loading systems for processing new types of semifinished workpieces. Let us examine the operational characteristics of the rotary orienting devices to evaluate the reconfiguration parameters of the proposed parts-feeding system. Figure 5 presents the set of initial values used in the subsequent calculation of the indicator quantifying the reduction in setup labor requirements. The efficiency values of the group-based setup method were calculated using:

$$\mathrm{L}_R = (T_C + T_{Ch}) * n \tag{5}$$

$$L^G{}_C = T_C k_{hd} + T_{Ch} k_{hc} \tag{6}$$

where L_R is individual setup labor intensity; T_{Ch} time required to replace the feed pawl (hook), in seconds; n – number of different workpiece types and size categories; $L^G{}_C$ – group setup labor intensity; k_{hd} – average number of adjustments; k_{hc} – number of complete replacements. $k_{hd}uk_{hc}$ – k_{hd} and k_{hc} denote the number of adjustments to the pawl position and the number of pawl replacements, respectively.

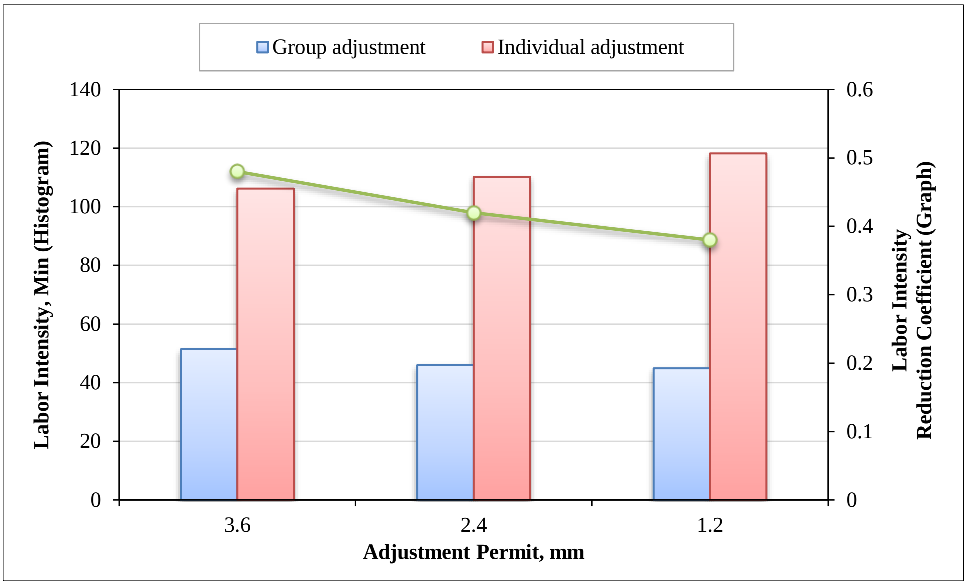

Figure 5. List of initial values used to compute the setup labor intensity reduction coefficient

As shown in Figure 5, the labor intensity reduction coefficient is calculated as the ratio of group setup labor intensity to individual setup labor intensity. The performance of group-based setup decisions is quantified by the coefficient k (group setup labor intensity), which reflects the relative difference in labor requirements between the two approaches:

$$k = \frac{T_C k_{hd} + T_{Ch} k_{hc}}{(T_C + T_{Ch}) * n} \tag{7}$$

The results indicate that, on average, the group-based reconfiguration approach reduces setup labor by 56% compared to the individual setup strategy. Furthermore, if the setup accuracy requirement is halved, the setup duration decreases by a factor of 1.2. Labor intensity can alternatively be expressed as the inverse proportion of the number of setups or reconfigurations performed per unit time.

5- Discussion

The results of the probabilistic simulation of high-mix manufacturing operations make a significant contribution to understanding the relationship between the flexibility of loading systems and overall production efficiency. A comparative analysis with relevant studies from the literature is presented in Table 2 to enable a systematic interpretation of the obtained findings.

Table 2. Comparative analysis of approaches to assessing production system flexibility

Study	Flexibility assessment method	Focus of research	Stochastics consideration
Behrendt et al. [29]	Software-Defined Manufacturing	Flexible production systems	Not considered
Höse et al. [30]	Mathematical modelling of operational flexibility	General-purpose production systems	Qualitative analysis
Cruz et al. [31]	Optimization and Monte Carlo simulation	Production planning for perishable goods	Customer demand
This study	Probabilistic model using the Monte Carlo simulation	High-mix manufacturing	Production batch size

A review of contemporary literature reveals a significant gap in the quantitative assessment of loading system flexibility within high-mix manufacturing environments. Behrendt et al. [29] proposed the concept of Software-Defined Manufacturing to enhance production system flexibility, reporting a 33% reduction in reconfiguration time. However, their approach primarily emphasizes software-based reconfiguration of machinery and does not consider the operational specifics of auxiliary systems, such as rotary orienting devices. Moreover, the absence of a quantitative model capable of predicting performance across varying batch sizes limits the applicability of their solution in highly volatile, high-variety production settings. This study addresses these limitations by introducing a mathematical model that not only evaluates the current flexibility of the system but also forecasts the impact of group-based setup strategies on the machine flexibility index under diverse operational scenarios. The established quantitative relationship between the proportion of parts requiring reconfiguration and system flexibility enables data-driven managerial decision-making.

Höse et al. [30] noted in their comprehensive review that existing mathematical models of operational flexibility often lack practical dimensionality and fail to incorporate the characteristics of auxiliary subsystems, such as loading mechanisms. The authors emphasize the need for models that effectively integrate Industry 4.0 concepts with concrete engineering solutions. This research directly responds to this call by developing a practically applicable model for loading systems. Unlike purely theoretical solutions, the proposed model has been experimentally validated on real industrial equipment, thereby confirming its operational relevance and robustness in real-world manufacturing environments.

A comparison of the results with recent studies further underscores its significance. For example, an analysis of studies in which the SMED method was used in combination with RACI matrices at apparel manufacturing plants shows that changeover time was reduced by 50-64%. This range largely coincides with the 51-61% reduction in setup labor costs achieved in the present study. However, this approach is deterministic and limited to a single case study at one enterprise, providing neither a probabilistic flexibility metric nor a confidence interval index applicable to batches of varying sizes [32]. It is also worth noting that there are many studies presenting lean manufacturing tools for evaluating SMED effectiveness that can predict potential time savings prior to implementation; however, such methods operate exclusively at the level of qualitative screening and do not provide a quantitative flexibility coefficient by which system performance could be assessed [33].

In the modern literature, one can also find the development of a multi-purpose scalability metric for reconfigurable production systems. Such systems demonstrate an advantage over classical production line metrics; however, the proposed evaluation method is oriented toward configurations with a single product line at the design stage and does not provide an operational flexibility index validated under stochastic batch size conditions [34].

A critical advantage of the proposed model is its explicit incorporation of the stochastic nature of batch sizes, spanning the realistic industrial range of 45 to 500 parts. Methodologically, this aligns with the study of Cruz et al. [31], who integrated optimization models with Monte Carlo simulation to plan production of perishable goods under stochastic demand. However, their study focuses primarily on inventory management and production volume planning, leaving the flexibility of loading systems entirely unaddressed. Moreover, such approaches typically lack explicit quantitative metrics for evaluating production system flexibility, limiting their scope to production scheduling optimization rather than equipment-level reconfiguration efficiency.

While current research emphasizes the role of digital twins and robotics in flexible manufacturing, the presented results demonstrate that equipment optimization through group logic remains a cost-effective alternative to full automation. These findings complement the work of Todescato et al. [35], who identified effective management of rapid changeovers as a key element of sustainable production. However, unlike their approach, the presented model provides a detailed quantitative assessment of how the setup time of auxiliary components determines overall system responsiveness, indicating its effective application in small-batch production. Similar conclusions regarding engineering-driven optimization and decision-support approaches as cost-efficient alternatives to full automation have been reported in related studies [33, 34].

Given the specifics of multi-product manufacturing, it is worth noting that the normal distribution method used to calculate sensitivity will reduce the dispersion of the simulated $K_{F.M.}$ values, resulting in narrow confidence intervals. In multi-product manufacturing, the effective average batch size will be lower, which will increase $K_{F.M.}$. When using seasonal demand models with large batches, the coefficient may, on the contrary, fall below the presented flexibility threshold, which allows us to conclude that the proposed model is well suited for systems with moderate demand variability, and also allows us to take into account that in further research it is worth considering empirical data on demand for the specific context of the enterprise.

The uniform distribution approach is regarded as a conservative strategy. In contrast to the normal distribution, which organizes values around the mean, the uniform distribution assigns equal probability to all possible batch sizes. This enables the evaluation of the system's performance under various loads without the necessity of constraining it to specific order patterns.

The results obtained for the flexibility coefficient show that, from a production perspective, high flexibility becomes less critical. Production can adapt to frequent product changes without significant downtime associated with equipment setup. In conditions where a large number of different products are manufactured in small volumes, the design focus shifts from minimizing the number of changeovers to managing families of parts and batch variability within the proposed structure.

The experiments confirmed that the performance of the ROD is largely insensitive to pawl positioning across a range of part types. This finding enables a single, group-based pawl setup for multiple parts without compromising efficiency. Performance degradation remains within 3-5%, and this loss can be readily offset by a minor increase in pawl rotation speed. This robustness significantly enhances practical applicability.

The proposed model addresses a fundamentally distinct problem by enabling a quantitative assessment of how variations in the proportion of workpieces requiring reconfiguration of the loading system directly affect the overall flexibility of the production system. By performing at least 100 repetitions of each numerical experiment, the study ensures statistical reliability of the results, as evidenced by the 90% confidence level derived from Chebyshev's inequality. This probabilistic foundation renders the model more robust and realistic compared to deterministic approaches, which often overlook operational variability.

A key advantage of the developed model lies in its comprehensive approach to assessing production system flexibility that integrates not only primary machining equipment but also auxiliary loading subsystems. This system-level perspective aligns with contemporary approaches to sustainable and intelligent manufacturing, where reconfigurable subsystems are considered integral components of overall production efficiency rather than isolated elements [35]. Experimental results confirm that adapting the loading complex to a group-based reconfiguration strategy leads to a 25% reduction in the machine flexibility index when one-third of the workpieces require setup changes, and a 35% reduction when two-thirds of the parts necessitate reconfiguration. These figures quantitatively demonstrate the substantial impact of loading system design on overall production efficiency. Furthermore, the model provides a practical decision-support tool for forecasting system performance under diverse production scenarios. It enables planners to schedule group setups based on anticipated part mix and batch sizes, without requiring investment in costly specialized software, thereby enhancing responsiveness, reducing setup labor, and supporting cost-effective, agile manufacturing in high-variety environments. Such improvements in operational responsiveness and reduction of manual intervention are consistent with broader trends in industrial automation, where optimization of auxiliary processes plays a critical role in enhancing overall system performance [36].

6- Conclusion

The findings of this study demonstrate that the desired level of machine flexibility in high-mix production is achievable when the proportion of workpiece types requiring loading system reconfiguration remains below one-third of the total scheduled for a given shift. This results in a machine flexibility index of $K\_F.M. = 0.088 \pm 0.014$, which is within the established threshold for high flexibility. As demonstrated by probabilistic modeling, batch size has been shown to have a considerable impact on the efficiency of the loading system. Within the range of 200 to 500 workpiece types, the production system demonstrates an approximate 33% increase in machine flexibility compared to the mean baseline. When group-based reconfiguration is applied, the machine flexibility index decreases by 25% relative to fully individual setup strategies, and setup labor requirements are reduced by 51-61% for systems handling 100 distinct part types. Experimental validation using a rotary orienting device across eight sleeve types confirmed that a uniform group-level pawl adjustment maintains operational efficiency deviations within 3-5%, demonstrating that the group strategy is robust across geometrically diverse part families. Spearman correlation analysis further confirmed the absence of statistically significant relationships between pawl position and device productivity, providing direct empirical justification for the group setup approach.

The principal contribution of this work lies in introducing a confidence-bounded, probabilistically validated machine flexibility coefficient that explicitly incorporates auxiliary loading subsystems. This aspect has been consistently neglected in existing deterministic models. The coefficient offers a practical, cost-effective decision-support tool for production planning without requiring investment in complex software infrastructure. The proposed methodology is expected to reduce production costs by enabling flexibility optimization without sacrificing throughput or increasing system complexity. The study's limitations include the exclusion of equipment wear and operator skill variability, both of which may influence real-world setup durations. Future research endeavors should extend the validation process to encompass a more extensive range of component geometries and alternative feeding mechanisms. Additionally, the incorporation of human factors and stochastic disturbances into the modeling framework is imperative.

7- Declarations

7-1- Author Contributions

Conceptualization, I.A. and A.Sh.; methodology, A.Sh.; software, N.I.; validation, D.K. and I.M.; formal analysis, D.K.; investigation, N.K.; resources, D.K.; data curation, I.A.; writing—original draft preparation, N.K.; writing—review and editing, A.Sh.; visualization, N.I.; supervision, I.A.; project administration, I.A. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The presented study was performed obtained within the work under the Additional Agreement dated 18 April 2024 No. 075-03-2024-278/1 to the Agreement dated 22 January 2024 No. 075-03-2024-278 between the Ministry of Science and Higher Education of the Russian Federation and IDTI RAS for the implementation of state assignments to create a new (youth) laboratory that will carry out research on the topic "Organization and management of hybrid multi-product engineering production".

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

Not applicable.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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