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# Human-Centered Multi-Objective Flow Shop Scheduling with Missing Operations under an Industry 5.0 Perspective

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***Abstract*– Industry 5.0 is transforming production planning by integrating human factors into decision-making. This paper addresses a multi-objective permutation flow shop scheduling problem with missing operations, where jobs may skip machines and processing times depend on worker-related factors such as skill level, age, learning, and forgetting. The model simultaneously minimizes makespan, total tardiness, and total earliness. To solve the problem, an NSGA-II-based evolutionary algorithm with permutation encoding was implemented. Computational experiments with 0%, 20%, and 40% missing operations show that greater route flexibility generally improves schedule quality, reducing makespan by 4.41% to 27.71% and total earliness by 18.11% to 77.53% in compromise solutions, while tardiness shows a more heterogeneous behavior. The results also indicate that missing operations reshape the trade-off structure among objectives rather than simply reducing problem size. Overall, the study provides a human-centered scheduling approach aligned with Industry 5.0 and relevant for production environments with workforce heterogeneity and route variability.***

***Keywords*-- Industry 5.0; flow shop scheduling; missing operations; multi-objective optimization; human factors**

## I. INTRODUCTION

Industry 5.0 reframes industrial transformation by elevating mass customization and human factors from peripheral concerns to core pillars of production design. Rather than treating customization as a downstream marketing challenge and workers as passive executors, Industry 5.0 positions personalized products and human capabilities as co-equal drivers of system architecture[1]. Mass customization demands production systems that can economically deliver individualized features at scale; human factors require those systems to be designed around real people (their skills, learning trajectories, physical limits, and cognitive states) so that productivity gains do not come at the expense of wellbeing, safety, or long-term resilience [2]. When these two attributes are treated as foundational, scheduling and planning cease to be purely machine-centric optimization tasks and become socio-technical design problems that balance throughput, service, and human flourishing [3].

On the shop floor, mass customization produces frequent route changes, variable operation sets, and "missing operation" scenarios where some jobs bypass certain machines[6],[7]. These patterns increase the combinatorial complexity of sequencing and setup decisions and amplify the importance of human performance variability. Workers do not perform identically across tasks or over time: skill levels, age, learning effects, and forgetting shape effective processing times and error rates[5]. Industry 5.0 therefore calls for models that translate nominal processing and setup times into worker-aware effective durations, and for planners who can reason about trade-offs that include human outcomes as first-class objectives[9].

Multi-objective scheduling is the natural methodological response[8]. Instead of optimizing a single metric, planners seek Pareto-efficient schedules that expose trade-offs among makespan (resource utilization), total tardiness (customer service), and total earliness (work-in-progress and inventory exposure), while also accounting for human-centered metrics such as fatigue risk, skill development opportunities, and ergonomic load. Embedding human factors into multi-objective formulations changes the geometry of the trade space: front-loading repetitive tasks can exploit learning and reduce makespan but may increase fatigue or reduce opportunities for cross-training; assigning tasks to match high-skill operators improves quality but may increase setups and delay other orders[11]; [12]. Missing operations interact with these dynamics by altering repetition counts and setup patterns across machines, which in turn affects both learning accumulation and setup discounts. A multi-objective approach makes these tensions explicit and supports decisions that reflect organizational values, whether prioritizing speed, service, workforce development, or a balanced compromise[10].

Practically, human-centered Industry 5.0 scheduling requires new modeling and algorithmic elements. First, effective processing times are computed by combining a bounded learning curve with multiplicative modifiers for skill, age, and forgetting, and setup times are adjusted by repetition discounts; lower bounds prevent unrealistic reductions. Second, the flow-shop simulator must allow missing operations so that jobs can bypass machines when appropriate. Third, solution methods must handle the resulting NP-hard combinatorial problem; evolutionary multi-objective algorithms (for example, permutation encodings with PMX crossover and swap mutation inside NSGA-II) are well suited to explore diverse schedules and return Pareto fronts that reveal trade-offs. Finally, evaluation metrics should include both classical measures (hypervolume, convergence, diversity) and human-centered indicators so that planners can compare schedules on operational and social dimensions.

## II. Related work

### A. Industry 5.0 background

Industry 5.0 reframes the factory not as a place where humans are merely overseers of automation, but as a collaborative ecosystem where people, machines, and digital systems co-design value. Building on Industry 4.0's connectivity, data, and autonomy, Industry 5.0 emphasizes human centricity, sustainability, and resilience: it seeks to restore human judgment, creativity, and well-being to the center of production while leveraging advanced technologies (cobots, AI assistants, digital twins, and edge analytics) to amplify human capabilities rather than replace them[4]. This shift recognizes that many competitive advantages come from human skills that are hard to automate (contextual decision making, tacit knowledge, and creative problem solving) and it intentionally designs systems that make those strengths more effective, safer, and more satisfying to exercise[3].

Human-centered production planning under Industry 5.0 therefore changes both objectives and methods. Planning moves beyond pure throughput and cost metrics to include worker ergonomics, cognitive load, job variety, and opportunities for learning[13]. Schedules and task assignments are optimized not only for machine utilization but for human well-being: balancing repetitive tasks with skill-building activities, limiting prolonged high-strain operations, and ensuring predictable recovery and rotation. Production plans incorporate human factors models (fatigue, learning curves, and error likelihood) so that cycle times and quality estimates reflect realistic human performance rather than idealized machine rates. This leads to more robust schedules that reduce rework, absenteeism, and safety incidents while preserving productivity[14].

Technically, human-centered planning integrates richer data sources into the planning loop. Wearable sensors, workstation telemetry, and self-reported readiness feed short-term scheduling adjustments and long-term capacity models. Digital twins simulate not only machine states but human workflows and interactions, enabling planners to test alternative layouts, staffing mixes, and training interventions before committing changes on the shop floor. AI and optimization tools are repurposed to propose human-aware solutions (suggesting task rotations that maximize learning, or sequencing jobs to minimize cognitive switching costs) while keeping humans in the decision loop to validate and adapt recommendations[15],[16].

Organizationally, Industry 5.0 requires new roles and governance. Planners, ergonomists, and frontline workers collaborate to define acceptable trade-offs between efficiency and human outcomes. Continuous improvement cycles include human experience metrics (satisfaction, perceived autonomy, and skill development) alongside traditional KPIs[9]. Training and upskilling become integral to planning: production plans explicitly allocate time for mentoring, cross-training, and micro-learning so that workforce capabilities grow in step with technological change[17].

Adopting human-centered production planning also supports sustainability and resilience. By valuing human judgment, systems can better handle variability, customization, and unexpected disruptions; by designing for worker well-being, firms reduce turnover and preserve institutional knowledge. In practice, the transition is incremental: start with pilot lines where cobots assist rather than replace, instrument tasks to capture human performance data ethically, and evolve planning algorithms to include human factors. Over time, these changes create workplaces that are more humane, adaptable, and innovative, where technology amplifies human potential and production planning becomes a tool for both operational excellence and human flourishing[2];[13].

### B. Scheduling in human centered and missing operations

Mass customization reshapes shop-floor operations by demanding flexibility, connectivity, and intelligence across production systems. Customers increasingly define product features in real time, which forces manufacturers to support a wide variety of product configurations without sacrificing scale economies; this trend is enabled by smart product design and digital integration that translate customer preferences into executable shop-floor instructions[18]. Prominent examples are: Nike's customizable sneakers, Dell's configurable computers, and automotive offerings from BMW and Tesla,[19],[20],[21],[22]. On the shop floor this means that not every unit follows the same sequence of operations: some jobs may skip stages entirely, creating "missing operation" scenarios that complicate sequencing and resource allocation[7].

To cope with this variability, physical layouts and workflows must become more modular and reconfigurable so lines can switch rapidly between different product routes; quick changeover techniques such as Single-Minute Exchange of Die (SMED) are therefore critical to minimize downtime during transitions[23]. Real-time data integration is equally essential: linking customer orders, inventory status, and production progress through sensors and information systems (for example, RFID) enables accurate, up-to-date decision making and reduces the risk of mismatches between demand and shop-floor actions[24]. Agile production planning methods (borrowing lean and just-in-time principles) help prioritize responsiveness and waste reduction when batch-oriented planning is no longer appropriate for individualized orders[25].

Inventory strategies must also evolve: mass customization increases the diversity of components required while pushing firms to avoid excess stock, so effective inventory management balances component variety with minimal holding costs through better forecasting, modular component design, and tighter supplier coordination[26]. Advanced manufacturing technologies (robotics, automation, and additive manufacturing) play a dual role by both enabling rapid customization and preserving throughput and precision across many product variants[27]. Quality assurance must adapt as well: with many process variants, robust and flexible quality-control protocols (Quality 4.0) are needed to ensure consistent outcomes across configurations and to maintain customer satisfaction[28].

Human capital remains central: operators require broader skills to handle diverse tasks, technologies, and rapid retooling, so targeted training programs are necessary to sustain performance and safety on more dynamic lines[12]. Finally, smart production planning and control (leveraging data analytics, AI, and machine learning) becomes the coordinating layer that integrates scheduling, sequencing, monitoring, and resource allocation to meet multiple objectives simultaneously (for example, throughput, lead time, and on-time delivery) in the presence of missing operations and high product variability[29 -30]. Together, these changes imply that successful mass customization depends not only on configurable products but on a holistic transformation of shop-floor practices, technologies, and workforce capabilities; addressing missing-operation scheduling and multi-objective planning is therefore a core research and practical priority for Industry 4.0 adopters[7],[10].

## III. Problem and Resolution Approach Description

### A. Flow shop scheduling problem addressed

The scheduling problem addressed is a permutation flow-shop with missing operations where each job may skip some machines, and processing times are explicitly influenced by human factors: skill, age, learning (practice), and forgetting. The decision variable is a permutation (σ) that defines the processing order on the first machine and, by permutation flow-shop assumption, the same order is used on all machines. Standard flow-shop constraints apply: no machine can process more than one job at a time (non-overlap) and each job must respect technological precedence between machines (a job's operation on machine ($m$) cannot start before its completion on machine ($m$ -1)).

Human performance is modeled through an efficiency factor ($E_i$) that depends on the job's position ($i$) in the sequence (capturing learning effects) and a lower bound ($L_{min}$) that limits maximum improvement. A commonly used formulation in the model is:

$$E_i = L_{min} + \left(1 - L_{min\{\backslash min\}}\right) \cdot i^{(-\gamma)}$$

where ($\gamma$ ) is the learning-rate exponent [31]. This efficiency multiplies base processing times and is combined multiplicatively with three worker-related modifiers: skill (α$\alpha$), age (β), and forgetting (λ). The effective processing time for the job placed at position ($i$) on machine ($m$) becomes:

$$P'_{im} = P'_{\sigma im} \cdot E_i \cdot (1-\alpha) \cdot (1-\beta) \cdot (1-\lambda),$$

with a practical lower bound enforced, e.g. $P'_{im} \geq 0.6 \cdot P_{\sigma im}$, reflecting that learning cannot reduce time below a fixed fraction ($L_{min}$)[5]. Completion times follow the usual recurrence:

$$C_{im} = max\left(C_{i-1,m}, C_{i,m-1}\right) + P'_{im}$$

and if a job does not require machine ($m$$m$) (missing operation) its base processing time ($P_{\sigma im}P_{\sigma im}$) is zero and the machine is simply bypassed for that job.

The problem is multi-objective, balancing three conflicting goals:

- makespan (minimize ($Z_1 = C_{\{n,M\}}$)),
- total tardiness ($min\, Z_2(\sigma) = \sum_{i=1}^{n} \quad T_{\sigma i}$ , where $T_{\sigma i} = max(0, C_{i,M} - D_{\sigma i})$
- total earliness ($min\, Z_3(\sigma) = \sum_{i=1}^{n} \quad E_{\sigma i}$), where $E_{\sigma i} = max(0, D_{\sigma i} - C_{i,M})$

These objectives capture resource utilization, customer service (deadlines), and inventory/work-in-progress exposure respectively; improving one objective typically degrades at least one other, especially when human-dependent times and missing operations create irregular processing patterns.

### B. Human worker modelling

This section explains how human factors are explicitly incorporated into a permutation flow-shop scheduling model so that processing times reflect realistic worker behavior rather than idealized machine rates. Four human dimensions: skill (α), age (β), learning ($\gamma$) and forgetting ($\lambda$), are combined with operational limits, as a minimum efficiency floor ($L_{min}$) to produce effective processing that feed the completion recurrence used by the simulator. The values for each factor follows literature benchmark standards[5]. Treating the worker as a dynamic modifier makes schedules sensitive to demographic and experiential differences and allows the algorithm to evaluate trade-offs that involve human performance as well as classical operational metrics.

Skill is encoded by the parameter $\alpha$ and models proficiency at a task. The model uses three discrete skill levels mapped to multiplicative factors: skilled = 0.9, semi-skilled = 1.0, and unskilled = 1.1. These values scale the base processing time so that skilled operators shorten effective durations, semi-skilled operators leave them unchanged, and unskilled operators lengthen them. This simple mapping captures heterogeneity in workforce capability and supports assignment or sequencing decisions that account for operator competence.

Age is represented by $\beta$ and captures broad physical and cognitive trends across working life. The model assigns age-band modifiers: 20–30 years = 0.8, 30–40 = 0.9, 40–50 = 1.0, and >50 = 1.1. Younger workers therefore tend to reduce effective times, while older workers may increase them. Including age acknowledges that a workforce is not homogeneous and that demographic composition influences throughput, error rates and the suitability of particular task assignments.

Learning is modeled through $\gamma$ and an efficiency term $E_i$ that depends on the job's position $i$ in the processing sequence. The efficiency formula uses a lower bound $L_{min}$ so that learning cannot reduce times indefinitely:

**TABLE 1.** Human worker characterization.

| Indicator | Year 2024 | | | Year 2025 | |
|---|---|---|---|---|---|
| | 2nd quarter | 3rd quarter | 4th quarter | 1st quarter | 2nd quarter |
| Employment rate | 44,8 | 45 | 45,7 | 44,4 | 44,5 |
| **Sex and age groups** | | | | | |
| Males up to 29 years | 4,3 | 4,3 | 4,5 | 4,1 | 4,2 |
| Males from 30 to 64 years | 14,8 | 14,7 | 15,1 | 14,6 | 14,7 |
| Females 65 years and over | 0,9 | 0,8 | 0,8 | 0,8 | 0,8 |
| Females from 30 to 64 years | 5,6 | 5,6 | 5,8 | 5,6 | 5,5 |
| Males from 30 to 64 years | 18,2 | 18,4 | 18,3 | 18,2 | 18,2 |
| Total | 1,1 | 1,2 | 1,4 | 1,2 | 1,1 |

$$E_i = L_{min} + (1 - L_{min}) \cdot i^{(-\gamma)}.$$

with $L_{min}$ = 0.6 and $\gamma$ = 1.1 in the implementation, early repetitions produce the largest gains and improvements diminish as experience accumulates. Learning factors are also associated with experience categories (freshers, experienced) and age groups in the parameter mapping, enabling the model to simulate how repeated execution reduces errors and shortens cycle times across a production run.

Forgetting is captured by $\lambda$ and models loss of procedural fluency when tasks are infrequent or when memory-related decline affects performance. The model assigns forgetting modifiers by age: 20–30 and 30–40 receive 1.0, 40–50 receive 0.9, and >50 receive 0.8. Higher forgetting increases effective times and error likelihood; lower forgetting indicates stable retention. Combining forgetting with learning produces a dynamic interplay where repetition builds efficiency but long gaps or age effects can erode gains.

To ground the model in a realistic workforce profile, the authors instantiate a representative Argentine worker based on national statistics: INDEC's Permanent Household Survey for the second quarter of 2025 reports an employment rate of 44.5%, and within that employed population people up to 29 years account for 21.8%, those aged 30–64 represent 73.9%, and those over 65 make up 4.3%. If these employment figures are paired with the 2022 Census (which shows that the single age band with the largest share of the Argentine population is 30–34 years) the model selects a 35-year-old semi-skilled operator as the standard profile. This pragmatic baseline maps to $\alpha = 0$ (semi-skilled), $\beta = 0.1$ (30–40 age band), $\gamma = 1.1$ (learning exponent) and $\lambda = 0$ (no forgetting penalty). The choice provides a pragmatic baseline that is neither extreme nor idealized and supports sensitivity analysis by allowing alternative profiles or heterogeneous assignments across stations. Overall, embedding these human factors yields schedules that favor front-loading repetitive tasks to exploit learning, avoid long runs that amplify forgetting or age penalties, and balance throughput against service and worker-centered considerations.

### C. NSGA-II implementation

From a solution perspective the problem is combinatorial and NP-hard; metaheuristics are appropriate. The implementation described uses a permutation encoding, Partially Matched Crossover (PMX) and swap mutation within a multi-objective evolutionary algorithm (NSGA-II). Population-based search explores trade-offs and returns a Pareto front of non-dominated schedules. Performance is evaluated with multi-objective metrics (e.g., hypervolume for convergence and diversity) and statistical tests (Friedman) to compare parameter settings or algorithm variants across instance sets with different percentages of missing operations.

In practice, incorporating human factors makes schedules more realistic and robust: learning reduces later processing times and favors front-loading repetitive tasks, forgetting and aging penalize long sequences of demanding tasks, and skill heterogeneity suggests assigning tasks to match worker capabilities. Missing operations increase sequencing flexibility but complicate learning patterns, so planners must trade throughput against service and worker well-being. I can produce a short pseudocode or a small numeric example showing how ($E_i$), ($P'_{i,m}$), and the completion recurrence interact if you'd like.

## IV. RESULTS

This section presents the results obtained and details the metrics used to evaluate the problem

### A. Parameter tunning

A parameter tuning analysis was conducted to assess the influence of crossover probability pc and mutation probability pm on the performance of NSGA-II. Several parameter configurations were tested across instances with different percentages of missing operations (0%, 10%, and 20%). For each configuration–instance combination, 30 independent runs were performed to account for the stochastic nature of the algorithm. As an evaluation metric, the RHV was used which is a multiobjective summary metric that allows exploring convergence and diversity of the obtained Pareto fronts.

**TABLE 2.** Parameter Configuration depending on the percentage of missing operations.

| Parametric configuration ( pc, pm) | Instance 0% | | Instance 20% | | Instance 40% | |
|---|---|---|---|---|---|---|
| | median | *iqr* | median | *iqr* | mediana | *iqr* |
| (0.7; 0.05) | 0.7116 | 0.0393 | 0.6541 | 0.0264 | 0.7156 | 0.0193 |
| (0.7; 0.1) | 0.6943 | 0.0436 | 0.6488 | 0.0259 | 0.7231 | 0.0323 |
| (0.7; 0.15) | 0.7053 | 0.0331 | 0.6577 | 0.0205 | 0.7174 | 0.0209 |
| (0.8; 0.05) | 0.6969 | 0.0413 | 0.6572 | 0.0195 | 0.7258 | 0.0343 |
| (0.8; 0.1) | 0.7098 | 0.0365 | 0.6549 | 0.0157 | 0.7058 | 0.0335 |
| (0.8; 0.15) | 0.7063 | 0.0375 | 0.6599 | 0.0207 | 0.7067 | 0.0232 |
| (0.9; 0.05) | 0.7051 | 0.0301 | 0.6527 | 0.0219 | 0.7168 | 0.0247 |
| (0.9; 0.1) | 0.6986 | 0.0286 | 0.6584 | 0.0190 | 0.7168 | 0.0270 |
| (0.9; 0.15) | 0.6968 | 0.0298 | 0.6588 | 0.0225 | 0.7242 | 0.0310 |

**TABLE 3.** Compromise solution.

| Instance | Instance 0% | | | Instance 20% | | | Instance 40% | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***C*** | ***T*** | ***E*** | ***C (%)*** | ***T (%)*** | ***E(%)*** | ***C (%)*** | ***T (%)*** | ***E(%)*** |
| 30J_10M | 1520 | 321 | 9678 | -10.22% | 166.43 % | -72.07 % | -23.42 % | 110.69 % | -58.99 % |
| 30J_20M | 1999 | 3.79 | 21180 | -8.22 | 15374.20 % | -18.11 % | -26.74 % | 25435 % | -58.78 % |
| 40J_10M | 1891 | 1144 | 3755 | -10.37 | -70.69 % | 69.41 % | -33.00 % | 126.75 % | -25.63 % |
| 40J_20M | 2390 | 54 | 32684 | -16.71 | 1672.41 % | -54.91 % | -22.87 % | 7797.15 % | -75.33 % |
| 50J_10M | 2120 | 4441 | 4412 | -18.67 | 91.16 % | -45.67 % | -27.71 % | 56.77 % | -61.23 % |
| 50J_20M | 2660 | 749 | 36659 | -4.41 | 288.08 % | -74.02 % | -22.02 % | 826.01 % | -77.53 % |

Firstly, the distribution of the obtained RHV values of the independent runs for each configuration and instance were analyzed. The Shapiro-Wilk normality test indicated that, for all tested configurations and instances, the results did not follow a normal distribution. Consequently, algorithmic performance is reported using the median as a measure of central tendency and the interquartile range (*iqr*) as a dispersion indicator of the obtained RHV in Table 1 for each parameter configuration and instance type. Secondly, the non-parametric Kruskal-Wallis test was applied and it was concluded that there are significant differences among the RHV results of the parametric configurations. Based on these evidence, the parametric configuration pc = 0.7 and pm=0.05 was selected for the computational experimentation.

### B. *Numerical results: Compromise solution*

Table 3 reports the compromise solutions obtained for each instance under different percentages of missing operations. For the baseline case (0% missing operations), the table presents the absolute values of the three objectives: makespan (C), total tardiness (T), and total earliness (E). For the scenarios with 20% and 40% missing operations, the table shows the relative variation of each objective with respect to the baseline solution. The relative variation ($\Delta(\%)$) is computed as:

$$\Delta(\%) = \frac{f_{x\%} - f_{o\%}}{f_{o\%}} * 100$$

where fx% denotes the value of the objective under x% missing operations and f0% corresponds to the baseline instance.

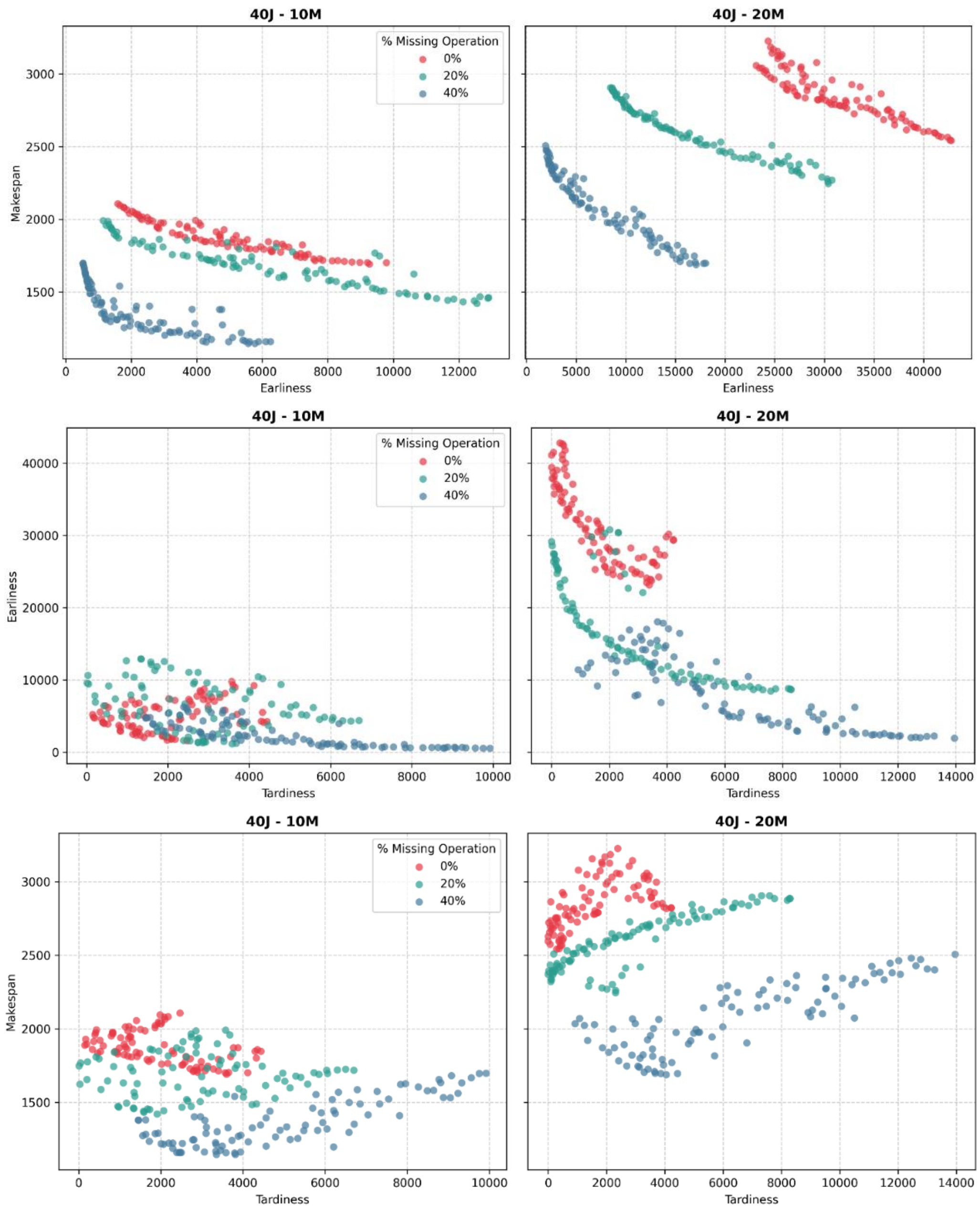
From the results, it can be observed that increasing the percentage of missing operations generally leads to a reduction in makespan across all instances, with improvements typically ranging between approximately 4% and 27%. This behavior suggests that the flexibility introduced by missing operations allows the scheduling process to better reorganize the sequence of tasks. Regarding total tardiness, the results exhibit a more heterogeneous behavior. In some instances, tardiness increases significantly, particularly when the baseline tardiness value is very small. In such cases, even moderate absolute increases produce very large relative percentages. Conversely, in other instances, tardiness decreases, indicating that the additional routing flexibility can sometimes improve due-date compliance. For total earliness, most instances show a substantial reduction as the percentage of missing operations increases. This suggests that the additional scheduling flexibility tends to reduce excessively early job completions, leading to more balanced schedules.

Overall, the results indicate that missing operations introduce additional flexibility that tends to improve makespan and reduce earliness, although the effect on tardiness depends strongly on the characteristics of each instance and on the baseline tardiness level.

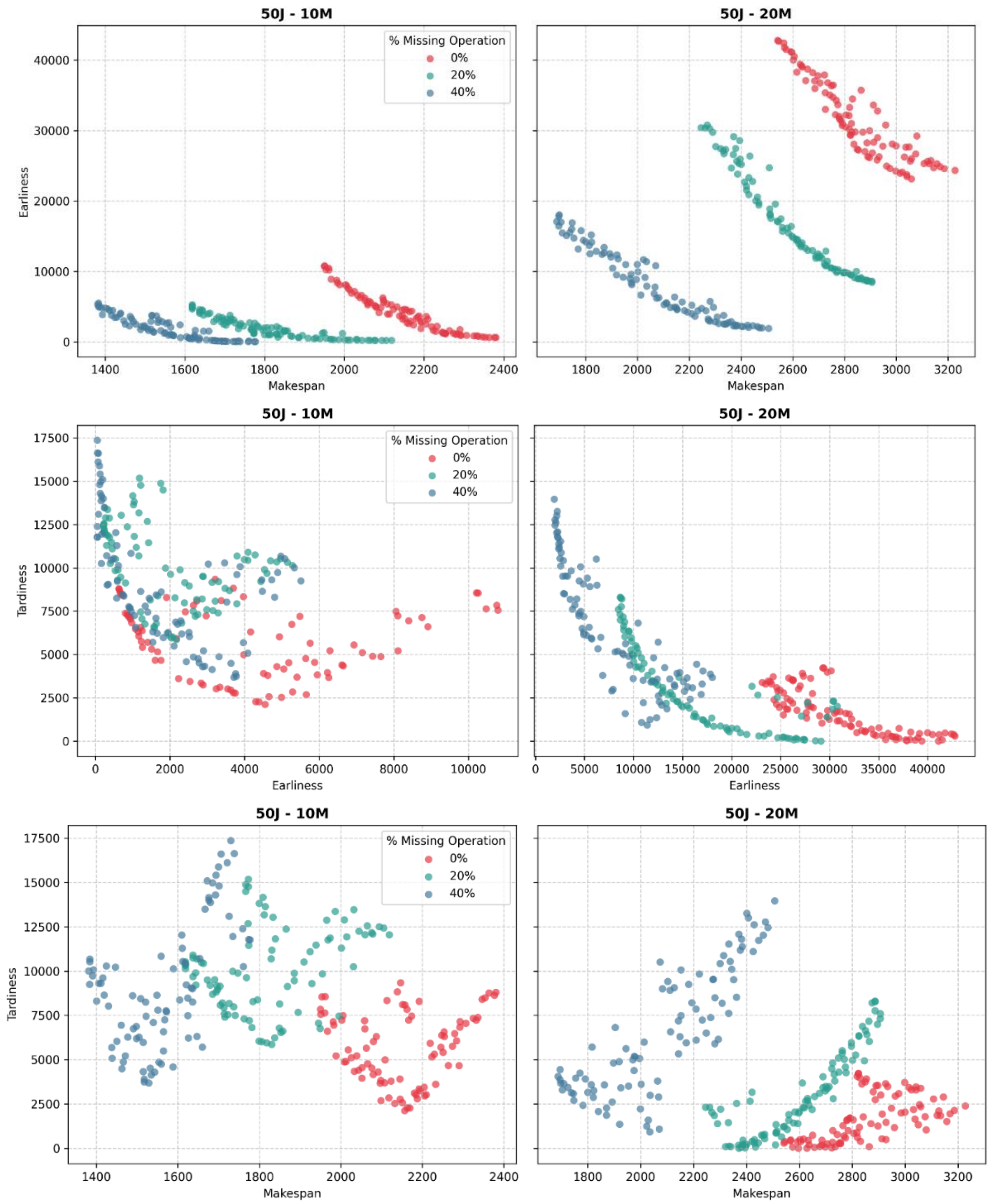
### C. Pareto front inspection

Figures 1a, 1b, and 1c present the Pareto fronts of the instance closest to the average front for each problem set. These two-dimensional scatter plots show, in pairs, the values of the three objective functions (makespan, total tardiness, and total earliness) obtained by the non-dominated solutions of NSGA-II for missing operation rates of 0%, 20%, and 40%, with each color encoding a different level. Results are organized by number of jobs across figures (30, 40, 50) and by machine configuration within each figure (10 and 20 machines); each row corresponds to one objective pair: Makespan vs. Earliness (top), Tardiness vs. Earliness (middle), and Makespan vs. Tardiness (bottom).

a) Pareto fronts for the three objective pairs obtained on instances with 30 jobs and two machine configurations (10 and 20 machines). Each row shows the same objective pair for the two configurations (left: 30J–10M; right: 30J–20M). Top row: Makespan vs. Earliness; middle row: Tardiness vs. Earliness; bottom row: Makespan vs. Tardiness.




b) Pareto fronts for the three objective pairs obtained on instances with 40 jobs and two machine configurations (10 and 20 machines). Each row shows the same objective pair for the two configurations (left: 40J–10M; right: 40J–20M). Top row: Makespan vs. Earliness; middle row: Tardiness vs. Earliness; bottom row: Makespan vs. Tardiness.




c) Pareto fronts for the three objective pairs obtained on instances with 50 jobs and two machine configurations (10 and 20 machines). Each row shows the same objective pair for the two configurations (left: 50J–10M; right: 50J–20M). Top row: Makespan vs. Earliness; middle row: Tardiness vs. Earliness; bottom row: Makespan vs. Tardiness.

Figure a) covers 30-job instances and reveals a clear and consistent trade-off structure across all objective pairs. In the Makespan vs. Earliness plane, reducing makespan forces an increase in earliness, as completing jobs well ahead of due dates accumulates work-in-progress. The Tardiness vs. Earliness pair exposes a symmetric tension between service level and inventory exposure, and the Makespan vs. Tardiness plots confirm that faster completions do not always reduce tardiness when due dates are heterogeneous and human-dependent times introduce variability. A well-defined clustering of solutions by missing operation percentage is visible in all plots: the 40% group occupies a distinctly displaced region relative to 0% and 20%, confirming that higher production customization structurally alters the achievable trade-off space. This effect is most pronounced in the 30J–20M Makespan vs. Earliness plot, where the larger machine set amplifies sensitivity to route variabilityFigure b) extends the analysis to 40-job instances (40J–10M and 40J–20M). With more jobs competing for machine time, the Pareto fronts become denser and the trade-off curves smoother, reflecting a richer diversity of non-dominated solutions. The same qualitative patterns observed in figure a) reappear, but with higher absolute values of makespan, tardiness, and earliness. The separation between color groups becomes even more distinct than in the 30-job case, suggesting that as problem size grows, the influence of missing operations accumulates: route variability alters the number of repetitions each job undergoes per machine, which modifies the learning gains embedded in the human factor model and produces increasingly differentiated outcomes across customization levels. In the 20-machine configuration, the Makespan vs. Earliness plot shows the widest spread of Pareto front positions across missing operation levels, reinforcing the observation that larger machine sets amplify sensitivity to route customization. The Tardiness vs. Earliness plots are particularly informative at this scale: the 20% missing operation front occupies a clearly separated region, indicating that higher customization alters not only the magnitude of the objectives but also the nature of the achievable compromises between service level and inventory exposure.

Figure c) covers the largest instances, with 50 jobs and the same two machine configurations (50J–10M and 50J–20M). At this scale the Pareto fronts are the most populated, offering decision-makers the broadest range of non-dominated schedules. The trade-offs between all three objectives are clearly delineated, and the tendency for gains in one objective to degrade others is more pronounced than in smaller instances, reflecting the higher combinatorial complexity. The color-based clustering by missing operation percentage remains unambiguous: the three solution groups are well separated, confirming that increasing production customization constitutes a structural change in the scheduling problem rather than a simple scaling effect. The most dramatic visual separation between the 0% and 20% missing operation fronts occurs in the 50J–20M Makespan vs. Earliness and Makespan vs. Tardiness plots, where a large number of jobs and a large machine set jointly amplify the interaction between route variability, learning dynamics, and due-date structures. Across all three figures, a consistent pattern emerges: the missing operation percentage is a key determinant of Pareto front geometry, and NSGA-II consistently produces well-distributed fronts at every scale, demonstrating its suitability for exposing trade-offs when human factors and route variability are jointly embedded in the optimization

## V. Conclusions

Industry 5.0 is redefining the boundaries of modern manufacturing by placing mass customization and human-centric design at the heart of production systems. Under this paradigm, workforce heterogeneity and route variability (including missing operations arising from highly personalized product configurations) are not peripheral complications but structural determinants of system performance. Production planning must therefore evolve beyond machine-oriented optimization to become a genuinely socio-technical discipline.

This article presented a multi-objective permutation flow-shop scheduling model with missing operations that explicitly incorporates human factors (skill level, age, learning effects, and forgetting) into effective processing time computation. By doing so, the formulation captures trade-offs among makespan, total tardiness, and total earliness that become increasingly complex when workforce variability and route heterogeneity interact. An NSGA-II-based algorithm with permutation encoding was developed to navigate this NP-hard problem, and computational experiments confirmed its ability to generate well-distributed Pareto fronts across varying levels of missing operations. The results demonstrate that production customization is not merely a scaling factor, it structurally reshapes the achievable trade-off space, with higher missing operation rates consistently shifting Pareto front geometry in ways that affect efficiency, service level, and inventory exposure simultaneously.

From an Industry 5.0 standpoint, the proposed framework offers a meaningful step toward decision-support tools that treat human performance as a first-class input rather than a post-hoc adjustment. Embedding worker characteristics directly into the optimization process produces schedules that are more realistic, more aligned with actual shop-floor conditions, and better suited to informing planners who must balance operational objectives with workforce considerations.

Several directions remain open for future investigation: extending the model to heterogeneous workforces with machine-dependent operator assignments; benchmarking against alternative multi-objective metaheuristics and problem-tailored operators; and broadening the computational study to larger instances while incorporating explicit human-centered performance indicators, such as fatigue risk, cognitive load, and skill development opportunities, as formal optimization objectives.

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