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RESEARCH ARTICLE

Dynamic scheduling of hybrid additive manufacturing–injection molding for surge capacity in polymer supply chains

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ABSTRACT

Demand volatility creates a persistent challenge for manufacturers seeking to balance the cost efficiency of conventional high-volume production with the responsiveness offered by additive manufacturing. This study develops a data-driven decision-support framework to deploy additive manufacturing (AM) as strategic surge capacity in a polymer pipe-fitting supply chain facing volatile demand. Following a 48-month screening of four unplasticized polyvinyl chloride tee joints, the 3/4-in. variant was selected, and a validated stream of 77 stochastic orders was used in a bi-objective order-assignment model that minimizes production cost and tardiness across injection molding (IM) and AM. The novelty lies in combining order-level hybrid routing, build-level parallel AM capacity, practical heuristic benchmarks, due-window sensitivity analysis, and a multi-run stability assessment within one industrially grounded framework. Under the baseline 48 h service target, the IM-only approach cost the least (EUR 296,396.19) but produced 244.15 h of tardiness and 23 late orders, whereas the AM-only approach eliminated tardiness at EUR 1,008,780.00. The non-dominated sorting genetic algorithm II Pareto frontier identifies a balanced solution that assigns 12 peak orders to AM, reduces tardiness by 69.2%, and improves on-time service from 70.1% to 85.7% at an 85.9% cost premium over the IM-only approach. The zero-tardiness endpoint requires 23 AM-assigned orders and costs EUR 759,250.77. Sensitivity analysis shows that the value of hybridization depends on the responsiveness requirement: at 24 h, AM capacity is stressed, whereas at 72 h or longer, the IM-only approach meets all due dates. The results therefore position AM as a selective surge capacity rather than a universal substitute for IM.

1. Introduction

The persistent challenge in efficient production planning within discrete manufacturing is presented by demand volatility, where irregular order arrivals and varying sizes exacerbate the accumulation of backlogs within high-throughput processes, such as injection molding (IM).[1,2] In polymer supply chains, demand volatility, manifesting as bursty replenishment requests from wholesalers and project buyers, presents a significant hurdle, as conventional manufacturing, despite its economic dominance, struggles with the inherent limitations of fixed, time-intensive setup configurations, thereby leading to queue instability and the occurrence of service failures under turbulent operational conditions.[2,3]

Conversely, additive manufacturing (AM) has emerged as a critical alternative, through the provision of superior responsiveness, reduced lot sizes, and an enhanced capacity for the absorption of capacity shocks, qualities that position it as

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an optimal solution for the mitigation of demand peaks, notwithstanding its associated higher per-unit production costs.[4-6]

The central managerial challenge in modern polymer supply chains is therefore not choosing between AM and IM, but optimally integrating both technologies into hybrid systems. Consequently, leveraging IM's scale and AM's agility helps firms balance cost efficiency with required service levels.[4,7-10] Recent advancements in hybrid AM–IM approaches, such as AM-produced mold inserts and freeform IM, further underscore the potential for synergistic process chains that enhance operational flexibility without sacrificing volume production capabilities.[11-13]

This study addresses these challenges by developing a data-driven hybrid scheduling model for a Saudi pipe-fitting manufacturer, focusing on the 3/4-in. unplasticized polyvinyl chloride (UPVC) tee joint, identified as the most volatile product through a 48-month screening, and a validated 77-order stochastic stream. The contributions of this study are threefold. First, it transforms static inter-process comparisons into a dynamic bi-objective scheduling problem amenable to meta-heuristic optimization, incorporating order-level assignment to either IM or AM while minimizing total cost and tardiness. Second, the work models parallel AM capacity alongside IM batch setups, grounded in case-specific parameters such as EUR 0.79/IM-part, EUR 2.72/AM-part, and 4.33-hour setups. Finally, applying non-dominated sorting genetic algorithm II (NSGA-II) to generate Pareto-optimal schedules helps quantify hybrid cost-service trade-offs, revealing balanced solutions that reduce tardiness by up to 69% at modest cost premiums.

The novelty of this study lies in a unified hybrid AM–IM framework that moves beyond static technology-selection logic. Unlike approaches that aggregate demand or assume complete technology substitution, the model uses a validated 77-order industrial stream, order-level assignment decisions, and parallel build-based AM capacity to quantify the joint cost–tardiness consequences of selective AM deployment. The revised analysis further benchmarks NSGA-II against practical dispatching heuristics, tests sensitivity to alternative due windows, and evaluates algorithmic stability across independent runs.

These findings provide managerial evidence for selective AM deployment while bridging production-scheduling theory and practical volatility management. The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 presents the case data, scheduling assumptions, and mathematical formulation. Section 4 describes the solution methodology, benchmark policies, sensitivity design, and robustness protocol. Section 5 reports the optimization, benchmarking, sensitivity, and convergence results. Section 6 discusses their implications, and Section 7 concludes the study.

2. Literature review

Economic comparisons between AM and conventional processes like IM have largely relied on static break-even logic. Early research established cost-per-part curves, demonstrating that while AM maintains relatively constant costs at low volumes, IM achieves significant scale economies beyond break-even points, typically ranging from 1,500 to 20,000 parts.[4,14] More recent literature extends this to hybrid tooling, such as soft tooling or laser powder bed fusion inserts, which shift break-even thresholds but continue to treat technology selection as a fixed, long-term capital decision.[15,16] However, while useful for initial investment planning, these static cost models do not adequately address the dynamic operational requirements of modern supply chains, where technology selection must adapt to stochastic demand and service-level constraints.[6,7]

Beyond cost-based benchmarks, AM scheduling research has addressed customer-order scheduling, sequence-dependent setups, genetic-algorithm time/cost optimization, and dynamic order acceptance.[17-20] More recent work has broadened the decision context toward demand-volatility economics and hybrid manufacturing integration.[21,22]

Recent studies from 2023–2025 further show a clear shift toward evolutionary optimization in hybrid manufacturing and AM scheduling. Kwon and Oh[23] optimized hybrid additive–subtractive process planning with a genetic algorithm. Sugarindra *et al.*[24] applied NSGA-II to multitask scheduling in cloud AM, jointly considering delay, makespan, and cost. Kucukkoc *et al.*[25] developed a bi-objective AM nesting-and-scheduling model solved by NSGA-II with problem-specific decoding mechanisms, while Liu *et al.*[26] proposed an improved NSGA-II for a multi-objective flexible flow-shop scheduling problem. These developments confirm the growing use of evolutionary algorithms for manufacturing scheduling, but the order-level decision of when AM should absorb demand from an established IM process remains underexplored.

A critical research gap remains: the absence of a scheduling framework that treats hybrid AM–IM operations as a unified, data-driven system under stochastic demand. While broader supply chain literature recognizes that AM enhances resilience against disruptions,[27-29] and fuzzy-stochastic models acknowledge the difficulty of scheduling volatile pipe-fitting demand,[3,30] there is a lack of models that dynamically assign orders to either technology at an individual level to minimize the conflict between production cost and delay exposure. This study addresses this void by embedding AM's agility into a batch-oriented IM environment, with three specific contributions:

(i) Develops an order-level assignment framework that captures operational trade-offs between IM's scale economies and AM's burst-absorption capacity, transcending static cost-per-part comparisons.
(ii) Implements a bi-objective approach using the NSGA-II algorithm to navigate the Pareto frontier, quantifying cost-tardiness trade-offs within a validated 77-order stochastic stream.
(iii) Provides empirical justification for selective AM deployment, demonstrating how hybrid configurations mitigate demand volatility and improve service levels without the economic infeasibility of an AM-only production strategy.

3. Materials and methods

3.1. Case context and data sources

This study is based on an industrial case study involving a Saudi manufacturer of plastic pipe fittings, with current production processes using the focal products through IM. The historical case identified four volatile UPVC tee joints based on 48 months of monthly demand data; consequently, the 3/4-in. variant was selected for in-depth analysis because it showed the highest volatility. The case also detailed the IM process characteristics; furthermore, it documented the AM build configuration, based on an EOS P770 system, along with a validated stochastic order-generation process that yielded a 77-order stream for experimentation.[9,21]

The analysis in this study combines three datasets: (i) the monthly demand history for the four volatile products; (ii) the 77-order scenario containing inter-arrival times and order quantities; and (iii) the case-study description document that explains the earlier supply-chain modeling assumptions and AM build logic. This study does not merely replicate the earlier simulation work; instead, it uses the acquired data to formulate a novel scheduling study oriented toward meta-heuristic optimization. **Table 1** summarizes the volatility screening, while **Figure 1** visualizes the corresponding coefficients of variation and confirms the 3/4-in. tee joint as the most volatile candidate.

Table 1. Demand volatility screening for the four candidate products

Product	Mean	Standard deviation	Coefficient of variation
UPVC tee joint 1-in.	13,204.2	20,195.6	153%
UPVC tee joint 3/4-in.	3,235.4	7,533.1	233%
UPVC tee joint 6-in.	2,624.9	2,321.3	88%
UPVC tee joint 8-in.	226.1	385.1	170%

Abbreviation: UPVC: Unplasticized polyvinyl chloride.

3.2. Descriptive analytics of the 77-order scenario

Table 2 reports the descriptive statistics of the 77-order optimization scenario.

Table 2. Summary statistics of the optimization scenario

Metric	Value
Orders	77
Mean inter-arrival (days)	23.38
Inter-arrival coefficient of variation	0.84
Mean order quantity (units)	4,816.56
Quantity coefficient of variation	0.888
Planning horizon (days)	1800
Total demand (units)	370,875
Min–max quantity (units)	200–11,198

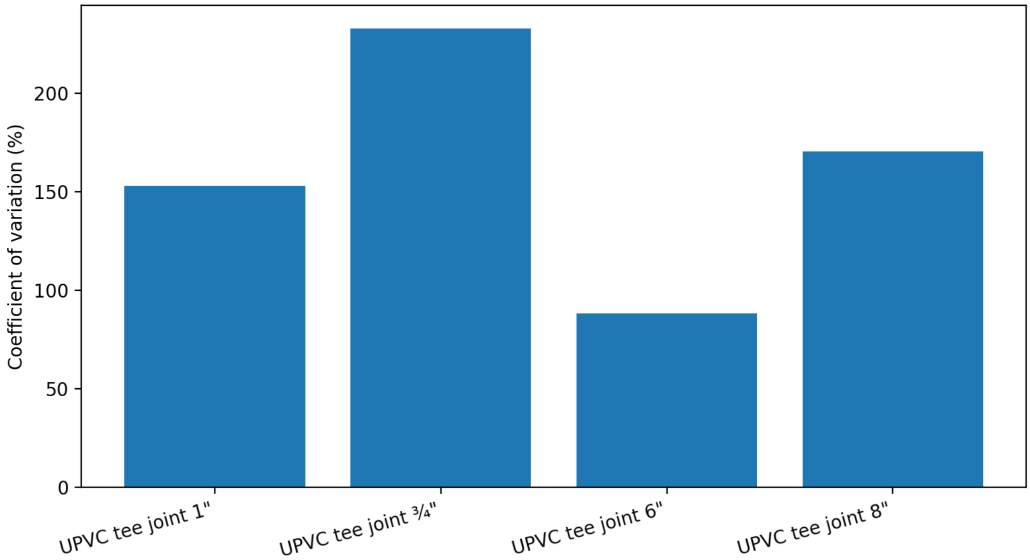

Figure 1. Monthly volatility levels of the four specified unplasticized polyvinyl chloride tee joint product configurations

The 77-order scenario spans 1,800 days and contains 370,875 units of demand. The average order quantity was 4816.56 units, with the presence of burst orders near the upper end of the observed range indicated by the wide range (200–11,198 units). Consequently, the order stream reflects both intermittency and magnitude volatility; this dynamic precisely defines the operational context where a hybrid AM–IM schedule may generate value.

Figure 2 graphically represents the order stream's temporal distribution. Specifically, large-order occurrences showed a non-uniform temporal distribution, manifesting as clusters, particularly in the latter segment of the planning horizon. This structural characteristic is critical: while IM performs well in economically processing large job volumes, its operational queue becomes demonstrably vulnerable when high-volume orders arrive with short inter-arrival intervals.

3.3. Scheduling assumptions

The scheduling model assumed a single-product environment utilizing one IM resource and five AM units. Orders were released at their observed arrival times and assigned to either IM or AM. The IM resource processes orders sequentially, whereas the five AM machines enable parallel execution of multiple builds.

For IM, the unit production cost was EUR 0.79 per part, with a setup cost of EUR 44.22 and a setup time of 4.33 h. The observed molding cycle was 74 s with four cavities, giving an exact effective processing time of $74/(3{,}600 \times 4) = 0.005139$ h per part. For AM, the unit production cost was EUR 2.72 per part. AM processing was modeled on a build basis rather than a part-by-part basis, reflecting its batch-oriented layer-by-layer operation.[31,32] A build accommodates 1,584 parts and requires 23 h. Each customer order is decomposed into the required number of builds; different builds from the same order may be processed simultaneously on different AM machines when capacity is available, but a single build is never split across machines. The decoder assigns each build to the earliest-available one of the five AM machines.

The baseline service target is 48 h. This value is not the company's contractual service-level agreement; it is derived from observed demand and AM capacity and used as a capacity-relevant responsiveness scenario. The largest observed order contains 11,198 parts, requiring eight AM builds ($\text{ceil}(11{,}198/1{,}584) = 8$). With five parallel AM machines, an isolated order of this maximum size can be completed in two build waves, requiring 46 h. Thus, 48 h was the shortest whole-day target under which the available AM fleet can, in principle, serve every observed order in isolation while remaining tight enough to expose congestion in the IM queue. To test whether the conclusions depend on this choice, Section 4.4 evaluates 24-, 48-, 72-, and 168-h due windows.

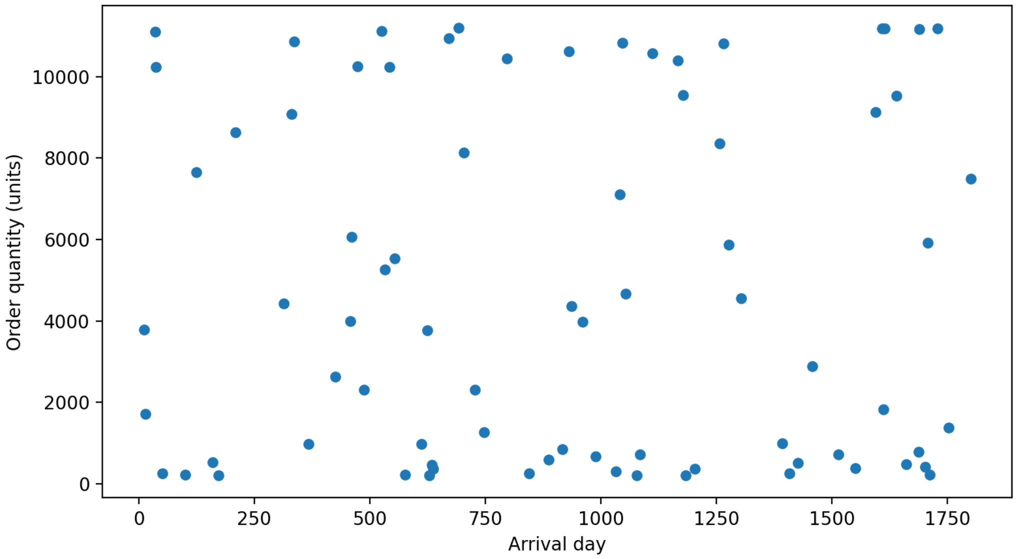

Figure 2. Order-arrival pattern for the 77-order dataset

The resulting sensitivity analysis explicitly treats the value of hybrid AM–IM scheduling as conditional on the required response time rather than universal.

3.4. Bi-objective mathematical formulation

The hybrid problem was formulated as a bi-objective assignment-and-schedule-evaluation model. The assignment vector determines whether IM or AM produces each order, while a deterministic decoder generates feasible start and completion times under the resource constraints. This separation keeps the optimization model compact while retaining the operational queueing logic.

3.4.1. Sets and indices

(i) $I = \{1,\ldots,n\}$: set of customer orders.
(ii) $M = \{1,\ldots,5\}$: set of parallel AM machines.
(iii) $B_i = \{1,\ldots,b_i\}$: set of AM builds required for order i.

3.4.2. Parameters

(i) a_i: arrival time.
(ii) q_i: order quantity.
(iii) H: service target.
(iv) c^{IM} and c^{AM}: unit production costs.
(v) s^{IM}: IM setup cost.
(vi) τ^{IM}: IM setup time.
(vii) p^{IM}: IM processing time per part.
(viii) K^{AM}: AM build capacity.
(ix) τ^{AM}: AM build time.
(x) A_m: current availability time of AM machine m.

The due date and number of required AM builds are defined as **Equation 1**:

$$d_i = a_i + H,\ i \in I$$

$$b_i = \mathrm{ceil}(q_i \,/\, K^{AM}) \tag{1}$$

The decision variable is $x_i = 1$ if order i is assigned to AM and $x_i = 0$ if it is assigned to IM. The complete bi-objective model is shown as **Equation 2**:

$$\min Z_1(x) = \sum_{i\in I}\left[(1-x_i)\left(s^{IM} + c^{IM} q_i\right) + x_i c^{AM} q_i\right]$$

$$\min Z_2(x) = \sum_{i\in I} T_i$$

$$T_i = \max\{0, C_i - d_i\},\ x_i \in \{0,1\}$$

$$C_i = (1-x_i) C_i^{IM} + x_i C_i^{AM} \tag{2}$$

The first objective minimizes total production cost. An IM-assigned order incurs its setup cost and per-part production cost, whereas an AM-assigned order incurs the AM per-part production cost. The second objective minimizes total tardiness. Completion time C_i is route-dependent and is produced by the decoder described next.

Injection molding schedule decoding is presented as **Equation 3**:

$$C_i^{IM} = S_i^{IM} + \tau^{IM} + p^{IM} q_i$$

$$S_i^{IM} = \max\left\{a_i, C_{p(i)}^{IM}\right\} \quad (3)$$

Here, p(i) denotes the immediately preceding IM-assigned order in first-come-first-served arrival order; for the first IM order, $S_i^{IM} = a_i$. Thus, the IM resource processes one order at a time, and each assigned order incurs one setup.

Additive manufacturing schedule decoding is presented as **Equation 4**:

$$C_i^{AM} = \max_{r \in B_i} F_{ir}, \quad F_{ir} = S_{ir}^{AM} + \tau^{AM}$$

$$m^* = \arg\min_{m \in M} A_m, \quad S_{ir}^{AM} = \max\left\{a_i, A_{m^*}\right\} \quad (4)$$

For each AM build *r* of order *i*, the decoder selects the machine m^* with the earliest availability A_m, starts the build at $\max\{a_i, A_m{}^*\}$, and then updates the machine availability to its finish time. Because each build is assigned independently, builds from the same customer order may run concurrently on different AM machines; the order is complete only when its final build finishes. The present model does not include separate AM material/color changeover time, an assumption revisited in the limitations and future research discussion. The compact formulation and explicit separation between mathematical model and solution procedure follow established approaches for complex scheduling problems.[33-35]

4. Solution methodology

4.1. Non-dominated sorting genetic algorithm II procedure

The NSGA-II procedure was selected because it combines elitist non-dominated sorting with crowding-distance preservation for bi-objective search.[36] Each chromosome is a 77-bit assignment vector, where each gene indicates IM or AM routing for one order. The initial population combines random individuals with simple quantity-threshold seeds and the two extreme policies (all-IM and all-AM); the predicted-lateness benchmark described in Section 4.3 was not used as a seed. Parent selection used binary tournament selection, uniform crossover was applied with probability 0.90, and independent bit mutation was applied with probability 1/77 per gene. Related applications demonstrate the suitability of NSGA-II for multi-objective production and supply-chain decisions.[37-39]

For every chromosome, the decoder processes orders in arrival order, simulates the single IM queue and the five parallel AM machines, and returns total cost and total tardiness. A population size of 100 and 150 generations was used in the main experiments; Section 4.5 reports parameter calibration, a 30-run stability assessment, normalized hypervolume indicator, and computational time.

4.2. Algorithmic representation

Algorithm 1 summarizes the assignment search and schedule-decoding procedure used in the study.

Algorithm 1. Non-dominated sorting genetic algorithm II hybrid additive manufacturing–injection molding scheduling procedure

Input: order arrivals and quantities; IM/AM costs and processing parameters; population $N = 100$; generations G = 150.
1. Initialize N assignment vectors using random solutions, all-IM/all-AM anchors, and quantity-threshold seeds.
2. For each chromosome, decode orders in arrival order:
2a. If $x_i = 0$, append order i to the single FCFS IM queue.
2b. If $x_i = 1$, split order i into b_i builds and assign each build to the earliest-available AM machine.
3. Compute total production cost Z1 and total tardiness Z2.
4. Apply non-dominated sorting and crowding-distance ranking.
5. Generate offspring by binary tournament selection, uniform crossover, and bit mutation.
6. Combine parent and offspring populations and retain the best N individuals by NSGA-II elitist selection.
7. Repeat Steps 2–6 until G generations are completed.
Output: non-dominated cost–tardiness solutions (Pareto frontier).

4.3. Heuristic benchmark policies

To benchmark the meta-heuristic against practical dispatching rules, two heuristic overflow policies were evaluated using the same demand stream and process assumptions. The first was a quantity-threshold rule that routes orders of 10,000 units or more to AM and retains all remaining orders on IM. The second was a predicted-lateness rule in which each order is first evaluated on the IM queue; if its projected IM completion exceeds the due date, the order is diverted to AM; otherwise, it remains on IM. The predicted-lateness rule was intentionally strict because it uses queue-state information that would be available to a planner at order release.

4.4. Due-window sensitivity design

A due-window sensitivity study was conducted to test whether the role of AM is robust to changes in the assumed service target. In addition to the baseline 48 h scenario, the IM-only policy, AM-only policy, and predicted-lateness heuristic were re-evaluated under 24 h, 72 h, and 168 h due windows. This design clarifies how the value of AM changes as responsiveness requirements become more or less stringent.

4.5. Parameter calibration and robustness protocol

The population and generation settings were selected through a preliminary five-run calibration. Three configurations were compared: 50 individuals/100 generations, 100/150, and 150/250. Performance was evaluated using normalized two-objective hypervolume, with cost normalized between the IM-only and AM-only costs, tardiness normalized by the IM-only tardiness, and a reference point (1.05, 1.05). The 100/150 setting achieved 99.95% of the mean hypervolume of the larger 150/250 setting while requiring less than half the runtime, so it was retained. For the final assessment, NSGA-II was executed 30 independent times with different random seeds. The reported Pareto frontier is the pooled non-dominated set across these runs. Computation was performed in Python 3.13 on an Intel Xeon Platinum 8370C CPU at 2.80 GHz.

5. Results

5.1. Baseline policies

Table 3 compares the four baseline and representative hybrid policies under the 48-h service target.

Table 3 clearly delineates the central trade-off. IM-only is the least expensive policy, but it produces 244.15 h of total tardiness and 23 late orders. Conversely, while the AM-only policy ensures complete responsiveness protection, its cost exceeds that of the IM-only policy by more than three times. Consequently, this observation unequivocally establishes the economic unjustifiability of exclusive AM substitution for the analyzed order stream.

The hybrid policies demonstrate dominance over the AM-only approach, achieving comparable or enhanced service provision at a substantially reduced cost. Specifically, the compromise hybrid solution generated by NSGA-II increased total cost by 85.9% relative to the IM-only approach, but reduced tardiness by 69.2% and improved the on-time service rate from 70.1% to 85.7%. The zero-tardiness hybrid solution remained substantially cheaper than the AM-only approach by eliminating all instances of lateness. **Figure 3** shows the pooled non-dominated frontier obtained across the 30 independent NSGA-II runs.

Table 3. Policy comparison under a two-day service target

Policy	Total cost (EUR)	Total tardiness (h)	Late orders	On-time rate
Injection molding-only approach	296,396.19	244.15	23	70.1%
Additive manufacturing-only approach	1,008,780.00	0.00	0	100.0%
Hybrid compromise	551,106.12	75.14	11	85.7%
Hybrid zero-tardiness	759,250.77	0.00	0	100.0%

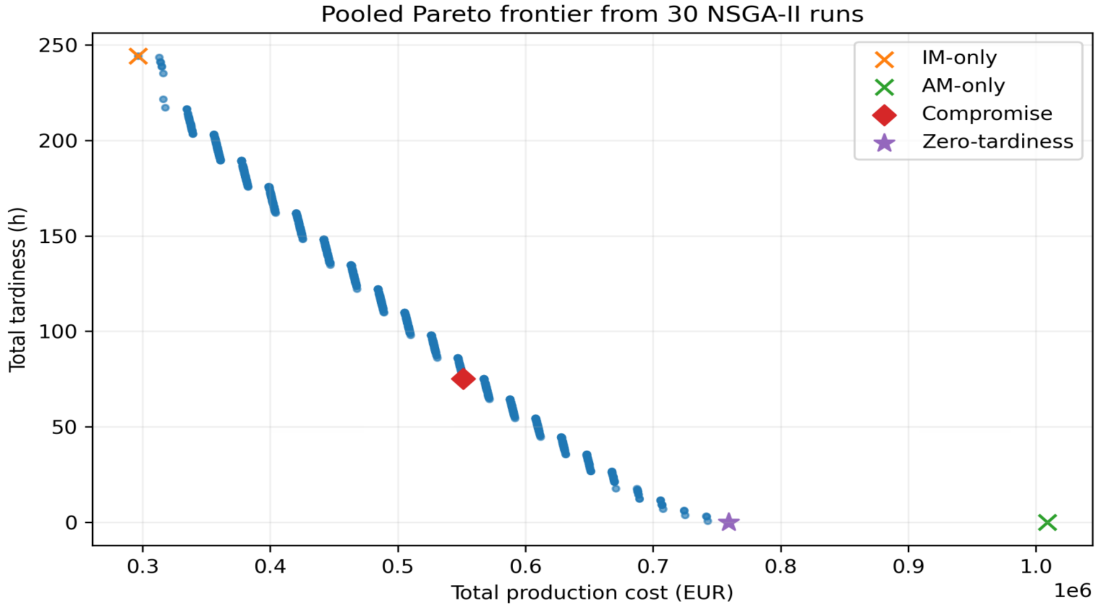

Figure 3. Pareto frontier obtained by non-dominated sorting genetic algorithm II for cost and tardiness

5.2. Structure of the Pareto frontier

Table 4 reports representative points spanning the pooled Pareto frontier.

Moreover, the Pareto frontier remained smooth rather than fragmented; this is a useful managerial outcome because it implies that decision makers can tune service performance incrementally by routing additional orders to AM. Near the low-cost end of the frontier, only one or two orders switched to AM, and service improved modestly. Larger improvements began once the optimizer diverted a limited set of high-volume peak orders from the congested IM queue.

Specifically, the compromise solution routed 12 orders to AM, corresponding to 35.7% of total demand volume; these orders were not randomly selected. They are predominantly large jobs above 10,000 units that arrive during periods of tight inter-arrival spacing. Consequently, the optimizer used AM as a targeted overflow mechanism for demand spikes rather than a routine production route. **Figure 4** maps the orders assigned to AM and IM in the balanced compromise solution and highlights the concentration of AM use among large, closely spaced demand peaks.

Table 4. Representative solutions on the Pareto frontier

Representative point	Cost (EUR)	Tardiness (h)	Additive manufacturing-assigned orders
Minimum cost	296,396.19	244.15	0
Lower-middle trade-off	444,486.28	141.27	7
Compromise solution	551,106.12	75.14	12
Upper-middle trade-off	649,778.22	30.17	17
Zero tardiness	759,250.77	0.00	23

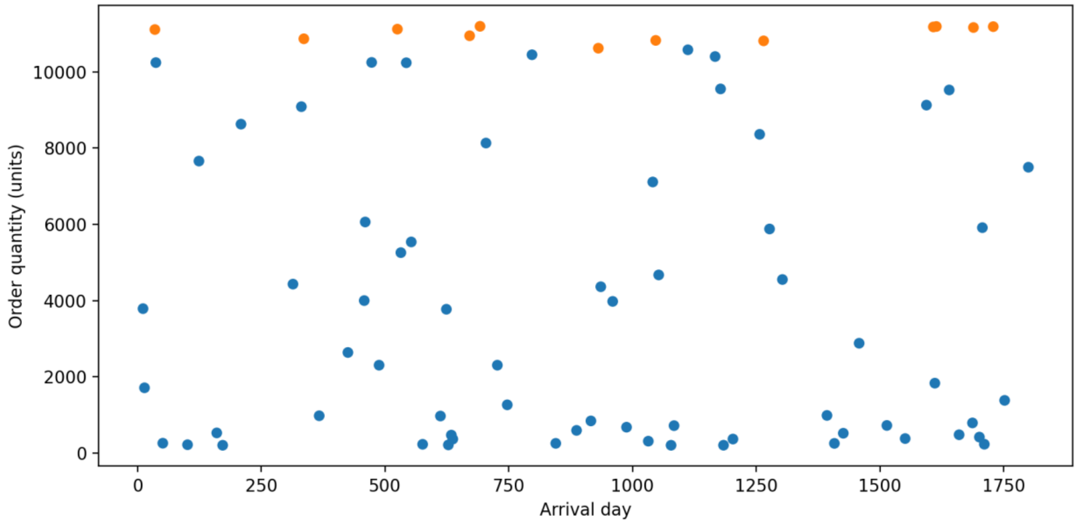

Figure 4. Additive manufacturing- and injection molding-assigned orders in the compromise hybrid schedule. Orange dots represent orders assigned to additive manufacturing, while blue dots represent orders assigned to injection molding

5.3. Comparison with heuristic benchmark policies

Table 5 compares NSGA-II with two intuitive dispatching benchmarks at the 48-h target.

Table 5 shows that the quantity-threshold rule performed well but still produced 17.66 h of tardiness while routing 18 orders to AM. The predicted-lateness rule eliminates tardiness by routing 23 orders to AM and reaches the same zero-tardiness endpoint as NSGA-II (EUR 759,250.77). NSGA-II therefore adds not a lower-cost zero-tardiness endpoint, but the systematic identification of the intermediate Pareto region: for example, the balanced solution reduces tardiness by 69.2% while routing only 12 orders to AM and costing EUR 208,144.65 less than the zero-tardiness heuristic. This comparison demonstrates the benefit of optimization when managers are willing to trade some lateness for substantially lower surge-capacity cost.

5.4. Sensitivity to due-window assumptions

Table 6 tests the dependence of the hybrid value proposition on the required response time.

The sensitivity results confirm that AM value depends on the service target. Under 24 h, the five-machine AM fleet became capacity-constrained for large orders requiring a second build wave; accordingly, both the AM-only and the predicted-lateness policy retained 550 h of aggregate tardiness. At 48 h, the AM fleet completed any isolated observed order within two build waves (46 h), and selective routing became effective: the predicted-lateness policy eliminated tardiness for 23 AM-assigned orders. Once the due window reached 72 h, the IM queue satisfied every order without tardiness, so hybrid routing is no longer economically justified for this demand realization. The conclusion is therefore conditional and generalizable in process terms: hybrid AM–IM scheduling creates value when the required response time lies between the response capability of the economical base-load process and that of the faster surge-capacity process.[9,10,21]

5.5. Non-dominated sorting genetic algorithm II convergence and robustness

Table 7 summarizes the parameter calibration and the final multi-run stability assessment.

The 100/150 configuration retained 99.95% of the mean hypervolume of the larger 150/250 setting while requiring less than half the runtime. Across the 30 final runs, the normalized hypervolume averaged 0.83377 with a standard deviation of 0.00004 (range 0.83366–0.83384), every run recovered the same minimum-cost zero-tardiness endpoint of EUR 759,250.77, and mean runtime was 0.433 ± 0.017 s. **Figure 5** further shows that most hypervolume improvement occurs within the first 50 generations and that the between-run variability becomes very small thereafter.

Table 5. Benchmark comparison under the 48-h service target

Policy	Total cost (EUR)	Tardiness (h)	Late orders	On-time rate	Additive manufacturing orders
Quantity-threshold heuristic ($q \geq 10{,}000$)	670,832.76	17.66	5	93.5%	18
Predicted-lateness heuristic	759,250.77	0.00	0	100.0%	23
NSGA-II compromise	551,106.12	75.14	11	85.7%	12
NSGA-II zero-tardiness	759,250.77	0.00	0	100.0%	23

Abbreviation: NGSA-II: Non-dominated sorting genetic algorithm II.

Table 6. Due-window sensitivity for baseline and benchmark policies

Due window (h)	Policy	Total cost (EUR)	Tardiness (h)	Late orders	On-time rate	AM orders	AM volume (%)
24	IM-only	296,396.19	961.38	39	49.4%	0	0.0
24	Predicted-lateness heuristic	938,795.60	550.00	25	67.5%	39	90.0
24	AM-only	1,008,780.00	550.00	25	67.5%	77	100.0
48	IM-only	296,396.19	244.15	23	70.1%	0	0.0
48	Predicted-lateness heuristic	759,250.77	0.00	0	100.0%	23	64.8
48	AM-only	1,008,780.00	0.00	0	100.0%	77	100.0
72	IM-only	296,396.19	0.00	0	100.0%	0	0.0
72	Predicted-lateness heuristic	296,396.19	0.00	0	100.0%	0	0.0
72	AM-only	1,008,780.00	0.00	0	100.0%	77	100.0
168	IM-only	296,396.19	0.00	0	100.0%	0	0.0
168	Predicted-lateness heuristic	296,396.19	0.00	0	100.0%	0	0.0
168	AM-only	1,008,780.00	0.00	0	100.0%	77	100.0

Abbreviations: AM: Additive manufacturing; IM: Injection molding.

Table 7. Non-dominated sorting genetic algorithm II parameter calibration and multi-run robustness

Configuration	Independent runs	Normalized hypervolume (mean ± standard deviation)	Mean runtime (s)
50 individuals/100 generations	5	0.83019 ± 0.00159	0.135
100 individuals/150 generations (pilot)	5	0.83374 ± 0.00005	0.414
150 individuals/250 generations	5	0.83415 ± 0.00002	1.006
100 individuals/150 generations (final)	30	0.83377 ± 0.00004	0.433 ± 0.017

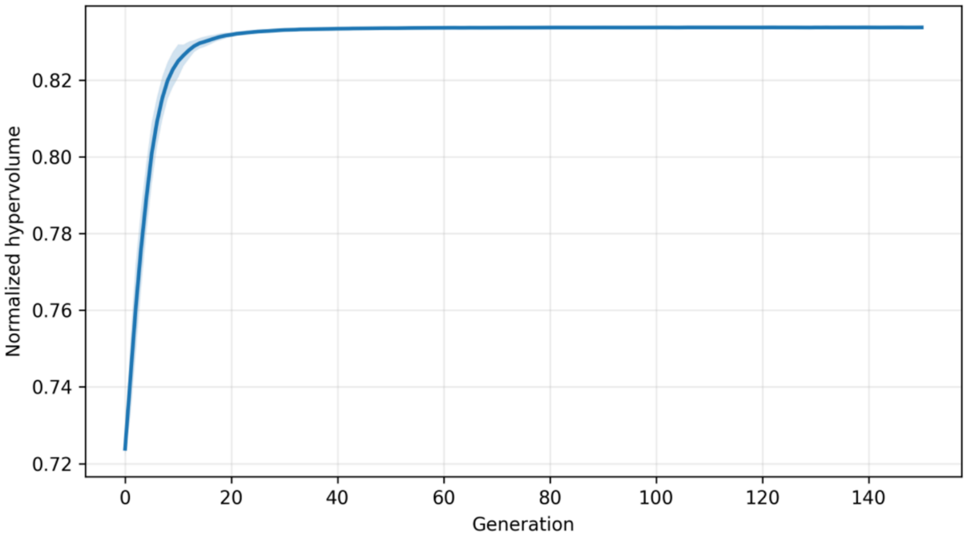

Figure 5. Mean normalized hypervolume across 30 independent non-dominated sorting genetic algorithm II runs; the shaded band represents ±1 standard deviation

5.6. Managerial interpretation

Three operational insights emerge. First, volatility alone does not justify AM adoption; value arises when volatility combines with a response-time requirement the IM queue cannot reliably meet. The due-window analysis identifies this regime explicitly: 48 h creates a meaningful hybrid decision for the observed system, whereas 72 h or more does not. Second, AM acts primarily as surge capacity, protecting service during clustered high-volume arrivals while leaving economical base-load volume on IM. Third, order-level routing is preferable to a fixed annual AM share because the cost–service outcome depends on which specific orders are diverted, not only on the total volume assigned to AM.[9,10,21]

6. Discussion

The findings demonstrate that the value of AM in industrial settings is best understood through dynamic scheduling under volatility, rather than static unit-cost assessments.[20,40] While traditional comparisons often favor IM for high-volume production,[4,41] such analyses overlook critical temporal dynamics, particularly the compounding of queue formation and service penalties during fluctuating demand.[42,43] In contrast, the NSGA-II-generated Pareto frontier illustrates how hybrid systems manage this tension: incremental AM adoption offers disproportionate service improvements, achieving an 85.7% on-time rate with an 85.9% cost increase relative to the IM-only baseline.[44]

The benchmark results sharpen this interpretation. The predicted-lateness rule reaches the same zero-tardiness endpoint as NSGA-II, confirming that a planner with accurate queue-state information can construct an effective reactive rule. However, the rule provides only a single operating point. NSGA-II exposes the full set of intermediate trade-offs, including solutions that accept limited tardiness in exchange for markedly lower AM usage and cost. This distinction is important for production economics because the preferred operating point depends on the marginal value assigned to service improvement.

The due-window sensitivity also limits the claim's scope in a useful way. The 48-h target is not presented as universally optimal; it is a capacity-derived threshold that lies between the practical response regimes of the two technologies for this case. At 24 h, even the AM fleet is stressed by orders requiring a second build wave, while at 72 h the IM resource alone meets all due dates. Hybridization is therefore economically relevant in the intermediate regime where IM is too slow for the required response, but AM retains enough reserve capacity to absorb the peaks.

Finally, the 30-run convergence analysis indicates that the optimization conclusions are not artifacts of one random seed. The very small hypervolume dispersion and identical zero-tardiness endpoint across runs support the stability of the reported Pareto frontier, while the calibration study shows that the retained population and generation settings capture nearly all of the improvement obtained with a substantially larger search.

This dynamic approach clarifies AM's industrial role: functioning effectively as a defensive, surge-capacity mechanism rather than a full substitute for established molding processes.[45,46] This research supports a targeted deployment approach, strategically routing high-risk-of-lateness orders, such as large, clustered peak arrivals, to AM to alleviate IM congestion without the prohibitively high cost of an AM-only infrastructure.[47] This mirrors flexible manufacturing system applications where secondary processes buffer primary queues during demand spikes.[48,49]

Order-level scheduling decisions are recommended, as selectively diverting volatile, high-priority orders to AM enhances resilience against demand uncertainty.[50,51] This dynamic perspective aligns with literature on scheduling under uncertainty, where hybrid systems leverage complementary technologies to optimize cost-service trade-offs.[52,53] Furthermore, the Pareto frontier's smooth curvature enables predictable trade-offs, allowing managers to tailor solutions to specific responsiveness needs, from moderate requirements to zero-tardiness targets.[53,54]

The developed methodology, utilizing NSGA-II with a time-based decoder, successfully bridges production scheduling under uncertainty with real-world volatility.[19,54,55] Its efficient exploration of the non-convex Pareto frontier, bolstered by heuristic initialization, demonstrates a practical approach for hybrid scheduling optimization.[53,54]

The deterministic processing-time assumption also provides a useful theoretical benchmark for interpreting real-world disruptions. If IM cycle or setup times vary, or an IM breakdown occurs, the resulting delay propagates through the single-machine queue and increases completion times for downstream orders. An AM machine breakdown similarly reduces effective parallel capacity, increases build waiting, and disproportionately affects Pareto solutions that rely heavily on AM. Under the present cost model, such time disturbances would primarily stretch the Pareto frontier upward through higher tardiness at the same nominal production cost; if repair, overtime, scrap, or additional setup costs were modeled, the frontier would also shift to the right. Variability would additionally turn each nominal Pareto point into a distribution of possible outcomes rather than a single deterministic pair. A robust extension could therefore optimize expected tardiness together with a risk measure such as service-level violation probability or conditional value-at-risk. This interpretation aligns with recent uncertainty-aware and resilient production-scheduling studies[50,51,54] and suggests that AM surge capacity should retain some reserve margin rather than operate at saturation. Non-zero AM material or pigment/color changeovers would produce a similar, although typically smaller, effect by increasing AM completion times and potentially moving low-tardiness solutions outward.[56]

7. Conclusion

The main outcomes of the study are summarized as follows. The two extreme policies were economically and operationally unbalanced. The IM-only approach minimized production cost at EUR 296,396.19 but accumulated 244.15 h of tardiness and 23 late orders under the 48 h target, whereas the AM-only approach eliminated tardiness but raised cost to EUR 1,008,780.00. The difference confirms that neither unit-cost dominance nor responsiveness alone is sufficient for technology selection.

Selective AM routing provides a meaningful middle ground. The balanced NSGA-II solution assigned 12 peak orders to AM, reduced total tardiness by 69.2%, and improved on-time performance from 70.1% to 85.7% at an 85.9% cost premium over the IM-only approach. The improvement occurs because AM removes the orders that create the largest queue externalities in the IM system.

The minimum-cost zero-tardiness endpoint was EUR 759,250.77 with 23 AM-assigned orders. The predicted-lateness heuristic reached the same endpoint, whereas NSGA-II additionally identified the lower-cost intermediate Pareto region. This shows that the main contribution of the meta-heuristic is the decision-maker's ability to choose among cost–service trade-offs rather than merely attain zero tardiness.

The benefit of hybridization is conditional on the response-time requirement. At 24 h, even the five-machine AM fleet experienced delay for large orders; at 72 h and 168 h, IM served every order on time. The hybrid strategy is therefore most relevant when the required response lies between the practical response capabilities of the base-load IM resource and the AM surge-capacity fleet.

The NSGA-II results are computationally stable. Across 30 independent runs, normalized hypervolume averaged 0.83377 ± 0.00004 and every run recovered the same zero-tardiness endpoint, supporting the reproducibility of the reported Pareto structure.

The study remains limited to one product, one validated demand stream, deterministic processing times, and a fixed five-machine AM fleet. Machine failures, labor constraints, quality differences, and explicit AM setup/changeover time were not modeled. In particular, future work should represent the shorter but non-zero AM setup associated with material or pigment/color changes when equipment is not dedicated to one polymer product. Further extensions should consider multi-product routing, stochastic build and breakdown times, rolling-horizon rescheduling, inventory/backorder interactions, and sustainability objectives.

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Conflict of interest

The author declares no competing interests.

Author contributions

This is a single-authored article.

Availability of data

The data that support the findings of this study are available from the corresponding author upon reasonable request. Some underlying industrial data are not publicly available due to confidentiality considerations.

AI tools statement

ChatGPT (OpenAI) and Jenni AI were used for language editing and drafting support. The author reviewed and takes full responsibility for the final manuscript.

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