

A PSO-BASED SIMULATION OPTIMIZATION FOR A COLLABORATIVE PRODUCTION SCHEDULING PROBLEM

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Abstract

This study addresses collaborative production scheduling in a resource-constrained three-tier equipment manufacturing supply chain. A bilevel optimization model captures interactions between centralized penalty/incentive policies and decentralized operational decisions regarding equipment utilization, pricing, and quantity. A particle swarm optimization (PSO)-based procedure solves the nonlinear bilevel problem. Numerical simulations examine convergence, optimal scheduling, and parameter sensitivity. Results show scheduling performance jointly depends on equipment utilization elasticity, switching cost, working-hour adjustment price, and demand. Low switching costs and moderate elasticity raise efficiency and profit; adverse parameter combinations lead to low-performance regimes. Properly designed penalties and incentives improve coordination, though their effectiveness hinges on operational flexibility and demand. The study offers a simulation-optimization framework for collaborative scheduling analysis in constrained equipment supply chains and supports decision-making for scheduling centres and enterprise planning.

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Key Words: Three-Tier Supply Chain, Simulation Optimization, Production Scheduling, PSO, Equipment Manufacturing

1. INTRODUCTION

Facing intensifying global manufacturing competition and tightening resource constraints, optimising production scheduling in the equipment manufacturing industry's three-tier supply chain has become a core strategy for competitiveness. Scheduling management is shifting from single-link to multi-agent, multi-resource coupling. Suppliers face capacity losses from procurement cycles and equipment ageing; manufacturers are constrained by assembly line conflicts and switching costs; retailers must balance inventory turnover with delivery cycles. As the central coordinator, the scheduling centre's policy tools critically influence supply chain delivery efficiency. Given the industry's intensive 'equipment-working hours-orders' nature and its vertical and horizontal heterogeneity, a 'macro-scheduling-micro-response' collaborative governance system is essential.

Existing research has explored supply chain production scheduling optimisation from multiple perspectives. Ellram and Tate highlighted the role of procurement collaboration in improving equipment utilisation [1]. BouAbid et al. developed an integrated model optimising production rates and maintenance scheduling under quality degradation [2]. Rentizelas et al. applied DEA to assess economic and environmental performance in biomass supply chains [3]. Skelton used input-output models to identify substantial carbon reduction potential in European supply chains [4]. El Ouardighi et al. examined double marginalisation effects on emissions and emission-reduction activities [5]. Nabernegg et al. analysed sectoral policies' impact on consumption-based emissions [6]. Barton et al. evaluated governance arrangements for UK power sector decarbonisation [7]. Eslamipoor compared contract types for supply

chain coordination under carbon pricing [8]. Sibanda and Padayachee proposed an enhanced NSGA-II algorithm for dynamic manufacturing system reconfiguration [9]. Taleizadeh et al. incorporated equipment switching costs into a quality-price-scheduling framework [10]. Mubarik et al. found digital scheduling tools increase utilisation but cross-enterprise collaboration showed limited mediating effects [11]. Ströher et al. developed a cross-organisational data sharing framework [12]. Hsieh et al. explored chemical waste remanufacturing strategies, demonstrating coordination aligns member preferences with system goals [13]. Mridha and Sarkar analysed controllable delivery times and carbon policies, identifying limited emissions regulation as optimal [14]. Palanivel and Venkadesh examined green technologies' emission reduction effects within an economic-environmental balance framework [15]. Mzili et al. [16] presented a novel hybrid approach, fusing genetic algorithms and penguin search optimization for scheduling problem optimization. Despite these contributions, three key limitations remain: limited research on scheduling adaptability across industrial sub-sectors or policy adaptability to multi-link coupling; no unified framework for equipment wear, fiscal budget rigidity, and order life cycles; and unquantified dynamic transmission from scheduling policies to enterprise responses, especially under demand fluctuations. To overcome these, this paper constructs a bilevel programming model. The upper level (scheduling centre) maximises total production efficiency (*TPE*) under fiscal budget constraints by optimising delay penalties and efficiency rewards. The lower level drives suppliers, manufacturers, and retailers to jointly optimise equipment utilisation, retail prices, and output, subject to working-hour quotas and delivery cycles. By decoding the 'policy tools→scheduling behaviour→market performance' mechanism, this paper provides a quantitative strategy to resolve the 'delivery delay-capacity idleness' paradox.

2. METHODS

2.1 Problem description

This study establishes a discrete-event stochastic simulation layer for collaborative production scheduling in a resource-constrained three-tier equipment manufacturing supply chain. The simulation models stochastic order arrivals, machine availability, processing disruptions, capacity fluctuations, and delivery uncertainty. The bilevel optimization is embedded in the simulation loop: simulation states are input to the optimizer, and adaptive decisions are returned to the simulation for evaluation [17-19].

The discrete-event simulation layer is implemented in Python 3.10 using a next-event time advancement mechanism. Three event types are defined: order arrival, machine breakdown, and processing completion. Order arrivals follow a Poisson process with a mean arrival rate of 5 per period. Machine breakdowns follow an exponential distribution with mean time between failures (*MTBF*) of 200 working hours. Processing time for each unit product at node i follows a triangular distribution with minimum as $0.85E_i$, mode = E_i , and maximum as $1.15E_i$. State variables include machine status (busy, idle, under repair), queue length at each node, and cumulative consumed working hours. Each simulation run includes a warm-up period of 10 periods to eliminate initialization bias, followed by a planning horizon of 100 periods. All reported results are averaged over 30 independent replications with different random seeds (1 to 30). At the end of each replication, the simulation returns average *TPE* and π to the optimizer for fitness evaluation.

2.2 Parameter and symbol definitions

The definitions of parameters and symbols are presented in Table I.

Table I: Definitions of parameters and symbols.

Parameter and Symbol	Definition
i	Node index (s : supplier, m : manufacturer, r : retailer)
P_i	Unit price (yuan)
p_e	Working-hour adjustment price (yuan per hour)
E_i	Standard working hour per unit (hour)
g	Utilization elasticity for per unit product
a	Potential market demand
b	Price sensitivity coefficient
Q	Production quantity
Q_{max}	Maximum production capacity
Q_{min}	Minimum production capacity
θ	Switching cost coefficient
μ_i	Equipment utilisation rate
R_i	Cost to increase utilization
C_i	Benchmark unit production cost (yuan)
ω_i	Initial working-hour quota
k	Initial working hour quota coefficient
G_i	Efficiency incentive (yuan/unit)
I_i	Delay penalty
T_{tax}	Delay penalty rate (yuan/hour)
C_c	Working-hour reward/penalty coefficient
t_{life}	Delivery cycle (periods)
λ	Idle capacity cost per unit

2.3 Basic assumptions

All nodes are rational profit-maximisers with complete information [20, 21]. Market demand is negatively correlated with product price and equipment utilisation rate [22]. Mathematically, it can be expressed:

$$Q = a - b \cdot P_r - g \cdot \sum_i E_i \cdot (1 - \mu_i) \geq 0 \quad (1)$$

The total working-hour consumption throughout the product process is proportional to the output, which can be expressed:

$$E_{total} = \sum_i E_i \cdot Q \quad (2)$$

The initial working-hour quota is proportional to the standard working-hour consumption [23, 24], which can be expressed:

$$\omega_i = k \cdot E_i \quad (3)$$

When the actual working hours exceed the quota, a penalty cost of $C_c \cdot (E_i \cdot Q - \omega_i)$ is incurred; when the working hours are saved, a reward of $C_c \cdot (\omega_i - E_i \cdot Q)$ is received. Based on the classical theoretical model, the cost of enhancing the equipment utilisation rate follows a quadratic convex function:

$$R_i = \frac{1}{2} \cdot \theta \cdot \mu_i^2 \quad (4)$$

The delay penalty is proportional to the ineffective working hours, which can be expressed:

$$I_i = T_{tax} \cdot E_i \cdot (1 - \mu_i) \quad (5)$$

where $E_i \cdot (1 - \mu_i)$ denotes the ineffective working hours; the price of working hour adjustment is determined by the external market. The cost of technological upgrading is correlated with the degradation of equipment state, expressed as follows:

$$B_i = F_s \cdot (M_{st} - M_{s0}) + F_m \cdot (M_{mt} - M_{m0}) + P_{upgrade} \cdot t_{life} \tag{6}$$

In Eq. (6), F_s and F_m are equipment depreciation rates of supplier and manufacturer; M_{st} and M_{mt} are current equipment states of supplier and manufacturer; M_{s0} and M_{m0} are initial states of supplier and manufacturer; $P_{upgrade}$ is the technology upgrade replacement rate. These parameters capture the cost of technological upgrading for suppliers and manufacturers. In addition, order arrivals, machine states, processing times, and delivery lags follow stochastic processes updated in each simulation run.

2.4 Model construction

Objective function of upper-level planning model is maximizing the *TPE*, expressed as:

$$\begin{aligned} \max TPE = & \sum_{i \in \{s,m,r\}} I_i \cdot Q - \lambda \cdot \sum_{i \in \{s,m,r\}} E_i \cdot (1 - \mu_i) \cdot Q \\ & - \sum_{i \in \{s,m,r\}} G_i \cdot Q + \sum_{i \in \{s,m,r\}} C_c \cdot [\omega_i - E_i \cdot (1 - \mu_i)] \cdot Q \end{aligned} \tag{7}$$

The *TPE* metric, though expressed with penalty revenue, incentive expenditure, and working-hour reward/penalty terms, is interpreted as the scheduling centre’s monetary-equivalent efficiency objective under budget balance. It directly drives upper-level decisions on delay penalties and efficiency incentives. The first is delay penalty revenue, the second is idle capacity cost, the third is incentive cost, and the fourth is working-hour quota reward or penalty. Constraints:

$$s. t. \left\{ \begin{aligned} & \sum_{i \in \{s,m,r\}} I_i \cdot Q - \sum_{i \in \{s,m,r\}} G_i \cdot Q \geq 0 \\ & 0 < Q_{\min} \leq Q \leq Q_{\max} \\ & \sum_{s=1}^S \sum_{m=1}^M \sum_{r=1}^R [E_s \cdot (1 - \mu_s) + E_m \cdot (1 - \mu_m) + E_r \cdot (1 - \mu_r)] \leq k \cdot \sum_{s=1}^S \sum_{m=1}^M \sum_{r=1}^R (E_s + E_m + E_r) \\ & 0 < k < 1 \\ & G_i > 0 \\ & E_i \geq 0 \end{aligned} \right. \tag{8}$$

Objective function of lower-level planning model is maximizing the π , expressed as:

$$\begin{aligned} \max \pi = & \sum_{i \in \{s,m,r\}} (P_i - C_i - R_i - I_i) \cdot Q - \left[(C_k + C_t) \cdot Q + \sum_{i \in \{s,m\}} (C_{\text{main},i} + B_i) \cdot Q \right] + p_e \\ & \cdot \sum_{i \in \{s,m,r\}} [\omega_i - E_i \cdot (1 - \mu_i)] \cdot Q - \sum_{i \in \{s,m,r\}} C_c \cdot [\omega_i - E_i \cdot (1 - \mu_i)] \cdot Q \\ & + \sum_{i \in \{s,m,r\}} G_i \cdot Q \end{aligned} \tag{9}$$

Each component reflects real operational cash flow in the simulation. The first is basic profit, the second is operational cost, the third is working-hour adjustment income, the fourth is working-hour quota reward or penalty, and the fifth is efficiency incentive income. Constraints:

$$\begin{aligned}
 s. t. \left\{ \begin{aligned}
 &\omega_i - E_i \cdot (1 - \mu_i) < 0 \text{ or } \omega_i - E_i \cdot (1 - \mu_i) \geq 0, \forall i \in \{s, m, r\} \\
 &0 \leq P_s < P_m < P_r \\
 &p_e > 0 \\
 &\pi_i > 0 \\
 &C_k > 0 \\
 &C_t > 0 \\
 &C_{main,i} > 0 \\
 &B_i > 0 \\
 &t_{process} = \sum E_i Q / \sum \mu_i Cap_i \leq t_{life}
 \end{aligned} \right. \quad (10)
 \end{aligned}$$

Here, $t_{process}$ is the total working-hour demand divided by the effective capacity, and Cap_i represents the maximum capacity of the node enterprise.

The improved PSO uses a two-layer particle encoding: the upper level encodes delay penalties and efficiency incentives; the lower level encodes equipment utilisation, retail price, and production quantity. Each particle represents a complete solution. Constraints are handled via a dynamic penalty function embedded in the simulation. Hard constraints (production bounds, working-hour quotas, price relationships) trigger an adaptive penalty term in the fitness function. Soft constraints (positive profit, delivery cycle) are evaluated from simulation outputs; severe violations reduce particle velocity. Stochastic constraints (machine availability, time-varying capacity) are updated in each replication. Four improvements are implemented. First, a hierarchical velocity update uses separate inertia weights for upper- and lower-level variables to stabilise search. Second, a simulation-guided local search refines the global best position using real-time simulation output. Third, an adaptive mutation operator increases mutation probability in later iterations by monitoring fitness improvement and swarm diversity, applying perturbation or re-initialisation when needed. Fourth, fitness evaluation averages over multiple simulation replications to reduce random error.

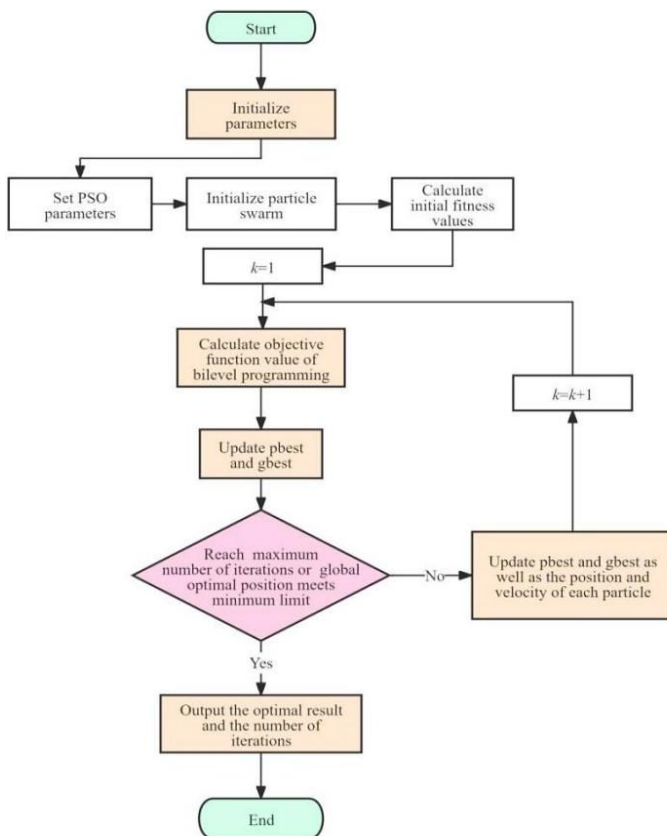


Figure 1: Flow chart of the improved PSO algorithm.

The bilevel problem is solved sequentially: the upper-level PSO optimises penalties and incentives to maximise total production efficiency; the lower-level PSO optimises operational variables to maximise profit. Fig. 1 shows the flow chart.

3. RESULTS AND DISCUSSION

3.1 Results analysis

In this study, a three-tier supply chain within a specific equipment manufacturing industry serves as the research subject. It is assumed that this supply chain encompasses 4 suppliers, 6 manufacturers, and 5 retailers. This setup is employed to validate the efficacy of the proposed model and algorithm [25, 26]. Given the complexity of the products, Python 3.10 is utilized for algorithm coding and optimisation computations. The simulations are executed on a Windows 10 computer featuring a 1.80 GHz Intel® Core™ i7-8565U CPU and 8 GB of RAM. The key parameters are set as follows: θ is 200, p_e is 80 yuan per hour, a is 10,000, b is 1.0, g is 0.5, k is 0.8, C_c is 6, $P_{upgrade}$ is 15, t_{life} is 5 and λ is 20. These fixed parameter values are applied consistently in all simulation replications and comparative experiments to ensure comparability and replicability.

To verify the performance of the proposed simulation-optimisation approach, a comparative experiment is carried out against two benchmark methods under identical settings. All results are averaged over 30 independent replications, as listed in Table II.

Table II: Performance comparison among different methods (mean \pm std).

Method	<i>TPE</i>	π	Convergence iterations	Constraint violation rate
Improved PSO	17050575.21 \pm 32410.36	65215015.40 \pm 48520.72	7 \pm 2	0.021
Standard PSO	15328742.35 \pm 156820.51	58692310.66 \pm 210430.88	15 \pm 3	0.108
GA	14865290.72 \pm 189550.27	56310985.33 \pm 243610.55	22 \pm 4	0.135

Statistical significance: Paired t -tests over the 30 replications show that improved PSO achieves significantly higher *TPE* and π than standard PSO and GA ($p < 0.01$ for both comparisons). The proposed method achieves higher total production efficiency and supply chain profit with significantly faster convergence, reaching a stable optimal solution within 7 iterations on average, compared with 15 iterations for standard PSO and 22 iterations for bilevel GA. The small standard deviations of convergence iterations and performance indicators confirm strong stability and reliability under stochastic simulation environments. When the PSO algorithm is run, the convergence process is depicted in Fig. 2. This clearly attests to the effectiveness and stability of the algorithm in addressing the collaborative production scheduling problem.

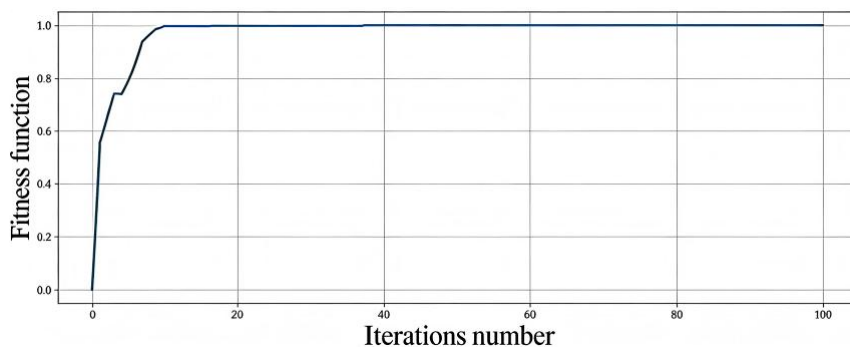


Figure 2: Convergence plot of fitness function.

Fig. 2 shows the algorithm's performance across iterations. During the early stage (0–7 iterations), the curve rises sharply, reflecting strong global search and rapid convergence to a high-quality solution domain. In the middle stage (7–10 iterations), the upward trend slows, indicating a shift from global exploration to local refinement, steadily improving solution quality. In the late stage, the curve flattens, showing stable convergence near an optimal region. The overall smoothness with minimal fluctuations demonstrates the algorithm's stability and its effective balance between convergence speed and solution quality, validating the adopted optimisation strategy.

Using the bilevel programming model and the parameter values mentioned above, the improved particle swarm algorithm was employed to obtain the optimal solution. The optimal combination of the three-tier supply chain consists of the second supplier, the fifth manufacturer, and the fourth retailer. Their respective equipment utilisation rates are 0.7863, 0.9743, and 0.4912. The delay penalty rate is 0.1890. The efficiency incentives provided by the scheduling centre to the supplier, manufacturer, and retailer are 5.53, 5.84, and 5.00 respectively. The retail price of the product is 4,500, and the product scale is 7,999. The optimal value of the upper-level objective function TPE is 17,050,575.21, and the value of the lower-level objective function π is 65,215,015.40.

3.2 Sensitivity analysis

Compared with a no-optimisation baseline (fixed parameters: $\mu_i = 0.7$, $P_r = 4,000$, $Q = 6,000$, no incentives), improved PSO increases TPE by 34.2% and π by 28.7%. To assess robustness, all sensitivity experiments were repeated with three different random seeds (1, 42, 100). The reported patterns (ridges, saddle regions, substitution effects) remained consistent across seeds, with coefficient of variation below 8% for key thresholds. Fig. 3 shows that TPE depends non-linearly on equipment utilisation elasticity (g) and switching cost (θ). At low g (< 0.65) and low θ (< 0.7), TPE exceeds 3.5×10^6 , forming a steep ridge that reflects full use of flexible capacity. Higher θ shifts the ridge rightward and reduces TPE sharply. For $g > 0.8$, TPE falls below 1.5×10^6 on a flat plateau, where θ 's impact weakens due to redundant capacity. In the saddle region ($g = 0.75$, $\theta = 0.85$), sensitivity is highest: a 0.05 rise in θ cuts TPE by 6%, and the same increase in g reduces it by 4%. Therefore, under low θ , keep g below 0.65 via flexible scheduling; under high θ , use demand forecasting or dynamic pricing to contain g , avoid the sensitive zone, and maintain TPE above 2.5×10^6 .

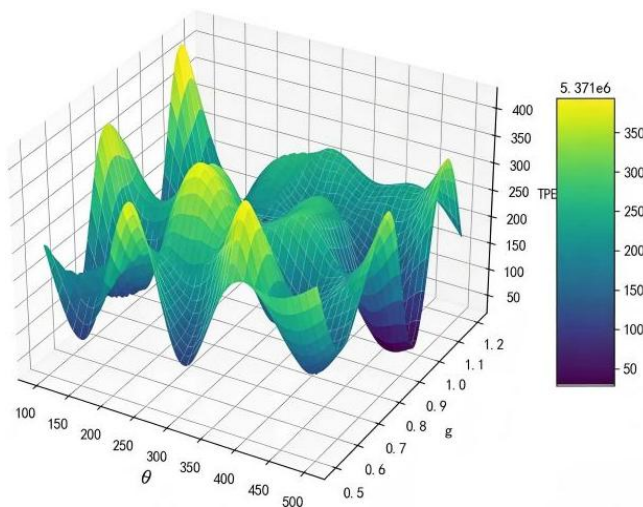


Figure 3: Influence of production system adaptability on TPE .

Fig. 4 shows a non-convex profit response to g and θ . At low g (below 0.65) and low θ (below 0.7), profit spikes to approximately 6.0×10^7 , forming a sharp 'profit ridge' due to low θ

amplifying marginal gains under flexible switching. As θ rises to 1.0, profit drops steeply, with high θ eroding profits via change-over costs and idle capacity. When g exceeds 0.8, profit falls below 4.0×10^7 and θ sensitivity weakens due to safety capacity buffers. In the saddle region ($g = 0.75$ and $\theta = 0.85$), an increase of 0.05 in g or θ reduces profit by about 3.5% and 4.8% respectively, highlighting a chain reaction. Thus, for low θ , target $g \leq 0.65$; under high θ , use demand forecasting, dynamic pricing, or capacity outsourcing to avoid the saddle area and maintain profit above 4.5×10^7 .

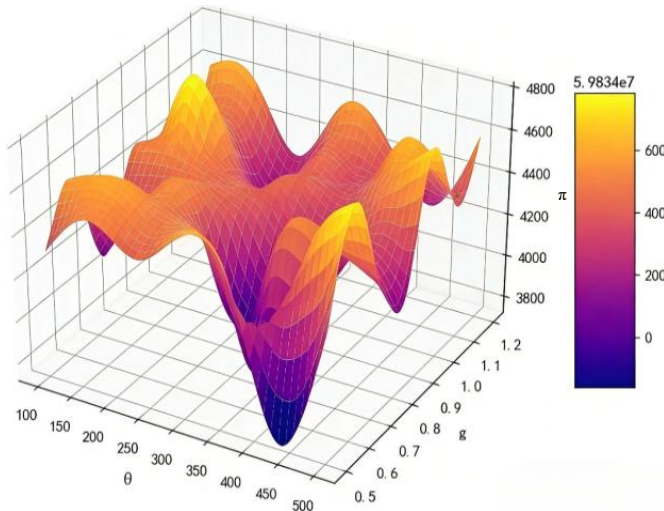


Figure 4: Influence of production system adaptability on π .

Fig. 5 shows *TPE*'s non-linear coupling with working hour adjustment price (p_e) and potential market demand (a). With $a = 9,000$, raising p_e from 60 to 110 increases *TPE* from 7,000 to over 11,000, with a marginal gain of approximately 80 *TPE* per unit of p_e , and diminishing returns beyond $p_e = 100$. At $p_e = 90$, each increase of 1,000 in a raises *TPE* by 400–500, making demand sensitivity 5 to 6 times that of p_e . The high-efficiency region ($TPE \geq 11,000$) is confined to $p_e > 95$ and $a > 10,500$. A significant substitution effect (interaction coefficient -4.2 , $p < 0.01$) means that when $a > 11,000$, a decrease of 5 in p_e reduces *TPE* by only 1.8%, but when $a < 8,500$ the same decrease causes a loss of over 8% in *TPE*. Therefore, during high demand, p_e may be relaxed to unleash capacity; during weak demand, p_e must be kept below 95 through lean scheduling and dynamic pricing to maintain *TPE* above 10,000.

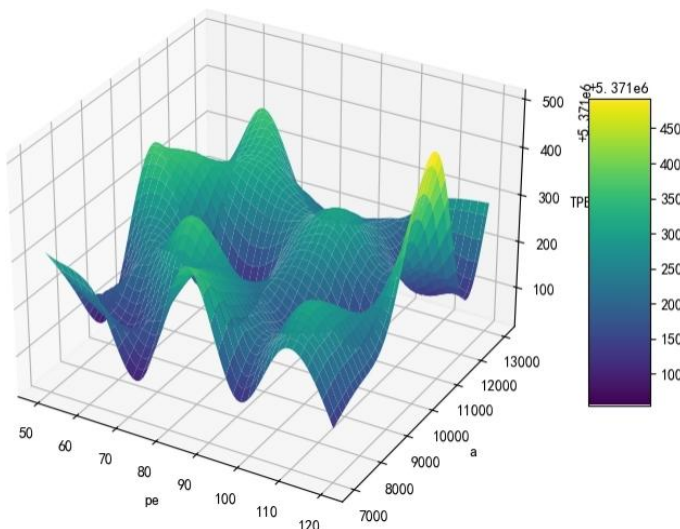


Figure 5: Influence of market-driven factors on *TPE*.

Fig. 6 shows profit π governed by a strongly non-convex surface of working hour adjustment price (p_e , range 60–120) and market demand (a , range 7,000–13,000). At $p_e = 90$, an increase of 1,000 in demand raises π by approximately 1,000, giving a quasi-linear response from 8,000 to 12,000. At $a = 10,000$, a one-unit increase in p_e reduces π by 37.5; above $p_e = 100$, the loss rate jumps by 52 %. The high-profit domain ($\pi > 12,000$) is a narrow corridor with $a > 11,000$ and $p_e < 85$. Strong asymmetric antagonism exists: when $a > 11,500$, a five-unit rise in p_e erodes only 1.2 % of profit, but when $a < 9,000$, the same price increase causes over 7 % loss. Therefore, during demand expansion, p_e may be relaxed; during contraction, enforce $p_e < 90$ via scheduling, dynamic pricing, and outsourcing to keep $\pi > 11,000$.

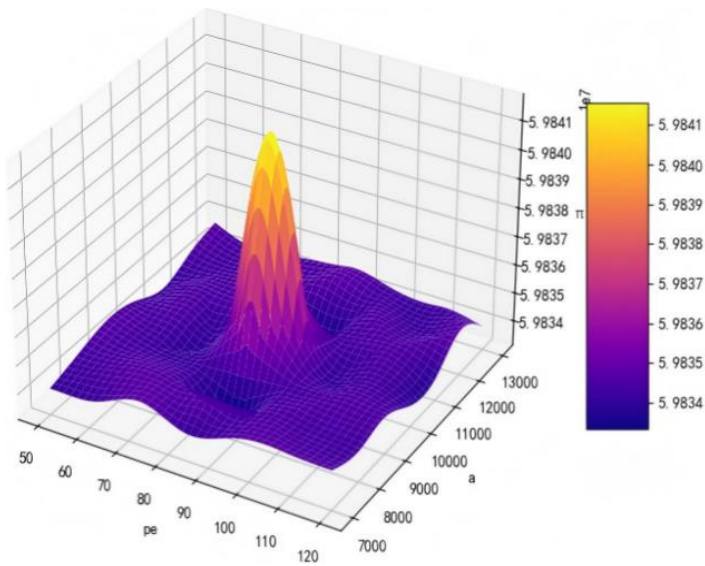


Figure 6: Influence of market-driven factors on π .

4. CONCLUSION

This study proposed a simulation-optimization framework for collaborative production scheduling in a resource-constrained three-tier equipment manufacturing supply chain. A bilevel model was developed to represent the interaction between scheduling-centre decisions at the upper level and operational responses of suppliers, manufacturers, and retailers at the lower level. The upper level determines delay penalties and efficiency incentives under budget constraints, while the lower level optimizes equipment utilization, retail pricing, and production quantity to improve supply-chain profitability. A PSO-based solution procedure was used to solve the nonlinear bilevel problem, and simulation experiments were conducted to examine convergence characteristics and system sensitivity under different operational and market conditions.

The results show that the scheduling system exhibits strong nonlinear behaviour. Equipment utilization elasticity, switching cost, working-hour adjustment price, and potential market demand jointly shape both production efficiency and profit. Favourable parameter combinations support stable high-efficiency operation, whereas unfavourable combinations may lead to significant deterioration in both efficiency and economic performance. These findings indicate that collaborative scheduling performance cannot be improved solely through stronger penalties or incentives; instead, policy intensity must be matched with operational flexibility, capacity conditions, and demand characteristics.

From a modelling perspective, the study demonstrates that simulation-assisted bilevel optimization can provide useful decision support for analysing multi-tier production

scheduling under resource constraints. From a managerial perspective, the results offer guidance for selecting appropriate scheduling policies and identifying parameter regions associated with stable and efficient operation. Future research should strengthen the simulation component by incorporating stochastic demand, machine breakdowns, processing-time uncertainty, and dynamic order arrivals, and should compare the proposed PSO-based method with alternative optimization and simulation-based scheduling approaches to improve robustness and generalizability.

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