Postprint: Research on Optimal Replacement Ratio of AGVs in Flexible Workshops

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Abstract

To address the problem of optimal AGV replacement ratio in flexible job shops, a flexible job shop scheduling model with joint handling by workers and AGVs is established. The model aims to minimize makespan and cost, and the optimal replacement ratio is obtained from both static and dynamic analysis perspectives. The static analysis is primarily conducted using linear programming, while the dynamic analysis is solved using particle swarm optimization. For the dynamic analysis, heuristic rules are proposed for assigning handling operations to AGVs and workers. Through numerical examples, the Pareto optimal solution set for the AGV optimal replacement ratio is obtained, and it is found that the AGV optimal replacement ratio is related to AGV price.

Full Text

Preamble

Research on Optimal Replacement Ratio of AGVs in Flexible Workshops

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Abstract: To address the optimal replacement ratio of Automated Guided Vehicles (AGVs) in flexible workshops, this paper establishes a flexible shop scheduling model that incorporates both human workers and AGVs for material handling. The model aims to minimize completion time and total cost, deriving the optimal replacement ratio through both static and dynamic analyses. The static analysis employs linear programming, while the dynamic analysis utilizes a particle swarm optimization algorithm. For the dynamic component, heuristic rules are proposed for allocating handling tasks between AGVs and workers. Computational experiments yield a Pareto optimal solution set for the AGV replacement ratio, revealing that the optimal ratio is correlated with AGV price.

Key words: FJSP; AGV; particle swarm algorithm; replacement ratio

0 Introduction

With technological advancement, industrial robots are increasingly deployed in production environments, gradually replacing traditional human-machine collaboration models. Robots offer compelling advantages including lower costs, higher work quality, superior precision, and energy savings, prompting manufacturing and service industries to adopt intelligent machines to replace manual labor for simple, repetitive tasks while improving profitability. The optimal human-machine replacement ratio refers to the proportion of workers to robots that maximizes benefits within an acceptable investment range.

Current domestic research on human-machine replacement primarily focuses on economic feasibility analysis. Xu et al. [?] identify the cost intersection point between robots and labor as the critical threshold for replacement decisions. Sun [?] examines government subsidy strategies for machine replacement initiatives. Studies [?, ?] analyze cost-benefit outcomes post-implementation, while Li and Zhang [?] investigate cost factors in automotive plant AGV deployments. However, these works demonstrate economic viability without addressing the optimal quantitative ratio of robots to workers during transition.

International research on human-machine ratios traditionally assumes non-autonomous machines, examining how many machines one operator can manage to maximize productivity. Syahir and Rashid [?] optimize human-machine ratios in semiconductor manufacturing through work measurement and standardization. Mehtre et al. [?] analyze ratio impacts on garment factory efficiency, and Ong [?] proposes simulation-based ratio determination. Notably, no existing studies integrate human-machine replacement economics with operational scheduling to determine optimal replacement ratios. This paper bridges this gap by combining both perspectives, making the research particularly relevant for China' s manufacturing upgrade initiatives. In flexible workshops where AGVs can replace manual material handling, determining the optimal number of AGVs and remaining workers carries significant practical value.

This study investigates the AGV replacement ratio problem in flexible workshops, considering both completion time and labor/AGV costs. We examine optimal ratios from two perspectives: a static view without job scheduling considerations, and a dynamic view incorporating scheduling decisions. This micro-macro approach provides realistic guidance for enterprise-level human-machine replacement decisions, where accurate order forecasting is critical—under-capacity leads to penalty costs while over-capacity reduces utilization.

1.1 Modeling Optimal AGV Replacement Ratio in Flexible Workshops

A company plans to introduce AGVs to replace partial or complete manual handling in its flexible production workshop. With limited working capital, the post-investment cost must not exceed pre-investment levels. The workshop originally employs X workers for handling, retaining x workers after AGV introduction. Workers earn w annually, with severance compensation of c per dismissed worker. The average handling speed is v_{human} items/minute. With average monthly order volume m, 8-hour shifts, two-shift operation, and 22 working days per month, the company considers purchasing AGVs at p per unit with n-year lifespan, totaling y units. AGVs operate at speed v_{AGV} items/minute with annual maintenance cost a per unit and installation cost s.

Objective Functions:

$$\begin{aligned} \min \quad & f_1 = C_{\text{time}} \\ \min \quad & f_2 = C_{\text{cost}} \end{aligned}$$

Constraints:

$$\begin{cases} C_{\text{cost}} \leq C_{\text{original}} \\ \text{Order fulfillment capacity} \geq m \\ x \in \mathbb{N}, \quad y \in \mathbb{N} \\ x < X \end{cases}$$

The cost components include worker wages, severance payments, AGV procurement, installation, and maintenance expenses. The static analysis solves this linear programming model to identify cost-minimal human-AGV combinations that satisfy production requirements.

1.2 Problem Solution

Consider a workshop with 15 pre-investment workers earning ¥60,000 annually, with severance cost of ¥5,000 per worker. Human handling speed is 1 item per 3 minutes (160 items/day). Post-investment AGVs cost ¥300,000 each, operate at 1 item/minute (960 items/day), incur ¥200,000 total installation cost, and require ¥3,000 annual maintenance per unit. Average monthly order volume is 52,000 items.

MATLAB computation yields the following Pareto-optimal solutions (columns represent: [AGV count, worker count, required days, total cost]):

$$\begin{bmatrix} 0 & 15 & 21.67 & 270 \\ 0 & 13 & 24.69 & 240 \\ 0 & 11 & 27.78 & 210 \\ \vdots & \vdots & \vdots & \vdots \\ 7 & 0 & 7.74 & 243.8 \end{bmatrix}$$

The pre-investment baseline $[0, 15, 21.67, 270]$ shows that AGV introduction reduces both cost and completion time. The optimal replacement ratio is 0:3 (workers:AGVs) when AGV unit price ranges between ¥100,000-¥500,000, reducing completion time by 3.61 days and cost by ¥1.498 million compared to the original configuration.

2 Dynamic Analysis: Optimal AGV Replacement Ratio

2.1 Problem Description and Modeling

2.1.1 Problem Description The dynamic analysis considers a flexible job shop with X original workers, where AGV investment aims to reduce labor costs. Post-investment, x workers and y AGVs jointly handle inter-machine transportation. Each transportation task is independent, with each job i requiring n_i operations O_{ik} that can be processed on multiple machines. Key assumptions include:

a) Fixed, non-interfering routes for both AGVs and workers

b) Transportation from previous operation's buffer to next operation's buffer

c) Zero initial setup time for all equipment

d) Instantaneous transfer from buffer to machine

e) Single-part processing without interruption

f) First-come-first-served (FCFS) processing discipline

g) Precedence constraints within jobs but not between different jobs

h) All raw jobs start at loading station M_0; completed jobs finish at unloading station M_{m+1}

2.1.2 Mathematical Model **Notation:** - $I = \{1, 2, \dots, n\}$: set of jobs - $M = \{0, 1, 2, \dots, m, m+1\}$: set of machines (including loading/unloading stations) - $H = \{1, 2, \dots, x\}$: set of workers - $R = \{1, 2, \dots, y\}$: set of AGVs - O_{ik}: k-th operation of job i - p_{ikj}: processing time of O_{ik} on machine j - t^b_{ik}: start time of O_{ik} - t^c_{ik}: completion time of O_{ik} - t^r_{ik}: AGV transportation time for O_{ik} - t^h_{ik}: worker transportation time for O_{ik}

Objective Functions:

$$\begin{aligned} \min \quad & f_1 = C_{\max} = \max\{t^c_{i,n_i}\} \\ \min \quad & f_2 = C_{\text{total}} = C_{\text{AGV}} + C_{\text{human}} \end{aligned}$$

Constraints:

a) **Operation precedence:** For each job i and operation k,

$$t^b_{i,k+1} \geq t^c_{ik} + \max(t^r_{ik}, t^h_{ik})$$

b) **Machine capacity:** For operations O_{ik} and $O_{i'k'}$ processed on the same machine j,

$$t^b_{ik} \geq t^c_{i'k'} \quad \text{or} \quad t^b_{i'k'} \geq t^c_{ik}$$

c) **Transportation capacity:** For AGVs,

$$\sum_{i,k} r_{ik} \leq y \quad \text{where} \quad r_{ik} \in \{0,1\}$$

d) **Worker capacity:**

$$\sum_{i,k} h_{ik} \leq x \quad \text{where} \quad h_{ik} \in \{0,1\}$$

e) **Exclusive assignment:** Each operation is assigned to either an AGV or a worker:

$$r_{ik} + h_{ik} = 1$$

f) **AGV task sequencing:** For consecutive tasks assigned to the same AGV,

$$t^b_{i'k'} \geq t^c_{ik} + T^r_{j \to j'}$$

g) **Worker task sequencing:** For consecutive tasks assigned to the same worker,

$$t^b_{i'k'} \geq t^c_{ik} + T^h_{j \to j'}$$

h) **Unloading constraint:** All jobs must be transported to unloading station M_{m+1} after final operation.

2.2 Constructing Pareto Optimal Solution Set

A solution x is Pareto-optimal if no feasible solution y exists that dominates x (i.e., improves at least one objective without worsening others). Solution x dominates y if all objective values of x are no worse than y' s, with at least one strictly better.

We employ binary tournament selection with dynamic elimination to construct the Pareto set [**?**]. Starting with solution set A, we iteratively compare each solution $x \in A$ against remaining solutions $B = A \setminus \{x\}$. If no solution in B dominates x, we add x to the Pareto set C and remove all solutions dominated by x from B. If any solution in B dominates x, we discard x and its dominated solutions. For mutually non-dominated pairs, we move x to C. This approach enables real-time elimination of dominated solutions, reducing computational complexity.

2.3 Particle Swarm Optimization Design

The flexible job shop scheduling problem with AGVs is NP-hard, requiring heuristic approaches. We propose an improved discrete PSO algorithm that integrates heuristic rules for AGV-worker allocation.

2.3.1 Algorithm Encoding Each particle represents a candidate schedule as a $3L$-dimensional vector: - **Tr (Transport sequence)**: Permutation of all operations - **M (Machine)**: Assigned machine for each operation
- **RH (Robot-Human)**: Transportation mode (1=worker, 2=AGV) for each operation

For example, with $x = 1$ worker and $y = 1$ AGV, an encoding might be:

Particle Encoding Vector Matrix

2.3.2 Population Initialization

1. Randomly generate multiple transport sequences (Tr vectors)
2. For each operation, assign the machine with shortest processing time (M vector) [?]
3. Apply heuristic rules to generate RH vectors: For each required transportation, select the available worker or AGV that can complete the task earliest

2.3.3 Particle Position Update The update combines three components: self-cognition, historical experience, and social collaboration [?]. The position update formula is:

$$\omega = \omega_{\text{self}} \otimes \omega_{\text{cognitive}} \otimes \omega_{\text{social}}$$

where $\otimes$ represents sequential operation execution.

1) Self-component: With probability c_1, apply one of three operations to Tr vector: - **Swap**: Exchange two random operations (Fig. 3 [Figure 3: see original paper]) - **Insert**: Move operation at position b before position a (Fig. 4 [Figure 4: see original paper])
- **Reverse**: Invert subsequence between positions a and b (Fig. 5 [Figure 5: see original paper])

Corresponding M and RH vectors follow Tr transformations (Fig. 6 [Figure 6: see original paper] for M, Fig. 7 [Figure 7: see original paper] for RH).

2) Cognitive component: With probability c_2, perform POX crossover with particle' s personal best p_i^k (Fig. 8 [Figure 8: see original paper]).

3) Social component: With probability c_3, perform RPX crossover with global best g^k using adaptive probability:

$$f = f_{\max} - (f_{\max} - f_{\min}) \times \frac{t}{T}$$

where t is current iteration and T is total iterations (Fig. 9 [Figure 9: see original paper]).

2.3.4 Algorithm Procedure The complete algorithm flow is shown in Fig. 10 [Figure 10: see original paper]. The AGV replacement ratio optimization pseudocode:

```
Initialize workers = -1, AGVs = 0
while (post-investment total cost  pre-investment cost):
    workers += 1
    while (post-investment total cost  pre-investment cost):
        AGVs += 1
        total_cost = AGV_cost + labor_cost
        compute minimum makespan
        update Pareto set
```

2.4 Experimental Results

2.4.1 Algorithm Performance Validation Experiments run on Windows 7 64-bit, 2.5 GHz CPU, 4 GB RAM, MATLAB R2014, with 20 runs per instance. Parameters: population size=500, iterations=100, learning factors $c_1 = c_2 = 0.9$, inertia weight $\omega = 0.9$ [?, ?, ?].

We test on selected instances from Bilge et al. [?] with 4 machines, loading/unloading stations, and various AGV layouts. Table 2 compares our improved PSO (PSO/FPSO) against MAS [?], GAHA [?], FDE [?], and FMAS [?]. Results show our algorithm achieves superior solutions: for job shop scheduling, 66.67% of solutions outperform MAS (R=2) and GAHA (R=2), with 100% outperforming GAHA (R=3). For flexible job shop scheduling, 50% outperform FDE (R=2) and FMAS (R=2). Fig. 11 [Figure 11: see original paper] illustrates makespan comparisons for R=2.

2.4.2 Example Solution Pre-investment: 15 workers, ¥60,000 annual wage, transportation time matrix (Table 3). Post-investment: AGV transportation time matrix, ¥300,000 AGV cost, ¥200,000 installation, ¥3,000 annual maintenance, ¥5,000 severance per worker. Processing task: 15×10[96].

The Pareto-optimal solution matrix [AGVs, workers, makespan, cost] yields optimal replacement ratio 1:7 (workers:AGVs), reducing makespan by 105 time units and cost by ¥87,000.

2.4.3 Sensitivity Analysis AGV Price Impact: With prices ranging ¥50,000-¥1,000,000, we analyze replacement ratios (Table 3). When AGV unit price is ¥100,000-¥500,000, the optimal ratio is 0:3. At ¥600,000-¥800,000, ratio becomes 2:3. For prices ¥900,000, AGV investment is not recommended.

Worker Wage Impact: Wage variations (¥60,000-¥100,000) show minimal effect on optimal ratio, maintaining 0:3 across this range (Fig. 1 [Figure 1: see original paper], Fig. 2 [Figure 2: see original paper]).

3 Conclusion

This paper innovatively proposes an AGV replacement ratio model for flexible workshops, analyzing optimal human-machine ratios through static and dynamic perspectives that align with practical production scenarios. Static analysis minimizes cost under equipment constraints, while dynamic analysis minimizes makespan under cost constraints. We introduce a 3L-dimensional encoding where the RH vector represents human/AGV allocation, employ tailored PSO update rules with heuristic allocation, and construct Pareto sets via binary tournament with dynamic elimination, reducing computational complexity.

Limitations include: (1) static analysis only considers cost-neutral scenarios without scaling effects; (2) lacks real factory case studies integrating financial metrics like cash flow and industry benchmarks; (3) focuses solely on material handling operations. Future research should extend to comprehensive human-machine replacement across all operational roles.

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Note: Figure translations are in progress. See original paper for figures.