Research on Scheduling Optimization of Mobile Robot Fulfillment System Considering Differentiated Power Consumption

Zhixiong Wang

Liaoning Technical University, School of Business Administration, Huludao, Liaoning, 125105, China
2524415964@qq.com

Abstract. With the advancement of Industry 4.0 and green logistics, Robotic Mobile Fulfillment System (RMFS) has emerged as the core of intelligent warehousing. Nevertheless, most existing scheduling strategies adopt a homogeneous energy consumption pattern, which leads to severe energy waste. To solve this problem, this paper formulates a multi-objective mixed integer programming scheduling model that takes the minimum total travel distance and minimum total power consumption as optimization objectives and incorporates differentiated power consumption characteristics. An adaptive improved NSGA-II algorithm is proposed to optimize the solving performance by virtue of three-stage selection, dynamic density perception and elite retention mechanisms. Numerical experimental results demonstrate that the proposed algorithm outperforms VNS, PSO, MOEA/D and the baseline algorithm in terms of optimization objective values and stability. In an ideal operating environment, the differentiated strategy can reduce energy consumption by approximately 8.23%–25.16% compared with the conventional strategy, which effectively improves the energy efficiency and operational continuity of the system.

Keywords: Mobile Robot Fulfillment System; Power Consumption; MIP; NSGA-II.

1 Introduction

Industry 4.0 drives intelligent upgrading of warehousing and logistics via industrial automation and information technology integration. Against this backdrop, mobile robot fulfillment systems represented by Amazon Kiva, JD Tianlang and Geek+ have seen wide application in recent years. As core system equipment, mobile robots achieve environmental perception and human-machine collaboration with IoT technology, mainly supporting the goods-to-person picking mode. This integrated handling mode greatly cuts manual order picking time. Spurred by the green logistics concept in recent years, stricter standards have been set for mobile robot power management, and enterprises keep exploring scheduling optimization strategies to lower energy consumption.

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On this basis, many scholars have conducted extensive research on power constraints in the task scheduling process of warehouse mobile robots and achieved certain research results; Riazi, S. et al[1]. targeted large-scale AGV clusters and proved that cruising speed and traveling distance are the core influencing factors of energy consumption, Sperling, M. et al[2]. proposed a system state-based AGV power demand model that integrates material flow characteristics and AGV operating conditions to realize accurate calculation and quantitative characterization of energy consumption in different warehouse operation scenarios, Mohamadi, P. et al[3]. put forward an energy consumption modeling method with hybrid parameter estimation for warehouse ground mobile robots under unknown loads, which can accurately decouple mass coefficients and realize real-time estimation of load and driving power consumption, Chen, W. et al[4]. revealed the influence mechanism of warehouse layout on robot efficiency and energy consumption through analyzing the aisle-less multi-depth shelf climbing robot system, Hou, L. et al[5]. incorporated special factors such as center of gravity, temperature and ground friction into the energy consumption research of warehouse omnidirectional robots from the perspective of mechanics and kinematics, showing advantages in narrow-channel and high-density scenarios, while Tomy, M. et al[6]. optimized and decided the battery charging scheduling strategy for long-lifetime autonomous mobile robots under uncertain working conditions to obtain the optimal charging sequence and power replenishment scheme.

In summary, most existing works focus on order volume and travel distance impacts on robot energy consumption and scheduling. Most adopt a fixed unit-distance power consumption and a static load-energy correlation, neglecting warehouse cargo differences and the varied power consumption from robot initial power and battery health disparities. Accordingly, this paper introduces differentiated energy consumption, builds a scheduling optimization framework, and investigates refined scheduling strategies.

2 Problem Description and Mathematical Modeling

2.1 Problem Description

The robotic mobile fulfillment system (RMFS) is a typical parts-to-picker system, with its warehouse layout and workflow shown in Figure 1. After receiving orders, the system dispatches autonomous mobile robots (AMRs) from the standby area. By navigation and positioning, robots travel to target racks and deliver them to picking stations for order picking. After task completion, robots take on subsequent tasks and proceed to charge when low on power. Scheduling is central to RMFS efficient operation, which coordinates task allocation and path planning under multiple constraints to shorten order fulfillment time and cut operational costs. In practice, mobile robots show differentiated power consumption affected by rack load, travel distance and individual battery status. These features directly determine robot endurance and operational continuity, and thus should be fully considered in scheduling optimization.

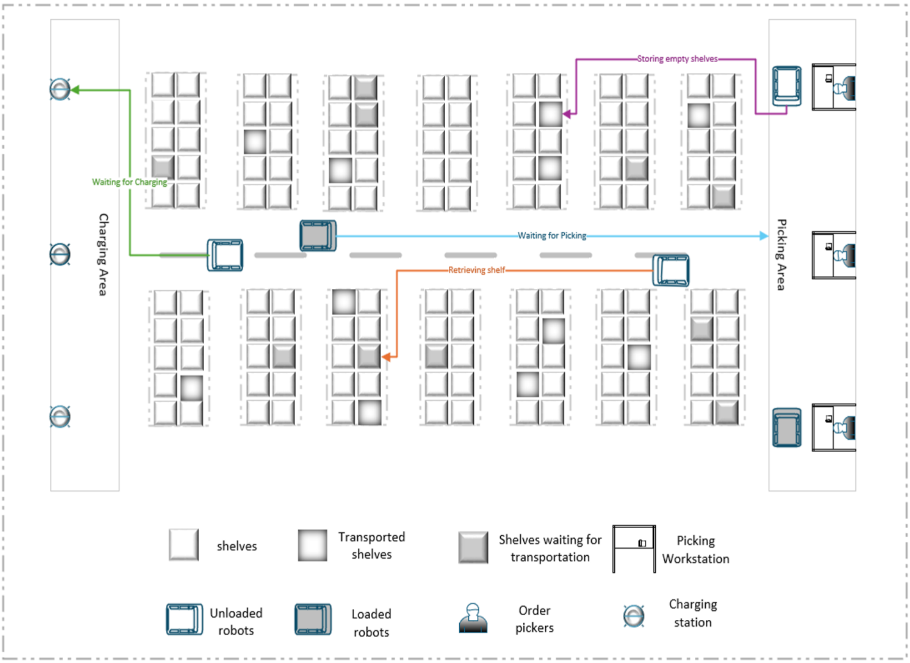

Fig. 1. Warehouse Layout and Operation Flowchart of RMFS.

To carry out the research of this paper, based on the actual warehouse operation scenarios and existing relevant studies[7][8], the research hypotheses are proposed as follows:

1)The traveling speed of the robot is constant, only affected by no-load and loaded conditions, and congestion and conflicts among multiple robots are not considered.

2)The load weight of each shelf is fixed and measurable, and the energy consumption increment generated when the same shelf is transported by different robots remains constant.

3)A mobile robot can only execute one task at a time, and each task can only be assigned to one mobile robot.

4)The initial power of all robots is a known fixed value, and unexpected failures and temporary power outages are not considered within the scheduling cycle.

2.2 Mathematical Modeling

The main involved parameters and variables are shown in Tables 1.

This paper constructs the following multi-objective optimization model based on mixed integer programming. The first objective is to minimize the total travel distance of AMRs (1), and the second objective is to minimize the total power consumption of AMRs (2).

Table 1. Main Parameters and Variables.

Parameters		Variables	
R	Set of mobile robots,R = {1,2, …, r}	$x_{r,t}$	Binary (0-1) variable, indicating whether robot r executes task t
S	Set of shelves,S = {1,2, …, s}	$y_{s,p}$	Binary (0-1) variable, indicating whether shelf s is transported to picking station p
P	Set of picking stations,$P = \{1,2,\dots,p\}$	$z_{r,c}$	Binary (0-1) variable, indicating whether robot r goes to charging pile c for charging
C	Set of charging piles,$C = \{1,2,\dots,c\}$	E_r^t	Power consumption of robot r when executing task t
T	Set of task orders,$T = \{1,2,\dots,t\}$	D_r	Travel distance of robot r
$d_{i,j}$	Travel distance from node i to node j	U_r	Power consumption of robot r
w_s	Load weight of shelf s		
e_s	Power consumption per unit distance when transporting shelf s		
E_r	Initial power of robot r		
E_{min}	Minimum power threshold of the robot		
M	A sufficiently large positive infinity constant		

$$minZ_1 = D_{total} = \sum_{r\in R}\sum_{i\in N}\sum_{j\in N} d_{i,j}\cdot f_{r,i,j} \quad (1)$$

$$minZ_2 = U_{total} = \sum_{r\in R}\sum_{t\in T}\sum_{s\in S} e_s\cdot d_{s,p}\cdot x_{r,t} \quad (2)$$

$$\text{s.t } \sum_{r\in R} x_{r,t} = 1,\ \forall t\in T \quad (3)$$

$$\sum_{t\in T} x_{r,t} \le 1,\ \forall r\in R \quad (4)$$

$$E_r^{init} - \sum_{s\in S} e_s\cdot d_{s,p} \ge E_{min},\ \forall r\in R,\ \forall t\in T \quad (5)$$

$$E_{min} \le E_r^{init} + \mu\cdot t_{change} \le E_{max},\ \forall r\in R \quad (6)$$

$$\sum_i f_{r,i,j} = \sum_k f_{r,j,k},\ \forall r\in R,\ \forall j\in N \quad (7)$$

$$f_{r,s,p} \ge x_{r,t}\cdot b_{t,s}\cdot q_{t,p} - M(1-x_{r,t}),\ \forall t\in T,\ \forall s\in S,\ \forall p\in P \quad (8)$$

$$D_r, E_r^t, U_r \ge 0,\ \forall r\in R,\ \forall t\in T \quad (9)$$

$$x_{r,t}, y_{s,p}, z_{r,c} \in \{0,1\},\ \forall r\in R,\ \forall t\in T,\ \forall s\in S,\ \forall p\in P \quad (10)$$

In this context, Eq. (4) requires each order task to be assigned to exactly one robot for execution. Eq. (5) limits each robot to at most one order task. Eq. (6) specifies each robot's remaining power is no less than the preset minimum safe power threshold. Eq. (7) ensures the rationality of robot power after charging. Eq. (8) guarantees node-level conflict-free robot paths. Eq. (9) acts as the linearization constraint. Eq. (10) sets non-negativity constraints for relevant variables. Eq. (11) defines the binary decision variables.

3 Design of Solution Algorithm

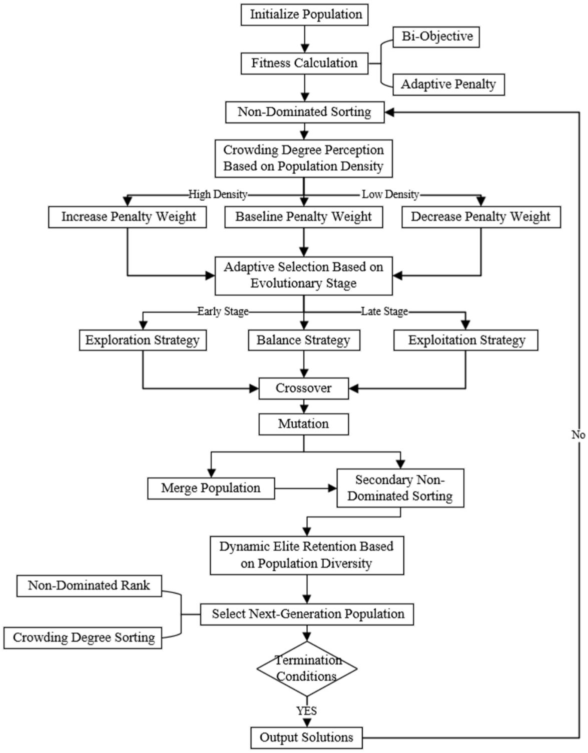

Fig. 2. Flowchart of Adaptive NSGA-II Algorithm.

Since the scheduling problem is NP-hard and the model is multi-objective[9], this paper improves traditional NSGA-II with an adaptive strategy. The technical route for algorithm implementation is shown in Figure 2. On the basis of standard NSGA-II chromosome encoding, three improvements are proposed for the algorithm.

1)The penalty weight is dynamically adjusted by population density: enhancing solution dispersion at high density and maintaining population diversity at low density. As shown in Algorithm 1: Input: Front set F, Number of objectives M; Output: Crowding distance d for each individual.

```
Initialize d[i] = 0 for each individual i ∈ F
For each objective m ∈ [1, M]:
    Sort F by objective m to get σ
    d[σ[1]] = d[σ[|F|]] = ∞
    Δf = max(F.m) - min(F.m)
    For i = 2 to |F| - 1:
        d[σ[i]] += |F.m[σ[i+1]] - F.m[σ[i-1]]| / Δf
Calculate density ρ = |F| / (range(f0) × range(f1))
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9: Adjust penalty based on ρ (penalty=1.5 if ρ>0.1, penalty=0.5 if ρ<0.01, else penalty=1.0)

10: For each individual $i \in F$:

11: if $d[i] \neq \infty$: $d[i] = d[i]$ / penalty

12: Return d

2)A three-stage selection strategy is used for parent individuals to guarantee randomness and elite retention. As shown in Algorithm 2: Input: Population P, Current generation t, Total generations T, Individual rank r, Crowding distance d; Output: Selected parent individual.

1: Calculate evolution progress: progress = t / T

2: Adaptively set tournament size k based on evolution phase:

3: if progress < 0.3:

4: k = 3, mutation_rate = 0.3

5: elif progress < 0.7:

6: k = 2, mutation_rate = 0.2

7: else:

8: k = 4, mutation_rate = 0.1

9: Randomly select k candidate individuals from P to form candidate set C

10: Sort C by non-dominated rank in ascending order

11: Sort individuals with same rank by crowding distance in descending order

12: Select the top-ranked individual as parent

13: Return selected individual

3)The elite retention ratio is adjusted according to the diversity of the Pareto front. As shown in Algorithm 3: Input: Merged population C, Front set $F=\{F_1,F_2,\ldots,F_k\}$, Population size N; Output: New generation population P'.

1: Calculate diversity of first front $D = |F_1|$

2: Dynamically adjust elite ratio: $r\_elite = \min\{0.5, 0.2 + 0.01\times D\}$

3: Initialize $P' = \emptyset$, $i = 1$

4: While $|P'| < N$ and $i \leq k$:

5: Compute crowding distance $c(j)$ for each $j \in F_i$

6: Sort F_i in descending order of crowding distance to get F_i'

7: $m = \min\{\lceil r\_elite\times N\rceil, |F_i'|, N-|P'|\}$

8: $P' = P' \cup \{$first m individuals $\in F_i'\}$

9: $i = i + 1$

10: Return P'

4 Experiments

This section performs numerical experiments on the constructed scheduling model and algorithm using order data from a 50×50 m parts-to-picker warehouse. Table 2 lists the scale configuration of four designed instance types. Classic scheduling optimization algorithms are adopted for comparison to verify the performance of the proposed improved adaptive NSGA-II. All experiments are implemented on a Windows 11 PC with an Intel Core i5-13400F CPU @ 2.5 GHz. The model and algorithms are programmed in Python 3.11, with each run independently repeated 10 times to obtain average results.

Table 2. Configuration Information of Benchmark Examples with Different Scales.

	Shelves	Orders	Mobile robots	Picking stations	Charging piles
I	10	8	3	3	2
II	30	26	6	4	2
III	60	55	9	5	3
IV	100	92	12	7	4

First, an algorithm performance comparison experiment is carried out. Table 3 lists the four algorithms' objective value (Z), generational distance (GD), hypervolume (HV) and charging times (CT) under different-scale instances. Results show the proposed NSGA-II yields the lowest objective value, charging times and GD across all instances except Instance I, with its HV only marginally lower than MOEA/D in Instance IV. Compared with the baseline, its average GD drops by 19.69% and average HV rises by 16.02%. This verifies the ANSGA-II can acquire lower objective values and get closer to the true Pareto front.

Table 3. Algorithm Performance Comparison.

	I				II			
	Z	GD	HV	CT	Z	GD	HV	CT
ANSGA-II	321.30	0.052	0.793	1	1180.58	0.055	0.902	3
NSGA-II	326.69	0.056	0.716	1	1224.71	0.073	0.845	3
MOVNS	347.29	0.178	0.665	1	1302.65	0.131	0.700	3
MOPSO	367.77	0.270	0.601	1	1354.51	0.117	0.596	4
MOEA/D	317.69	0.125	0.681	1	1186.72	0.078	0.698	3
	III				IV			
	Z	GD	HV	CT	Z	GD	HV	CT
ANSGA-II	2862.06	0.056	0.855	4	5071.12	0.046	0.824	10
NSGA-II	3091.38	0.074	0.636	6	5177.05	0.057	0.712	11
MOVNS	3356.27	0.073	0.814	5	5211.63	0.094	0.770	12
MOPSO	3695.34	0.107	0.694	7	6225.74	0.0642	0.503	19
MOEA/D	2911.38	0.071	0.526	6	5172.79	0.096	0.840	12

Figure 3 shows each algorithm's fitness over 100 iterations in different examples. The proposed NSGA-II is only slightly outperformed by MOVNS in Example I. It quickly converges to high-quality solutions in early iterations and has smaller fluctuations than other algorithms in later stages. The results confirm the improved algorithm has fast convergence and good stability.

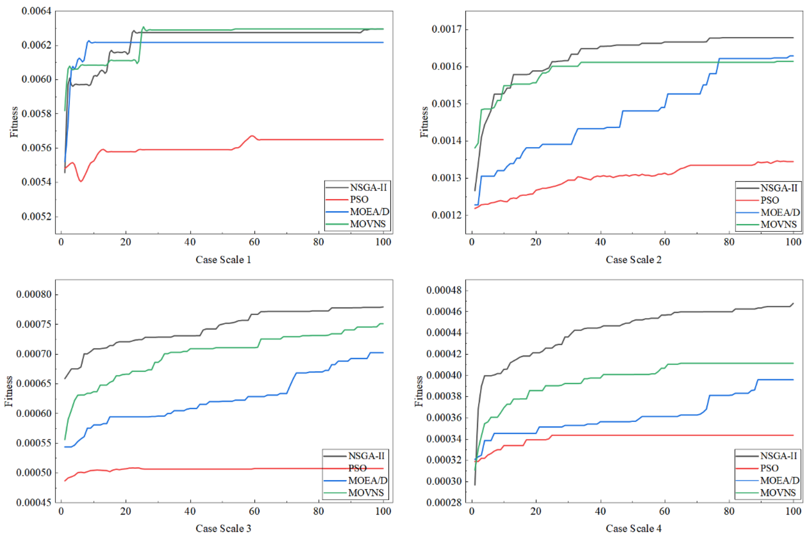

Fig. 3. Fitness Values of Each Instance.

In addition, given the close link between safe power threshold, battery health and task continuity, this paper analyzes its sensitivity for medium and large-scale cases (Figure 4). Results show that when the threshold rises from 10% to 35%, energy consumption and charging time present an inverse trade-off, while the energy consumption reduction rate gradually declines. It proves a higher safe power threshold cannot always achieve better performance.

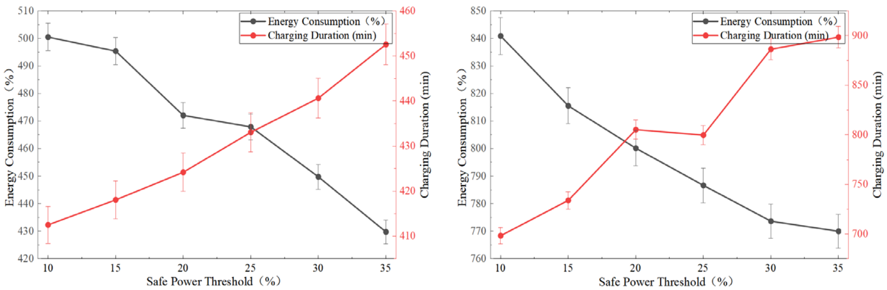

Fig. 4. Analysis of Safety Power Threshold.

Finally, to validate the proposed strategy, simulation tests are performed on the differentiated and conventional non-differentiated power consumption strategies. With five fixed picking stations, power consumption differences under different robot and shelf layouts are analyzed. As shown in Figure 5, total power consumption rises with the number of robots and shelves. The differentiated strategy maintains a consistently low consumption level across all scenarios, cutting energy use by 8.23%–25.16%. This proves the strategy enables finer power consumption control. Nonetheless, per existing research[10][11], when considering robot dynamics and multi-robot congestion in real scenarios, the optimization effect is expected to drop to 6.09%–18.61%.

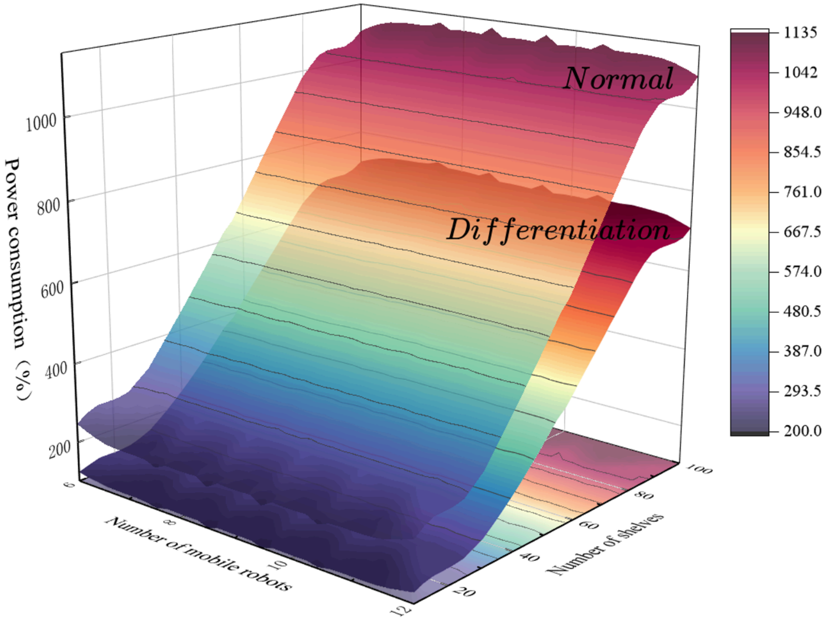

Fig. 5. Strategy Comparison.

5 Conclusion

Taking the mobile robot fulfillment system as the research object, this paper addresses the problem of differentiated power consumption caused by load, initial robot power and battery health state, which has not been fully considered in existing studies. A multi-objective scheduling optimization model is constructed to minimize both the total travel distance and total power consumption. An improved NSGA-II algorithm is designed to solve the model. Experiments are carried out with multiple numerical examples of different scales. The results show that the proposed algorithm outperforms VNS, PSO and MOEA/D algorithms in terms of objective values and stability. The scheduling strategy considering differentiated power consumption can effectively reduce system energy consumption, and significantly improve the operational energy efficiency and operation continuity of intelligent warehouses.

This study still has certain limitations. Future research can further integrate multi-robot obstacle avoidance and real-time order disturbance, optimize model constraints and algorithm adaptability, and enhance the practical application capability of the scheduling scheme.

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