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A Comprehensive Framework for the Design of Modular Robotic Mobile Fulfillment Systems

WEI WANG[1,2], YAOHUA WU[1], JUN ZHENG[3], AND CHENG CHI[1]
[1]School of Control Science and Engineering, Shandong University, Jinan 250061, China
[2]Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA
[3]School of Mechanical and Energy Engineering, Zhejiang University of Science and Technology, Hangzhou 310023, China

Corresponding author: Yaohua Wu (yaohua.wu@sdu.edu.cn)

ABSTRACT This paper focuses on the design of modular Robotic Mobile Fulfillment Systems. A Robotic Mobile Fulfillment System is an automated storage and retrieval system, in which mobile robots are deployed to deliver storage shelves for picking operation. This paper proposes a modular robotic system with aisle-captive robots for small and medium-sized logistics warehouses. Then analytical models, including a bottleneck-based model and an open queueing network model, are developed to estimate system throughput and average order flow time. Last, a two-stage design framework is proposed to rapidly identify an optimal system configuration. The main contributions are that: first, the proposed modular robotic system is free of traffic congestion and blocking; second, the comprehensive framework highlights some significant guidelines for warehouse developers during the ''conceptualization'' phase of system development. Simulation experiments indicate that the open queueing network model can provide accurate system performance estimation. The effectiveness of the proposed design framework is validated through practical application in real cases.

INDEX TERMS Robotic mobile fulfillment system, material handling, open queueing network, logistics warehouses.

I. INTRODUCTION

Robotic mobile fulfillment system (RMFS) is a new type of automated storage and retrieval system, which consists of picking workstations, pickers, mobile robots and movable storage shelves, namely pods. In an RMFS, pods are transported by mobile robots for picking operation, eliminating unnecessary traveling time of pickers. Therefore, pickers can concentrate more on picking operation, improving picking efficiency and decreasing the probability of misoperation.

As a typical RMFS, Kiva system is a revolution in warehouses and has been successfully deployed in some of Amazon's distribution centers [1]. Practical application suggests that RMFS has higher order throughput capacity than traditional picking system. However, the investment of RMFS is extremely high due to huge device costs. Seeking for an effective system configuration in the initial design phase is an effective way to decrease investment cost [2].

There may be hundreds of mobile robots in a large robotic system. An ideal scheduling scheme is essential to help such a complicated system run smoothly, otherwise there might be severe traffic blocking, even deadlock [3]. However, there are different scales of logistics warehouses. It is extremely hard and time-consuming to design proper scheduling schemes to suit all robotic systems. Therefore, this paper presents a modular RMFS which is free of blocking, to solve this problem. The overview of system layout is shown as Fig. 1. The system consists of two main parts: the picking area and the storage area. The picking area comprises workstations and pod stations, and the storage area consists of pod storage units.

The proposed RMFS is partitioned into independent modules. Each module consists of a workstation, a picker, and pod stations in picking area and several independent aisles in storage area. Robots are aisle-captive, that means each robot is dedicated to a designated aisle. Similarly, each pod station is available for a specific aisle. A picker is responsible for order retrieval transactions occurred in the whole module. The proposed modular system has three advantages: First, traffic blocking and deadlock would never happen. Second, it is much easier for pickers to get familiar with product distribution on pods in one module, which results in higher

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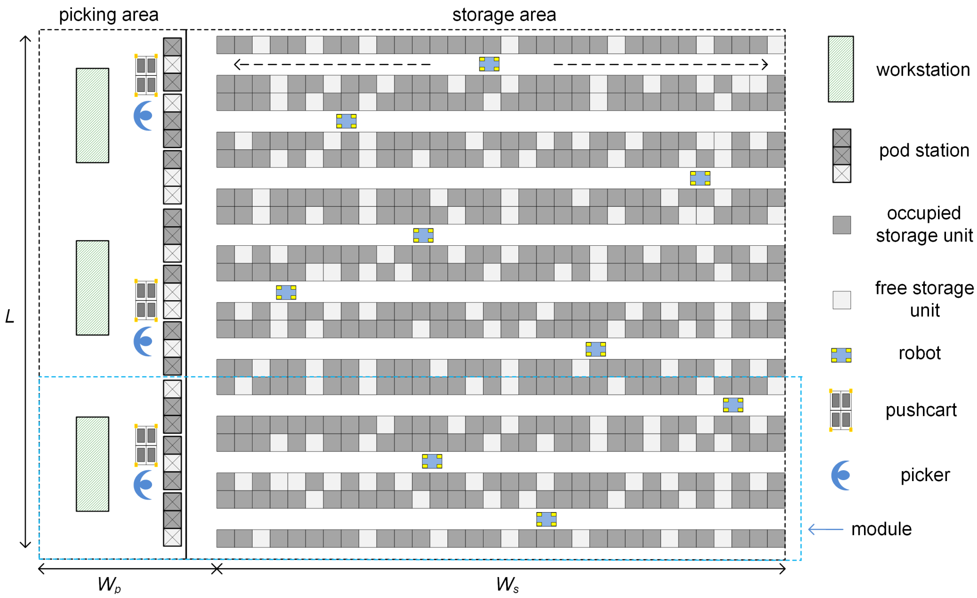

FIGURE 1. Top view of the modular RMFS.

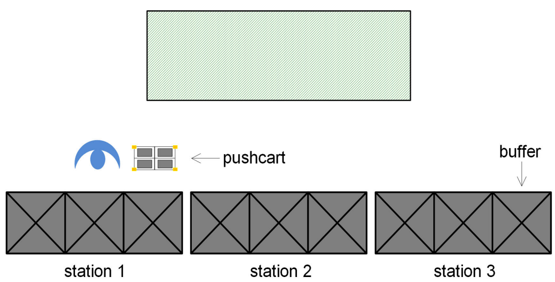

FIGURE 2. Top view of the picking area in a module.

operational proficiency. Third, the pod stations separate picking operation of pickers from robot transportation, enabling parallel operation and improving picking efficiency.

Fig. 2 provides a top view of the picking area in the highlighted module in Fig. 1. There are three pod stations in the module, corresponding to three aisles. Each pod station has three buffers. With this design, pickers are required to walk among pod buffers when conducting picking operation. This design provides several benefits: first, proper exercise may contribute to human health; second, pickers can move in a more efficient and flexible way than robots within such a small area; third, robot can be released once it has transported the required pod to a pod buffer, without waiting. Moreover, robot can bring a previously handled pod to storage area at the beginning of a new order retrieval task.

Fig. 3 illustrates the whole picking process for an order retrieval task. Note that robots always start new transportation tasks from pod stations, the picking process can be described in detail as follows:

① Once an order retrieval task is generated in RMFS, the required pod is determined, and it enters the queue of the corresponding robot.

② If there is at least one pod buffer available for the currently required pod, then the robot can go directly to retrieve the pod.

③ If all pod buffers at the pod station are occupied, the robot has to take the earliest handled pod to storage area, to provide an available buffer for the upcoming pod. Sometimes the robot has to wait for the earliest arrived pod to be handled, though this seldomly happens.

④ The robot transports the previously handled pod.

⑤ The robot unloads the pod at a random storage unit.

⑥ The robot runs to the currently required pod.

⑦ The robot loads the required pod.

⑧ The robot takes the required pod to pod station.

⑨ The robot unloads the required pod at an available buffer, then it runs to the earliest arrived pod in the pod station.

⑩ The required pod waits until the picker picks required product, then the order is released.

This paper contributes by presenting a modular RMFS with aisle-captive configuration and developing an effective two-stage design framework. The design framework considers trade-off between system performance and costs, to help warehouse developers identify the most suitable system design. Two analytical models are developed to provide system performance estimation, where the key performance indicators (KPIs) consist of system throughput (T_h) and average order flow time (FT). Through the design framework, the following design related variables for the proposed RMFS can be rapidly addressed: the number of modules, the total number of aisles and columns, and the layout of each module.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 describes the KPIs and main assumptions in detail. The analytical models to evaluate RMFS performance and the simulation results for

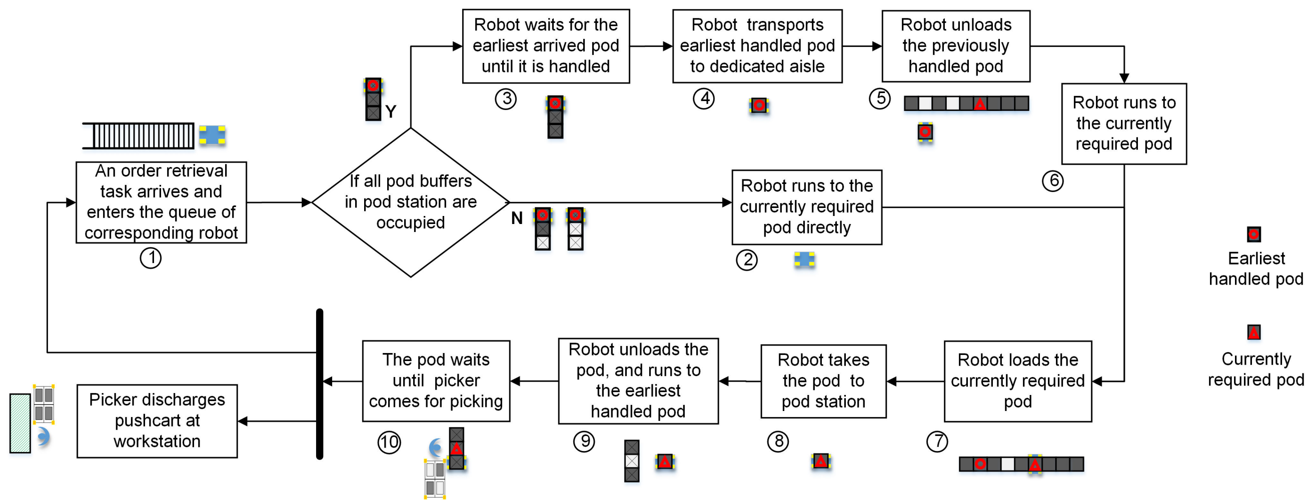

FIGURE 3. The whole picking process of an order retrieval task.

validation are presented in Section 4. Section 5 defines the two-stage design framework, and presents experiment results and discussions. Section 6 draws conclusions and provides insights for future research.

II. LITERATURE REVIEW

In logistics warehouses, order picking is originally conducted in a manual way (i.e. picker-to-picker system), which works best when orders comprise numerous SKUs [4], [5]. However, the traveling of picker is thought to be time-consuming and unproductive. Therefore, RMFS is developed and has attracted much attention and technological innovation as a pioneer of parts-to-picker systems [6], [7].

Automated parts-to-picker systems have several advantages over picker-to-parts systems [8], such as higher operational proficiency and lower long-term costs. Accompanied with technological innovation in industrial automation (e.g., Internet) [9], various automated picking systems have been developed, such as AS/RS [10], automated vehicle storage and retrieval system (AVS/RS) [11], and RMFSs. Kaveh Azadeh *et al.* have made an overview of all these technologies [12]. An open queueing network is proposed to analyze the performance of the AS/RS and AVS/RS [13], and the comparison results indicate that AVS/RS outperforms AS/RS in terms of flexibility and modularization. Kiva system is pointed out to have poor cube utilization but higher flexibility and scalability over mini-load system in [14]. Therefore, RMFS is thought to be suitable for contemporary E-commerce warehouses which have fluctuated customer demands and large assortments of products [15].

Studies on robotic systems mainly focus on two research areas: system design [16] and operational decisions. As for operation related problems, research about path planning [17], [18], task scheduling strategy, and storage assignment [19], [20] etc. have been developed for a long time. Besides, operational cost is also investigated by researchers [21]. Reference [22] proposes a collision free path planning algorithm, to generate feasible paths for mobile robots. In [8], a nested semi-open queueing network (SOQN) is developed to evaluate performance of different battery recovery strategies, and a decomposition method is presented to solve the SOQN models. A handling-speeds-based assignment rule is proposed by Bipan Zou to motivate the picking process in [15], where a neighborhood searching algorithm is developed to speed up searching process. In [23], a resource allocation scheme for cloud robotics is obtained through reinforcement learning, which realizes autonomous task allocation and improves overall system utility. Nils Boysen proposes optimized decomposition procedures to formulate order scheduling and rack sequencing [6], which halves the fleet of robots. In [24] a fluid model is developed to analyze the performance of velocity-based storage policies, and class-based storage policies are deployed to enhance system robustness. In order to promote storage assignment, Marius Merschformann proposes both passive and active repositioning methods [25], whereas the latter technique boosts throughput performance. References [26], [27] investigate the importance of incorporating real-life features into order picking strategies, and provide robust policies for organizing operations efficiently.

With regard to system design, many researchers have devoted themselves to study how warehouse layout and device configuration influence system performance. Some significant guidelines have been highlighted for warehouse developers to optimize system configuration during initial system design phase. Several challenging allocation and design related problems are highlighted by Peter R Wurman [28]. Similarly, the storage allocation strategy and the replenishment allocation problems are proposed in [29]. Reference [11] develops analytical models for AVS/RS to evaluate system performance, in which an approximate method is presented to solve the open queueing network (OQN) model. A SOQN is proposed in [30] to evaluate performance for Kiva system, where both single-line and multi-line orders are considered, and the impact of workstations and length-to-width ratio of storage area on system performance are investigated. Robin Hanson *et al.* have identified the performance characteristics of RMFS in [31], which provides insights into how system performance relates to system design. Resource allocation problems like where to store the buckets are presented and a java-based model is designed to assist research on these problems in [32]. In [4], the number of robots, workstations and SKUs in RMFS are varied and how these decision variables affect seven performance measures, are investigated. Reference [33] improves system throughput by identifying appropriate number and velocity of mobile robots in RMFS.

Based on previous research about RMFS, this study presents a modular robotic system which is free of congestion and blocking. The modular RMFS can be deployed in different scales of automated warehouses quickly with no additional scheduling scheme required. To further shorten the set-up time of RMFS, a comprehensive design framework is first time proposed in this paper. With the support of analytical models, the design framework provides design insights for warehouse developers, which assists them to identify the optimal system configuration rapidly.

III. RMFS DESCRIPTION

This paper only considers order retrieval transaction since it is the most decisive activity which represents system service level. This section provides description about KPIs, main notations and assumptions for order retrieval process in RMFS.

A. KEY PERFORMANCE INDICATORS

Analytical models are developed to evaluate performance of the proposed RMFS, considering only single-line orders, which contributes a large majority to E-commerce orders. Referring to the highlighted components of the whole picking process in Fig. 3, T_h and FT can be described in detail as follows.

The FT means the interval time between order arriving at and leaving the system, which can be expressed as (1):

$$FT = \tau_r + W_{t1} + W_{t2} + \tau_p, \tag{1}$$

where:

- τ_r represents the time related to robot movements, including movement elements ④ -⑥ (or ②), and ⑦-⑧;
- W_{t1} represents the waiting time for robot, corresponding to process ① and ③;
- W_{t2} represents the waiting time for the picker in procedure ⑩;
- τ_p represents picking time of pickers.

The system throughput T_h is denoted as the number of order retrieval tasks handled per time unit (an hour in this paper). In RMFS, since multiple resources are applied, T_h is up to the operational bottleneck. The system bottleneck can be either robots or pickers. Therefore, T_h is closely related to the system configuration, such as the number of aisles and modules.

B. MAIN NOTATIONS

In order to simplify the description of analytical models, main notations used in the remainder of the paper are listed as follows.

- L : the system length.
- W_p : the width of picking area.
- W_s : the width of storage area.
- λ : order arrival rate for whole system (retrievals/hour).
- A : the number of aisles.
- M : the number of modules.
- a_i : the number of aisles in module i, where $i \in [1, M]$.
- C : the number of columns.
- N : the total number of storage positions, $N = 2 * A * C$.
- w : width of a single storage position (m).
- l : length of a single storage position (m).
- w_a : width of each path in aisle (m).
- V_r : average velocity of robots (m/s).
- $\tau_{l,u}$: mean time that robots need to load/unload pods (s).
- τ_p : average time that a picker needs to pick up the requested item, including the traveling time (s).

C. MAIN ASSUMPTIONS

The research is based on some assumptions which are in accordance with real situations in RMFS, and the main assumptions are listed as follows:

1) A storage pod can be repositioned stochastically within one aisle.
2) The location of the required pod is random according to assumption 1. Therefore, the probability that an order retrieval task occurs in a specific aisle is equal to $1/A$, similarly, the probability that it occurs in a specific column equals to $1/C$.
3) A picker is only responsible for order retrieval tasks occurred in one module.
4) There is no robot downtime since there are spare robots which can take place of out-of-order robots. The time for replacing is negligible.
5) The number of spare robots is closely related to the battery capacity and robots failure rate, which is not discussed in this study.
6) The order arrival process follows a Poisson distribution with mean rate λ
7) The picking time follows a Uniform distribution $U[a, b]$, therefore the mean τ_p is denoted as
$$\tau_p = (a + b)/2, \tag{2}$$
8) The time that robots need to load or unload pods $\tau_{l,u}$ is identical
9) Assume that the robot moving time within a pod station is constant, since the travel distance is comparatively short.

TABLE 1. Basic parameters in experiments.

Variable	Value
w_a	0.6m
w	0.8m
l	0.8m
V_r	1.35m/s
$\tau_{l,u}$	3s
τ_p	$U[6, 10]$

TABLE 2. Throughput capacity analysis for a single module.

Scenario	Target through-put	Number of aisles	Number of columns	TH_p	TH_r	TH_m	Meet retrieval demand?
1	360	4	50	450	294	294	No
2	360	5	40	450	413	413	Yes
3	360	6	34	450	533	450	Yes
4	420	4	50	450	294	294	No
5	420	5	40	450	413	413	No
6	420	6	34	450	533	450	Yes

IV. ANALYTICAL MODELS TO EVALUATE SYSTEM PERFORMANCE

In this section, T_h is analyzed by a bottle-neck based model, and an OQN is presented to estimate FT. The values of some basic parameters are shown in Table 1:

A. ANALYZE THROUGHPUT CAPACITY

In the proposed modular RMFS, the throughput capacity T_h can be derived as the sum of expected throughput capacity of each module TH_m. According to previous studies [2], TH_m depends on the expected throughput of the picker TH_p and the expected throughput of all robots TH_r within a module. TH_p can be computed as

$$TH_p = \frac{3600}{\tau_p}. \tag{3}$$

whereas TH_r can be calculated as (4):

$$TH_r = \frac{a_i * 3600}{\tau_r}. \tag{4}$$

In a module, when $TH_p < TH_r$, the bottleneck is the picker, since the picker's service rate is lower than that of robots. On the contrary, when $TH_p > TH_r$, robots turn to be the bottleneck. Therefore, TH_m can be denoted as

$$TH_m = \min(TH_r, TH_p). \tag{5}$$

Then T_h can be calculated by (6),

$$T_h = \sum_{i=1}^{M} TH_{m,i}. \tag{6}$$

Experiments are performed over a module with an approximate storage capacity of 200, to show how the analytical model works. The results are shown in Table 2, where two retrieval demand levels combined with three types of system layouts are examined.

The results in Table 2 indicate that the configuration of the module has a significant impact on throughput capacity.

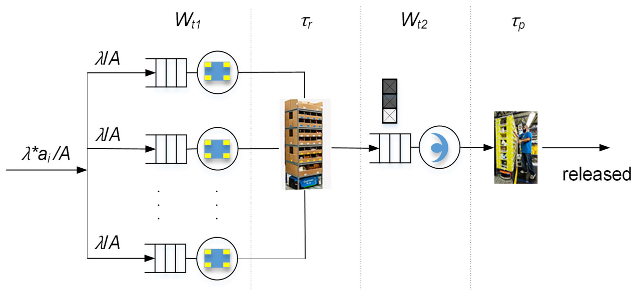

FIGURE 4. An open queueing network for a single module.

With fewer number of long aisles, there are fewer robots, and the average traveling distance is longer. Therefore, robots are the bottleneck, and the expected throughput capacity of the module TH_m is determined by that of all robots TH_r (e.g., scenarios 1,2,4,and 5). Conversely, TH_m is consistent with TH_p when $TH_p < TH_r$ (e.g., scenarios 3,6). As for two target throughput levels, the retrieval demand can be satisfied when TH_m is higher than the target throughput (e.g., scenarios 2,3, and 6), otherwise it can not be fulfilled (e.g., scenario 1,4,and 5). Therefore, it is essential to evaluate the throughput performance of the proposed robotic system during the design phase, to find an available system configuration which can satisfy customer demand.

B. ANALYZE AVERAGE ORDER FLOW TIME

In order to obtain FT, the waiting time for robots W_{t1} and the waiting time for pickers W_{t2} should be estimated. In the proposed RMFS, robots are released once they have transported requested pods to pod stations. Therefore, a computationally efficient OQN is presented to provide accurate estimation of W_{t1} and W_{t2}, given system configuration. The OQN is illustrated in Fig. 4.

In the proposed OQN, robots and pickers are regarded as servers, and order retrieval transactions are customers. The customer type is recognized by aisle in which the required pod locates. In this section, an OQN model is implemented over module i, which has a_i aisles. The OQN is analyzed based on the approximate method in [34], through which W_{t1} and W_{t2} are obtained. The method can be briefly described as follows:

Step1: Calculate service rate and utilization of each server.

Based on the assumptions 1, 2, and 3, the customer arrival rate of each robot is equal to λ/A, while the customer arrival rate of the picker is obtained as (7),

$$\lambda_p = \frac{a_i * \lambda}{A}. \tag{7}$$

The service rate of robot ε_r can be derived as inverse of average time that robot needs to handle order retrieval tasks occurred at each column in the aisle,

$$\varepsilon_r = \frac{C}{\sum_{j=1}^{C} t_j}, \tag{8}$$

TABLE 3. Comparison between analytical model and simulation results with respect to FT, W_{t1} and W_{t2}.

Scenario	Arrival rate	Number of aisles	Number of columns	FT			W_{t1}			W_{t2}		
				model	simulation	deviation	model	simulation	deviation	model	simulation	deviation
1	240	5	45	88.0	87.7	0.3%	32.8	32.9	3%	3.1	2.7	14.8%
2	240	6	42	73.5	73.0	0.7%	19.5	19.6	0.5%	3.6	3.1	16.1%
3	240	7	39	65.8	65.2	0.9%	13.2	13.2	0%	4.0	3.5	14.2%
4	280	5	45	106.1	104.3	1.7%	50.2	48.9	2.7%	3.8	3.4	11.7%
5	280	6	42	81.9	80.7	1.5%	26.8	26.5	1.1%	4.8	4.0	20%
6	280	7	39	71.2	70.2	1.4%	17.2	17.0	1.2%	5.4	4.6	17.3%
7	320	5	45	139.7	132.9	5.1%	83.4	76.9	8.4%	4.4	4.2	4.7%
8	320	6	42	93.6	92.8	0.9%	36.9	37.2	0.8%	6.3	5.3	18.8%
9	320	7	39	78.4	76.8	2.1%	22.3	21.9	1.8%	7.5	6.3	19%

where t_j represents the time for transporting pod at column j. Similarly, the service rate of the picker is equal to the inverse of the average picking time,

$$\varepsilon_p = \frac{1}{\tau_p}. \tag{9}$$

Therefore, the utilization of each robot and the picker can be calculated respectively as follows,

$$\mu_r = \frac{\lambda}{A * \varepsilon_r}, \tag{10}$$

$$\mu_p = \frac{\lambda_p}{\varepsilon_p}. \tag{11}$$

Step2: Calculate the mean waiting time and queue length of robots.

Since the customer arrival of a robot follows Poisson distribution with mean rate λâA̦"A, and the service time follows a General distribution, the service of each robot can be described as a M/G/1 queue. Then the queue length L_{q1} and waiting time W_{t1} for robot can be computed as (12) and (13),

$$L_{q1} = \frac{C_{a,r}^2 + C_{e,r}^2}{2} * \frac{\mu_r^2}{1-\mu_r}, \tag{12}$$

$$W_{t1} = \frac{L_{q1} * \lambda}{A}. \tag{13}$$

where $C_{a,r}$ and $C_{e,r}$ represent the variation coefficients of the order inter-arrival time and robot service time, which are calculated referring to the method in [11].

Step3: Calculate the mean waiting time and queue length for picker.

Similarly, the picker can also be described as a M/G/1 queue and the average queue length L_{q2} and waiting time W_{t2} can be derived as (14) and (15) respectively.

$$L_{q2} = \frac{C_{a,p}^2 + C_{e,p}^2}{2} * \frac{\mu_p^2}{1-\mu_p} \tag{14}$$

$$W_{t2} = \frac{L_{q2} * \lambda}{A} \tag{15}$$

The validation experiments for the proposed OQN model are performed through simulation using Arena. The simulation is implemented based on the workflow of picking process in Fig. 3. However, procedure ③ may be entered only several times in the beginning, which is not necessary to consider in simulation. The simulation results are obtained as an average of ten independent simulation runs, with each run simulating real operation for 100 hours. The data collected during the two-hour warm up stage is discarded.

TABLE 4. Comparison between analytical model and simulation results with respect to μ_r and μ_p.

Scenario	μ_r		μ_p	
	model	simulation	model	simulation
1	58.7%	58.9%	53.3%	52.4%
2	47.0%	46.6%	53.3%	51.9%
3	38.6%	38.3%	53.3%	52.7%
4	68.5%	66.9%	62.2%	61.3%
5	54.8%	54.6%	62.2%	60.1%
6	45.0%	44.8%	62.2%	61.6%
7	78.3%	76.5%	71.1%	70.5%
8	62.6%	63.4%	71.1%	70.2%
9	51.4%	50.7%	71.1%	70.3%

The analysis is performed over an individual module, which has a storage capacity of 180 more or less. In the experiment, three order retrieval demand levels are considered, with three different layouts in each case examined. Table 3 shows the comparison between OQN model and simulation in terms of FT, W_{t1} and W_{t2}. Table 4 presents utilization comparison.

The results in Table 3 indicate that the OQN model can provide precise performance estimation for the modular robotic system. Even though the percentage deviation for estimation of W_{t2} is a little high, the estimation deviation of FT is relatively low in most scenarios, within 5%. From the results in Table 3, the FT increases with order arrival rate (λ), therefore, it is necessary to optimize system configuration to satisfy customer demands. Table 4 further validates the effectiveness of the OQN through comparison of μ_r and μ_p. The results also indicate that when the resource utilization increases, the queue increases correspondingly, as well as the waiting time. Therefore, resource utilization should be maintained within a reasonable level to achieve desirable system performance.

In Fig. 5, how the FT affected by W_{t1} and W_{t2} with respect to different levels of arrival rate is illustrated. First, the module with higher number of short aisles always outperforms the one with fewer number of long aisles, since more robots are deployed as servers and the average traveling distance in shorter aisles is much shorter. Therefore, the performance can be promoted by optimizing the layout of the module, and this can be extended to the whole system. Second, as Fig. 5-b and Fig. 5-c show, when λ_p remains the same, W_{t1} decreases but W_{t2} increases with the number of robots increasing, thus the

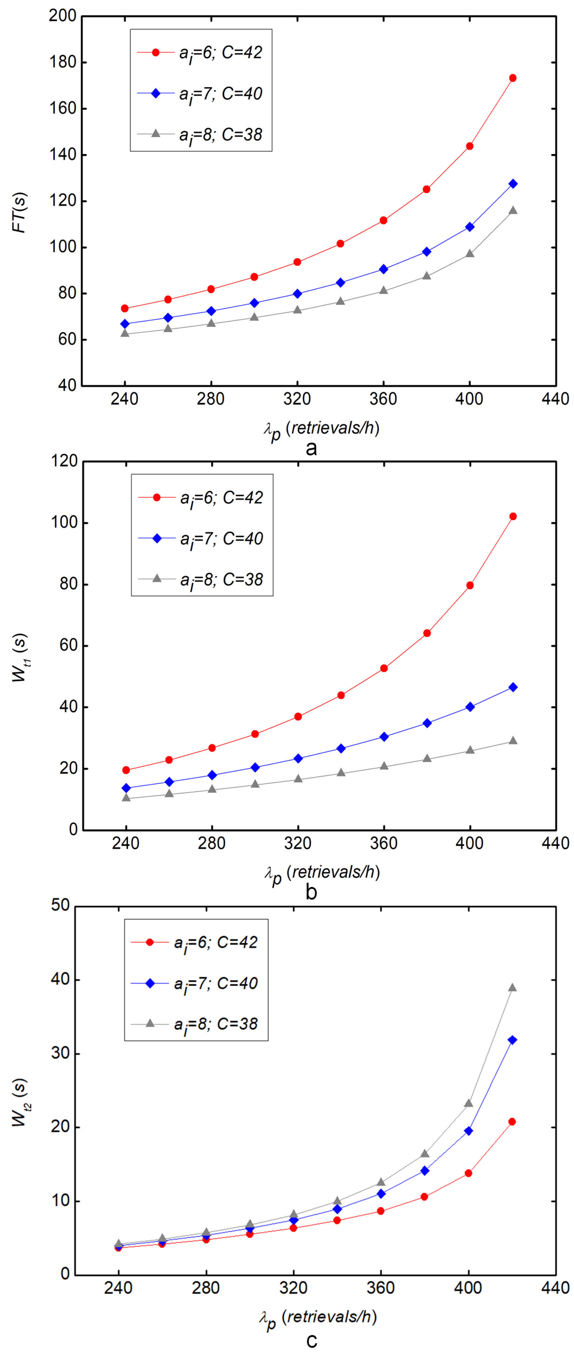

FIGURE 5. (a) FT varies with λ_p; (b) W_{t1} varies with λ_p; (c) W_{t2} varies with λ_p, with regard to different configurations for module i.

picker turns to be the bottleneck. Then, with λ_p growing, W_{t2} increases faster, as well as FT. In particular, when the ratio of λ_p to TH_p is beyond 0.8, W_{t2} increases considerably and contributes much more to FT. This provides an important guideline for the design of RMFS.

V. DESIGN FRAMEWORK FOR MODULAR RMFS

During system design phase, it is extremely time-consuming to compare performance of all potential system configurations, even though the analytical models are computationally efficient. Therefore, a comprehensive two-stage design framework is proposed to highlight some intelligent rules for warehouse designers, to guide them to examine system configurations in a sensible order. With the assistance of the design framework, warehouse designers can rapidly identify the most suitable system configuration for the modular RMFS during the initial design phase.

TABLE 5. Basic parameters in experiments.

Parameters	Value
T_{tar}	Target throughout, which is regarded as equal to λ
τ_{FT}	Required threshold of FT
r_p	The expected ratio of target throughput to expected throughput of pickers
L_{max}	Length of available storage area
W_{max}	Width of available storage area
N_s	Number of SKUs
N_{item}	Total number of items
N_p	Average number of items stored on a single pod
ρ_s	The expected utilization of storage positions

A. MAIN IDEA OF THE DESIGN FRAMEWORK

In practical application during the system design phase, the following basic parameters should be determined before implementing the design framework, in Table 5.

The main purpose of the design framework is to find the trade-off between system performance and investment cost. Since the investment cost is positively related to the number of robots and pickers, the main idea for our design framework is to initialize the system layout with minimum number of robots where only physical restrictions are considered. Then we change system configuration, increasing the number of robots and using shorter aisles, to improve system performance until customer demands are satisfied.

The design framework consists of two stages: first, rough calculating stage, in which the target throughput is roughly fulfilled by optimizing system configuration in a faster way; second, fine tuning stage, in which a reasonable FT is obtained by gradually varying the system layout, with the help of the OQN model. The flow chart of the design framework is shown as Fig. 6.

Step 1: N can be determined according to the parameters given. Based on the analysis in section 4.2, the ratio r_p should be limited and a threshold of 0.8 is suggested. Then M_{min} can be computed by (16). As for the cost that originates from robots, the longer aisle should be deployed in priority to decrease the number of robots. Therefore, the maximum number of columns C_{max} should be set with respect to the maximum width W_{max} of the storage area, thus the minimum number of aisles A_{min} can be obtained correspondingly.

$$M_{min} = \lceil \frac{\lambda * \tau_p}{0.8 * 3600} \rceil \tag{16}$$

$$C_{max} = \lfloor \frac{L_{max}}{W_r} \rfloor \tag{17}$$

$$A_{min} = \lceil \frac{N}{2 * C_max} \rceil \tag{18}$$

where the symbol $\lceil\rceil$ and $\lfloor\rfloor$ represent the higher and lower integer bound respectively.

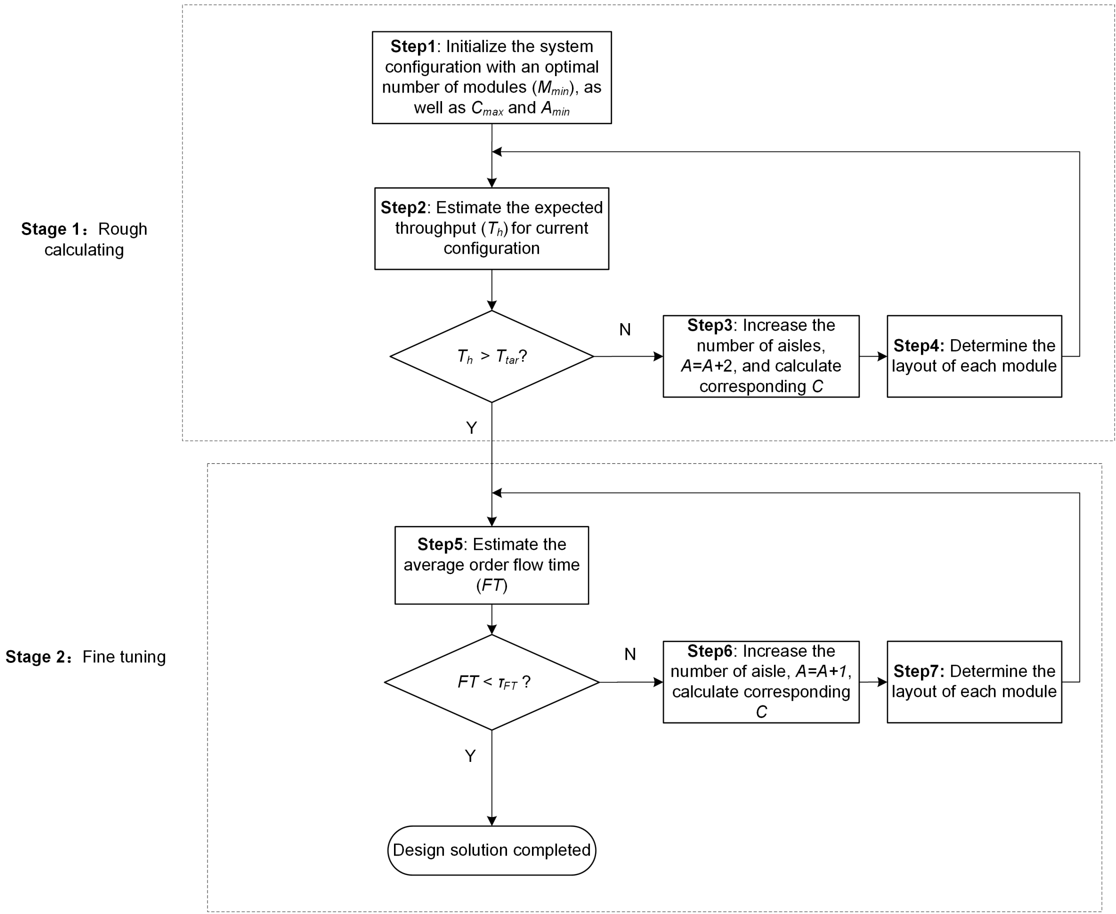

FIGURE 6. Two-stage design framework for the modular RMFS.

Step 2: In the rough calculating stage, expected system throughput T_h should be estimated. If T_h meets the requirement, (i.e, $T_h > T_{tar}$), the procedure moves to step 5 in fine tuning stage, where the current solution is modified gradually to obtain a reasonable FT. On the contrary, if $T_h < T_{tar}$, the procedure enters step 3.

Step 3: The number of modules is determined reasonably according to previous analysis, and the pickers are assumed capable to work all the time. Therefore, robots are the only potential bottleneck. In this step, the layout of the system is modified with two aisle and two robots added, in order to improve system performance. As a consequence, the number of columns should be derived from N and A.

Step 4: Once the total number of aisles and modules are determined, the layout of each module, i.e., the number of aisles in each module, should be decided. In RMFS, aisles should be evenly allocated to each module. Therefore, there are two kinds of modules: big modules and small modules. The allocation strategy is explained as follows. First, the quotient Q and remainder R of A divided by $P-1$ are computed. Then there should be Q-R small modules, which consists of $Q-1$ aisles. On the other hand, the number of big modules equals to $A-Q+R$. In each big module there are Q aisles.

Step 2, step 3, step 4 are repeatedly implemented until the T_h reaches the target throughput. Then the process moves into step 5, entering the fine-tuning stage.

Step 5: Though target throughput is satisfied, the FT should also be taken into consideration to prevent long queues in the system. The waiting time should be maintained in a low level to guarantee real-time picking operation. The FT for current system configuration should be estimated using the analytical model. If FT is less than threshold τ_{FT}, the current solution is regarded as an effective solution. Otherwise, the procedure moves to step 6, to find a better system configuration.

Step 6: In this step, system layout is optimized in a similar way to step 3,but the number of aisles is increased only by 1, in order to find a more appropriate solution.

Step 7: This step is the same as step 4, to figure out the layout of each module.

B. NUMERICAL EXPERIMENT

Two numerical experiments are performed to validate the effectiveness of the proposed design framework. In these experiments, the basic parameters remain the same as those in Table 1. The experiments are implemented based on real

TABLE 6. 19 System configurations examined for practical application of the two-stage design framework in a large E-commerce distribution center.

Scenario	Number of aisles	Number of columns	Number of big modules	Aisles in big modules	Number of small modules	Aisles in small modules	Storage capacity	Expected T_h	FT
1	46	108	4	4	6	5	9936	2034	–
2	48	105	2	4	8	5	10080	2170	–
3	50	100	0	4	10	5	10000	2349	–
4	52	96	8	5	2	6	9984	2519	–
5	54	93	6	5	4	6	10044	2680	–
6	56	90	4	5	6	6	10080	2851	–
7	58	86	2	5	8	6	9926	3053	–
8	60	84	0	5	10	6	10080	3214	–
9	62	81	8	6	2	7	10044	3412	2330
10	63	80	7	6	3	7	10080	3498	913
11	64	78	6	6	4	7	9984	3620	512
12	65	77	5	6	5	7	10010	3711	395
13	66	76	4	6	6	7	10032	3804	325
14	67	75	3	6	7	7	10050	3899	279
15	68	74	2	6	8	7	10064	3995	246
16	69	73	1	6	9	7	10074	4094	221
17	70	72	0	6	10	7	10080	4194	201
18	71	71	9	7	1	8	10082	4296	185
19	72	70	8	7	2	8	10080	4400	176

"-" in any scenario means it is not necessary or unable to calculate FT

cases in the VIPS's automated warehouses, which is the third biggest E-commerce company in China.

In the first case, the basic user requirements are obtained from customers as follows: L_{max} is 150 m; W_{max} is 65 m; W_p is set as 10 m; the number of SKUs is around 167500; the total capacity N_{item} is about 1350000; N_p is set around 150; ρ_s is set as 90%; r_p is set as 0.8; T_{tar} is set as 3360 retrievals per hour; τ_{FT} is 180 s.

In practical application, some more variables should be determined to initiate the design framework. First of all, N can be derived as 10000 based on above mentioned storage requirements. According the maximum width of the storage area, the corresponding C_{max} is derived as 108, thus A_{min} equals to 46. Then through the proposed design framework, the optimal system configuration is found efficiently. The experiment results are shown in Table 6.

As the results show, the most suitable system configuration is identified after 19 configurations examined. From scenario 1 to 19, each system configuration is presented and system performance is evaluated. For the first 8 scenarios, only the rough calculating stage is executed. During this stage, only T_h is estimated, and the number of aisles is increased by 2 at one time to speed up the searching process. Then in scenario 9, T_h exceeds target throughput, thus the fine tuning stage is entered. Note that from scenario 9 to 19, the system configuration varies gradually, and both T_h and FT are estimated for each system configuration. When both T_h and FT satisfy user requirements (scenario 19), the current configuration is regarded as the most suitable design solution. In this case, the optimal system configuration has 72 aisles and 70 columns, and it is partitioned into 10 independent modules. There are 9 small modules and 1 big module, whereas each small module contains 7 aisles and big module consists of 8 aisles.

TABLE 7. Experiment results for the application of two-stage design framework in smaller systems.

Demand level	Number of configurations	Optimal layouts M	A	C	Expected T_h	FT
1	5	2	16	56	900	106
2	6	3	19	47	1350	114
3	9	5	25	36	2250	113

In the second case, the proposed design framework is deployed in a smaller warehouse for daily-life products. Similarly, the basic user requirements should be collected first: L_{max} is 60 m; W_{max} is 50 m; W_p is set as 10 m; the N_s is around 2500; the total capacity N_{item} is about 243000; N_p is set as 150; ρ_s is set as 90%. In this case, three design solutions are required with respect to three different levels of customer demands: level 1 requires a target throughput of 680 retrievals/hour, during weekdays; level 2 requires the T_{tar} no less than 1020 retrievals/hour, during weekends; for level 3, T_{tar} is 1740 retrievals/hour, during "Promotion days"P. For all cases, FT is set as 120 s. Then N is derived as 1800, and C_{max} is obtained as 75.

The designed framework is deployed to identify the most suitable design solutions for these three user demands. Table 7 shows the experiment results. For each demand level, the optimal system configuration and the corresponding system performance are presented. The results indicate that different levels of user requirement can be satisfied by the corresponding optimal system configuration. The number of system configurations that being examined for each demand level are also provided. From the data we can see that, through the proposed design framework, the optimal system configuration can be found with a minority of configurations examined. Besides, more potential system configurations have to be examined for a higher user demand.

VI. CONCLUSION

This paper mainly studies the design of RMFS. A congestion-free modular RMFS is presented for small and medium-sized logistics warehouses. The modular RMFS can be deployed uniformly for automated warehouses in different scenarios. Furthermore, this paper proposes a comprehensive two-stage design framework to speed up the design process of the modular RMFS. A bottleneck-based model and an OQN model are developed to provide efficient and accurate system performance assessment for the design framework, to rapidly identify the optimal system configuration for an RMFS. Experiment results indicate that the design framework helps reduce the set-up time for the proposed modular RMFS, and supports warehouse designers to find the most appropriate system design which meets customer demands while decreasing the overall system cost.

In summary, the main implication of the design framework is to provide a valuable tool in the ''conceptualisation'' phase of system design. Through this framework, economy and performance comparison of the modular and non-modular system may be investigated in further research.

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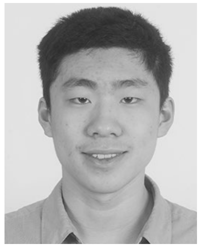
WEI WANG was born in Anqing, China, in 1993. He received the B.E. degree in logistics engineering from Shandong University, Jinan, China, in 2015. He is currently pursuing the Ph.D. degree with the School of Control Science and Engineering, Shandong University, and has spent one year studying in the School of Industrial Systems and Engineering, Georgia Institute of Technology. His research interests are mainly focused on mobile robots and robotics systems.

YAOHUA WU received the M.E. degree from Shandong University, Jinan, in 1991, and the Ph.D. degree in mechanical engineering from Tsinghua University, Beijing, China, in 1996. He is currently a Professor with the School of Control Science and Engineering and the Head of Modern Logistics Research Center, Shandong University. His research interests include automated logistics system, autonomous logistics devices, and logistics software design.

JUN ZHENG was born in Zhejiang, China, in 1981. He received the Ph.D. degree in mechanical engineering from Zhejiang University, Hangzhou, China, in 2014. He is currently an Associate Professor and a Master Instructor with the School of Mechanical and Energy Engineering, Zhejiang University of Science and Technology. His research interests focus on sustainable design and manufacturing, manufacturing system optimization, and processing methods in low-carbon optimization.



CHENG CHI was born in Jinan, China, in 1989. He received the B.E. degree from the Harbin University of Science and Technology. He is currently pursuing the Ph.D. degree with the School of Control Science and Engineering, Shandong University. His fields of research interests are motion control of mobile robot and robot localization.