Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

OPTIMAL TEAM FORMATION AND JOB ASSIGNMENT TO OPTIMIZE WAREHOUSE OPERATIONS

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ABSTRACT

We study optimal container unloading and warehouse replenishment at a manufacturing plant. The warehouse inventory is depleted as parts are consumed in the manufacturing process. The inventory level is replenished using the parts stored in sea-containers and trailers available at the plant. Our goal is to determine the optimal team formation, buffer allocation, and job assignment for teams of workers. The teams work at two tandem stations, each with several finite-buffered parallel queues. The objective is to minimize the total time required to process all containers and trailers. There are operational constraints on the number of teams that can be formed, the number of servers in each team, and the number of buffer spaces allotted to each team. We use a simulation-based optimization approach, and the results consistently show a reduction in the processing time. Further, we also observe that the optimal team formation is dependent on the total workload.

1 INTRODUCTION

In a warehouse, inventory gets depleted as the parts are consumed to support the manufacturing processes. Therefore, the inventory needs to be replenished regularly using incoming shipments of parts. We consider a manufacturing plant that receives parts in sea-containers and trailers, and stores them on site until a part replenishment is needed. Multiple sea-containers and trailers, which from here on we refer to as containers, are often received daily by the manufacturing plant, and each container may hold a different mixture of parts with potentially different packaging. Thus, the unloading of parts from these containers and their storage in the warehouse may require unpacking of pallets and/or repacking of materials on a daily basis before they can be scanned, transported, and stored. As it is often the case that workers have limited physical space (i.e., one or more staging areas) for unloading, unpacking, and scanning materials, completing these tasks often requires coordination between multiple workers to avoid backlogs and disruption of production. Such coordination can be achieved by having workers work in teams to process contents of each container.

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Optimization of the put-away operations is vital for timely processing and storage of materials delivered to the warehouse. Therefore, our goal in this research is to minimize the total time required to unload, scan, breakdown, and store all pallets from containers that must be unloaded by determining the optimal number of teams to be formed and the optimal worker to task assignment in these teams. To address these operational questions, we build a simulation-optimization model and analyze it using the daily container and processing time data obtained from our industrial partner, BMW Manufacturing Company.

2 LITERATURE REVIEW

There are several previous studies on the optimization of warehouse operations. However, very few of these studies have focused on receiving and shipping processes that are part of the warehouse operations (Gu, Goetschalckx, and McGinnis 2007). Further, most of the studies related to receiving and shipping processes are concerned with truck-to-door assignment problems in cross-dock facilities (Gu, Goetschalckx, and McGinnis 2007). An exhaustive review of inventory replenishment problems that were addressed using simulation-based optimization methods is provided by Jalali and Nieuwenhuyse (2015). In addition, Negahban and Smith (2014) performed a comprehensive review of studies on manufacturing design and operations-related problems That were tackled via discrete event simulation. According to their review, manufacturing operations planning and scheduling is a popular area for the use of discrete event simulation as an analysis tool. In this section, we review the simulation studies that have focused on optimizing worker and resource allocation to improve healthcare, manufacturing, and warehouse systems.

Resource allocation problems in healthcare systems have been widely studied using simulation-based optimization methods. Weng, Cheng, Kwong, Wang, and Chang (2011) used simulation optimization to study a physician and nurse allocation problem in the emergency department of a hospital to minimize the NEDOCS value, which is an indicator of crowdedness. Optimal staffing levels that balance the service level (i.e., quality of care) and nurse utilization in each shift was studied by Sarno and Nenni (2016). Lucidi, Maurici, Paulon, Rinaldi, and Roma (2016) studied the optimal allocation of a hospital's obstetrics ward resources such as stretchers, gynecologists, nurses, beds, and operating rooms. Their objective was to maximize the profits of the hospital and minimize the cesarean section birth rates.

A study on optimal resource allocation for a production logistics system was done by Li, Yang, Xu, Wang, Ren, and Li (2020) using discrete event simulation. Their objective was to maximize the throughput of the system while minimizing the economic input, which is achieved by determining the optimal number of automatic guided vehicles (AGVs), speed and load capacity of AGVs, and buffer capacity. Ekren, Evans, Heragu, and Usher (2012) studied the problem of reducing the cycle time in the receiving area of a warehouse by determining the optimal number of workers at each workstation. The truck's arrival to the warehouse is considered deterministic. At the same time, each truck's contents are probabilistically known. A simulation-based optimization model is proposed to decide the optimal staffing level at each station. In our study, we also minimize the total completion time for the put-away operations. However, we achieve this objective by determining the optimal number of teams (parallel workstations) to be formed, the number of workers and worker to task assignment in each team, buffer space allocation, and the number of forklift operators needed. Ganbold, Kundu, Li, and Zhang (2020) studied an optimal workforce allocation problem to improve the warehouse service level using a simulation-based optimization model. They considered a warehouse with inbound and outbound areas, each with various workstations. In their model, there are multiple employees with different skills, and the goal is to optimally allocate these employees to workstations while considering the warehouse operational constraints. However, the constraints related to warehouse storage capacity, working areas, and buffer zones between activities are not considered in this problem. In contrast, we determine the optimal number of parallel workstations (teams of workers) that need to be created, the number of workers at each workstation, and the buffer space for each workstation.

3 PROBLEM DESCRIPTION AND SIMULATION MODEL

Containers are delivered to the manufacturing plant daily to support the manufacturing process. Each container holds multiple pallets containing a mixture of different parts with potentially different packaging. The set of containers that need to be unloaded is known at the beginning of the day. Additionally, each container is assigned a priority level for unloading such that containers that have the parts with the least supply in the warehouse are assigned the highest priority. The manufacturer follows a defined procedure to unload these containers in order to replenish warehouse stock. A container is docked, pallets are unloaded and processed in a primary staging area, and then they are transported either to the warehouse for storage or to a secondary staging area if they need further processing. In the primary staging area, two types of workers, known as the *Scanners* and the *Breakdowners*, process the unloaded pallets. A scanner must scan all unloaded pallets. Some pallets may also need to be broken down into individual boxes by a breakdowner. The entire process is illustrated in Figure 1.

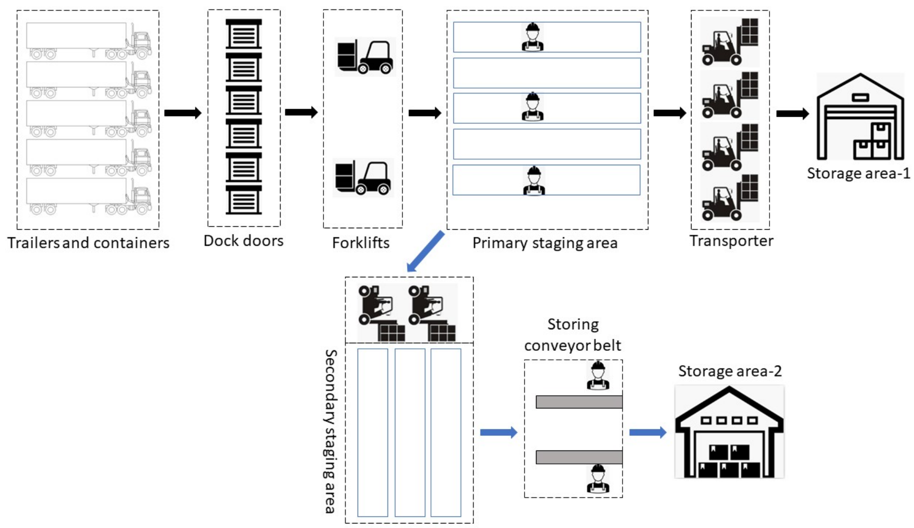

Figure 1: Process flow chart

In this paper, we only focus on the part of the receiving process until the parts are ready to be transported out of the primary staging area. The equivalent queuing representation for this process is shown in Figure 2. Process 1 has a finite number of containers whose contents need to be unloaded and processed. Different containers that need to be unloaded are represented using dark gray colored trapezoids in Figure 2. The number of parallel queues in Process 1 is equivalent to the number of teams. Queues at Process 2 are capacitated, and once again, the total number of parallel queues is equivalent to the number of teams. The capacity of each queue in Process 2 is equal to the buffer size (i.e., number of staging areas) allocated to each team. Not all pallets unloaded from a container are identical. In Figure 2, various shapes are used to differentiate different types of pallets waiting in a queue at Station 2. Additionally, pallets unloaded from the same container are depicted using the same color. Two different teams are represented in Figure 2 with the colors orange and purple. Figure 2 illustrates the entire procedure with two teams. Thus, at Process 1, there are two parallel queues depicted, *Queue 1* and *Queue 2*. Similarly, at Process 2, the figure shows two parallel queues, *Queue 1* and *Queue 2*. In our problem, the number of teams that need to be formed is a decision variable and thus, the number of queues that will be formed at each process is determined by the simulation-optimization model.

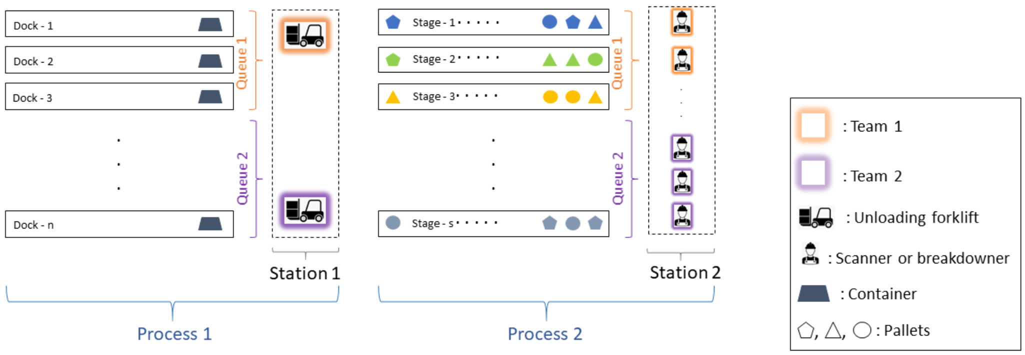

Figure 2: Queue representation of the process

One or more unloading forklifts work at Station 1 to unload the pallets from the containers. At *Station 2*, scanners and breakdowners work in teams to process (scan and breakdown) the unloaded pallets. The order of processing for each container is determined by its priority level and known in advance. Only one forklift can work on a container to unload all its contents. The unloaded pallets are then placed into the staging area. Contents of a container can be placed in any of the available staging areas, however, a staging area cannot simultaneously hold pallets from different containers. Once a container is completely unloaded, the scanner starts scanning the unloaded pallets. After all pallets of a container are scanned, the breakdowners can break down the pallets if required. The scanner starts scanning the pallets from a new container while the breakdowners work on pallets from the previous container. The scanners and breakdowners work in a team. In each team, there is one scanner and one or more breakdowners. Collaboration between teams is not permitted. Furthermore, once the teams are formed at the beginning of the day, they cannot be changed until all containers are processed. At the beginning of each day, every team is assigned a set of staging areas to be used throughout the day. When the scanning and breakdown operations are completed for a container, the transporter forklifts transfer the processed pallets to the warehouse storage spaces and clear the staging area. The transporter forklifts can work for any team. Similar to the unloading forklifts working at Station 1, only one transporter forklift can transport the materials belonging to a container.

On a given day, there are S staging areas available, as well as T transporter forklifts, and N workers who can serve as a scanner, breakdowner, or an unloading forklift's driver. Teams must be formed optimally using the available resources (i.e., staging areas and workforce) to minimize the time required to process and store the materials from the containers that must be unloaded for the day. We develop a simulation-based optimization model to solve this problem. A detailed discussion of the simulation model is provided below.

The simulation model is built in Arena, and OptQuest is used to build the optimization model. Figure 3 shows a representation of the simulation model we developed. The process starts with the arrival of all containers (i.e., jobs). The containers enter the system in priority order. A container is held until a forklift and a buffer space (i.e., staging area) are available to unload it. This process is executed using the Hold module labeled as *Hold containers* in Figure 3. Once a forklift and buffer space is available, the Process module labeled as *Sieze forklift and buffer space* seizes one unit of both resources for a container. The Process module labeled as *Release forklift* releases the forklift after an Erlang distributed amount of time, once all pallets from the container are unloaded. The service times per pallet for a forklift, scanner, and breakdowner is assumed to be exponentially distributed, therefore, the service time for a container containing n pallets is Erlang distributed. Our industrial partner had conducted the time study for each of these servers (i.e., forklift, scanner, and breakdowner) and provided us with the mean service time for each process.

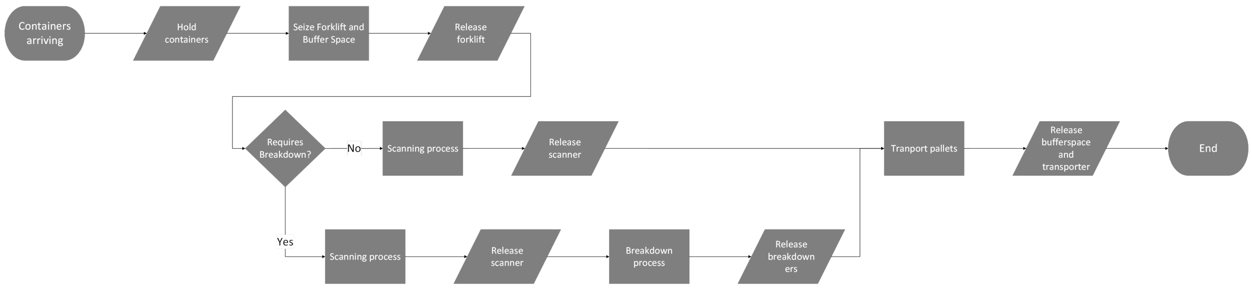

Figure 3: Representation of the simulation model

As mentioned previously, each team is allocated buffer spaces within which they are allowed to work. Therefore, if a container is unloaded into the buffer space of a team, then only members of that team can process it. Using the Assign module in Arena, we keep track of the team assignments. The job is then routed to the specific team that needs to process it. Scanning is required for all pallets in a container. However, there are two possibilities for the breakdown: (i) breakdown is not required for any of the pallets in a container, and (ii) breakdown is required for some or all pallets in a container. We use the Decide module labeled as *Requires breakdown* to route the job appropriately. In case (i), only scanning is required, and therefore only the scanner resource is seized. Process times for scanning follow an Erlang distribution. In case (ii), first, the scanner is seized to scan the pallets and released after and Erlang distributed amount of time. Then, the breakdowners are seized to breakdown the pallets, and they are released after an Erlang distributed amount of time. After scanning and breakdown of all pallets belonging to a container is completed, the transporter forklift is seized using the Process module labeled as *Transport pallets* to clear all materials from the staging area. Process times for transportation also follow an Erlang distribution. Finally, the buffer space is released upon completion of the transporter forklift process. A summary of the process time distributions per container used in the model is provided in Table 1.

Table 1: Summary of the process time distributions

Process	Distribution	Shape parameter
Unload	Erlang distribution	Total pallets in a container
Scanning	Erlang distribution	Total pallets in a container
Breakdown	Erlang distribution	Total breakdown pallets in a container
Transporting to warehouse shelves	Erlang distribution	Total non-breakdown pallets in a container
Transporting to secondary staging	Erlang distribution	Total breakdown pallets in a container

Note: Rate parameter of each Erlang distribution was estimated by the industry partner using propriety data.

Using the input parameters defined in Table 2 and the decision variables defined in Table 3, we formulate the optimization model given by equations (1) – (13).

Table 2: Input parameters notation and description

Notation	Description
t_{min}	Minimum number of teams to be formed
t_{max}	Maximum number of teams that can be formed
S	Total staging areas
N	Total number of individuals available

Table 3: Decision variables notation and description

Notation	Description
s_i	Binary variable, equals to 1 if *Team i* is formed. $(where\ i = 1,\ 2, \ldots\ t_{max})$
b_i	Number of breakdowners in *Team i*. $(where\ i = 1,\ 2, \ldots\ t_{max})$
x_i	Number of staging areas allocated to *Team i*. $(where\ i = 1,\ 2, \ldots\ t_{max})$
f	Number of unload forklifts

$$\text{minimize:} \quad \textit{Expected total time required to process and put-away all the containers} \tag{1}$$

Subject to:

$$\sum_{i=1}^{t_{max}} s_i \geq t_{min} \tag{2}$$

$$\sum_{i=1}^{t_{max}} s_i \leq t_{max} \tag{3}$$

$$b_i - s_i \geq 0 \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{4}$$

$$x_i - s_i \geq 0 \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{5}$$

$$s_i * b_i - b_i = 0 \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{6}$$

$$s_i * x_i - x_i = 0 \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{7}$$

$$f + \sum_{i=1}^{t_{max}} s_i + \sum_{i=1}^{t_{max}} b_i = N \tag{8}$$

$$\sum_{i=1}^{t_{max}} x_i = S \tag{9}$$

$$s_i \in \{0,\ 1\} \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{10}$$

$$b_i \in \mathbb{Z}_{\geq 0} \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{11}$$

$$x_i \in \mathbb{Z}_{\geq 0} \quad \ldots i \in \{1,\ 2, \ldots,\ t_{max}\} \tag{12}$$

$$f \in \mathbb{Z}_{>} \tag{13}$$

Constraints defined by equations (2) and (3) provide a lower and upper bound on the number of teams that need to be formed. When *Team i* is formed, it is assigned a scanner using the decision variable s_i. If *Team i* is formed, then it gets assigned a minimum of one breakdowner and one buffer space; constraints (4) and (5) ensure this. Further, if *Team i* is not formed, then no breakdowner and buffer space are assigned to *Team i* due to constraints (6) and (7). Constraint (8) ensures that all the available individuals are assigned, and constraint (9) ensures that all the buffer spaces are allocated to teams.

4 EXPERIMENTAL SETUP

We analyzed the data provided by our industrial partner for the number of containers unloaded on a given day in the warehouse. We observed that around eight percent of the time, the number of containers unloaded was less than 75. Most of the time, around 100 containers were unloaded daily, with the maximum being 115 containers unloaded on a single day. Therefore, we chose to run our experiments using 75, 100, and 125 as the number of containers to be unloaded. Further, by discussing with the process associates at the BMW Manufacturing Company, we decided to vary the percentage of containers requiring breakdown as

25%, 50%, and 75%. Using this information, we construct nine scenarios for our simulation experiments. The number of pallets in each container is generated using the discrete uniform distribution, U{15, 25}, as estimated by our industrial partner. The percentage of pallets to be broken down in each container that requires breakdown is estimated to follow the continuous uniform distribution $U[30,70]$ based on the analysis carried out by our industry partner.

On each day, 14 individuals are available to work as either a forklift operator, scanner, or breakdowner. A minimum of 2 and a maximum of 4 individuals need to be assigned as forklift operators. The remaining individuals need to be assigned to a minimum of 3 and a maximum of 5 teams, each team consisting of one scanner and at least one breakdowner. There are 13 staging areas available that need to be distributed amongst the teams. These details on capacity of resources and process requirements were provided by the industrial partner.

The optimization model was constructed in OptQuest using the parameters mentioned above. The number of solutions to be explored in OptQuest was set as 100. Additionally, the number of replications performed for each simulation run was dynamically determined by OptQuest using the 95% confidence interval built around the mean of the total time required to complete all jobs, with a minimum of 30 and a maximum of 50 replications. The best solution obtained by OptQuest was then evaluated using the simulation model with 100 replications. We test the solutions obtained using OptQuest, against the currently practiced team formation. For this purpose, we simulated the unloading process with the current team formation under each scenario considered. These simulations were also run using 100 replications.

5 RESULTS

In this section, we discuss the results obtained using the simulation optimization model. In Table 4, the currently practiced team formation is presented. Currently, the same team formation with three teams and two forklifts is used every day, regardless of number and characteristics of containers to be unloaded. Each team has an equal number of breakdowners and an approximately equal number of buffer spaces allocated. The best solutions (i.e., solutions with a minimum total time for processing all jobs) for nine different scenarios obtained using the OptQuest are presented in Table 5.

Table 4: Currently practiced team formation

Breakdowner allocation			Buffer space allocation			Scanner allocation			Number of forklifts
T_1	T_2	T_3	T_1	T_2	T_3	T_1	T_2	T_3	
3	3	3	4	4	5	1	1	1	2

Table 5: OptQuest solution for best team formation

Breakdown (%)	Number of containers	Breakdowner allocation				Buffer space allocation				Scanner allocation				Number of forklifts
		T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	
25	75	2	1	2	1	8	2	2	1	1	1	1	1	4
25	100	3	1	1	1	8	2	2	1	1	1	1	1	4
25	125	3	1	1	1	8	2	2	1	1	1	1	1	4
50	75	1	1	1	3	2	2	2	7	1	1	1	1	4
50	100	1	1	3	1	2	2	8	1	1	1	1	1	4
50	125	1	1	3	1	2	2	8	1	1	1	1	1	4
75	75	2	1	2	2	2	2	4	5	1	1	1	1	3
75	100	2	1	2	2	2	2	4	5	1	1	1	1	3
75	125	3	1	2	1	4	2	6	1	1	1	1	1	3

Results reported in Table 5 show that currently, the forklift operators are a bottleneck. Further, we observe that the optimal team formation is dependent on the breakdown percentage. The optimal team formation remains the same for the scenarios with 25% – 50% breakdown and 100 – 125 containers. A similar observation can be made in the case of 75% breakdown and 75 – 100 containers. Having fewer solutions to implement in different scenarios is better from a practical perspective for our industrial partner. Furthermore, some of the solutions presented in Table 5 may be statistically equivalent in terms of performance under a given scenario. To reduce the number of solutions we propose and eliminate statistically equivalent solutions, we have performed 95% t-tests to compare the performance of the solutions in Table 5 across scenarios. Based on this analysis, we present the proposed solutions that depend on the breakdown percentage in Table 6. The solutions presented in Table 5 and Table 6 are statistically equivalent as per our analysis.

Table 6: Proposed solution for best team formation

Breakdown (%)	Number of containers	Breakdowner allocation				Buffer space allocation				Scanner allocation				Number of forklifts
		T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	
25	75	2	1	2	1	8	2	2	1	1	1	1	1	4
25	100	2	1	2	1	8	2	2	1	1	1	1	1	4
25	125	2	1	2	1	8	2	2	1	1	1	1	1	4
50	75	2	1	2	1	5	2	4	2	1	1	1	1	4
50	100	2	1	2	1	5	2	4	2	1	1	1	1	4
50	125	2	1	2	1	5	2	4	2	1	1	1	1	4
75	75	2	1	2	2	2	2	4	5	1	1	1	1	3
75	100	2	1	2	2	2	2	4	5	1	1	1	1	3
75	125	2	1	2	2	2	2	4	5	1	1	1	1	3

The average time required to complete all jobs under different scenarios using the current team formation (i.e., Table 4) and the proposed solution (i.e., Table 6) is presented in Table 7. These results suggest a minimum 19% and maximum 39% of performance improvement under the various scenarios considered.

Table 7: Performance improvement

Breakdown (%)	Number of containers	Currently practised team formation		Proposed solution		Average performance improvement
		Average (min)	Half-width (min)	Average (min)	Half-width (min)	
25	75	545.65	4.85	341.46	4.65	37.42%
25	100	714.40	4.94	434.10	4.26	39.24%
25	125	884.30	4.98	534.52	5.01	39.55%
50	75	554.11	4.37	391.39	5.00	29.37%
50	100	722.14	4.90	504.16	5.27	30.19%
50	125	896.92	4.99	615.53	5.77	31.37%
75	75	558.11	4.17	451.07	4.65	19.18%
75	100	728.99	4.56	582.69	4.77	20.07%
75	125	898.06	4.07	710.43	5.61	20.89%

The details related to the average utilization of each resource under the current team formation and the proposed solution are presented in Table 8 and Table 9, respectively. We observe that utilizations of breakdowners and buffer spaces increase when the breakdown percentage or number of containers increases. In comparison, the average utilizations of scanners and forklifts increase only with an increase in the number of containers. Additionally, the average utilization per scanner and the average utilization per forklift remain the same for different breakdown percentages as long as the number of containers remain the same. This is because the workloads of the forklifts and scanners are unaffected by the amount of breakdown needed. These results also show that the average utilization per forklift is higher using the presently practiced team formation because of the lower number of forklifts deployed when compared to the proposed solution. Furthermore, the average utilization per scanner is higher under the currently practiced team formation because of the lower number of teams formed when compared to the proposed solution. On the contrary, the average utilizations of breakdowners and buffer spaces under the current team formation is lower than under the proposed solution because improper resource allocation in the current practice results in a longer putaway time required to process all containers. Table 10 presents the detailed per resource utilization in each team for all resources under the proposed solution given in Table 6.

Table 8: Average resource utilization using currently practised team formation

Breakdown (%)	Number of containers	Breakdowner	Buffer space	Scanner	Forklift
25	75	0.056	0.184	0.063	0.425
25	100	0.073	0.245	0.083	0.566
25	125	0.092	0.307	0.104	0.709
50	75	0.111	0.214	0.062	0.426
50	100	0.148	0.284	0.084	0.566
50	125	0.185	0.356	0.104	0.711
75	75	0.164	0.243	0.063	0.425
75	100	0.221	0.326	0.084	0.567
75	125	0.277	0.407	0.104	0.708

Table 9: Average resource utilization using proposed solution

Breakdown (%)	Number of containers	Breakdowner	Buffer space	Scanner	Forklift
25	75	0.084	0.226	0.047	0.212
25	100	0.110	0.301	0.062	0.284
25	125	0.139	0.381	0.078	0.354
50	75	0.167	0.271	0.047	0.213
50	100	0.223	0.363	0.062	0.283
50	125	0.279	0.455	0.078	0.354
75	75	0.211	0.305	0.047	0.283
75	100	0.285	0.408	0.063	0.378
75	125	0.351	0.510	0.078	0.475

Table 10: Resource utilization for proposed solution

Breakdown (%)	Number of containers	Breakdowner utilization				Buffer space utilization				Scanner utilization				Forklift utiliza -tion
		T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	T_1	T_2	T_3	T_4	
25	75	0.16	0.07	0.04	0.03	0.24	0.22	0.21	0.19	0.12	0.03	0.03	0.01	0.21
25	100	0.21	0.09	0.05	0.04	0.31	0.30	0.28	0.26	0.16	0.04	0.04	0.02	0.28
25	125	0.26	0.13	0.06	0.05	0.39	0.38	0.36	0.34	0.20	0.05	0.05	0.02	0.35
50	75	0.21	0.15	0.16	0.13	0.28	0.28	0.26	0.26	0.08	0.03	0.06	0.02	0.21
50	100	0.27	0.19	0.21	0.18	0.37	0.37	0.35	0.34	0.10	0.04	0.08	0.03	0.28
50	125	0.34	0.24	0.26	0.23	0.47	0.46	0.44	0.44	0.13	0.05	0.10	0.04	0.35
75	75	0.14	0.22	0.24	0.26	0.33	0.33	0.31	0.28	0.04	0.03	0.06	0.07	0.28
75	100	0.18	0.29	0.32	0.35	0.43	0.44	0.41	0.39	0.05	0.04	0.08	0.09	0.38
75	125	0.22	0.35	0.39	0.44	0.54	0.54	0.52	0.48	0.06	0.04	0.10	0.11	0.47

Based on the experimental results, we make three important observations. First, the unloading forklifts are a bottleneck in the currently practiced team formation. Therefore, according to our proposed solution, more forklift operators (3–4) must be assigned. Second, the number of workers assigned as breakdowners should increase with the increase in the breakdown percentage. This is because the breakdown process becomes a bottleneck as breakdown percentages increase. The number of breakdowners is increased by reducing the number of forklift operators assigned in our proposed solution. Third, four teams should be formed instead of the three teams formed in the current practice. This is evident from the higher average breakdowner and buffer space utilization achieved using the proposed solutions.

6 CONCLUSION

We study the problem of optimal team formation, buffer allocation, and job assignment to teams of workers to optimize the container unloading and warehouse replenishment process. We solve this problem using a simulation optimization approach. Currently, the industrial partner forms three teams with equal sizes and approximately equal buffer space allocations. The solutions obtained using the simulation optimization model suggest that the team formation should be dependent on the percentage of containers that require additional processing (i.e., breakdown). Further, the unloading forklift operators are the bottleneck in the current process. This bottleneck can be alleviated by increasing the number of unloading forklift operators. A considerable reduction in the total time required to putaway all needed materials can be achieved by increasing the number of forklift operators and adjusting the number of teams formed depending on the percentage of containers that require additional processing.

ACKNOWLEDGMENTS

We are thankful to BMW Manufacturing Co., LLC, located in Spartanburg, South Carolina, for funding this project. Next, we would like to thank Vishnunarayan Prabhu for answering all the questions related to the problems faced while building the simulation optimization model. We would also like to thank Yogaditya Modukuri for taking the time and explaining the warehouse receiving process thoroughly.

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