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Cyber collaborative warehouse with dual-cycle operations design

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ABSTRACT

Warehouse operations have been significantly improved because of the rapid advancement of cyber-physical system technologies, preparing for Work-of-the-Future. The challenge, however, is how to design a collaborative system to deliver optimal performance by multiple agents who are highly distributed but interconnected and operate with technologies that provide massive amounts of real-time data. To address the challenge, in this article, the Cyber Collaborative Protocol for Dual-Cycle Task in Future Warehouse is developed to minimise total operation cost and time. The problem is addressed in two phases; the Global and Local phases. The global phase has higher computational power, maintaining a mathematical model, while the local phase has limited computational power and time, utilising heuristics to deliver the outcome. Computer experiments are utilised for validating the designed protocol compared with other alternatives. The results show that, in all given scenarios, the newly designed protocol outperforms alternatives with statistical significance. The original contribution of this research is the design and control of Cyber Collaborative Warehouse operations with a new focus on collaborative multi-agent interactions. In addition, a major implication is that future warehouses can benefit competitively by operating with Task Administration Protocols such as the new Cyber Collaborative Protocol for Dual-Cycle Task in Future Warehouse.

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Collaborative robot; Task Administration Protocol; Multi-agents system; Factories of the future; Cyber-physical system

Introduction

The convergence of digital technology and cyber-physical system collaboration has emerged as one of the most significant challenges in global supply chains, particularly in the design and implementation of warehouses and distribution centres (Önüt, Tuzkaya, and Doğanç 2008; Dolgui and Ivanov 2022). Warehouses have played an essential part in supply chains (Jayaraman and Ross 2003; Yu and De Koster 2012) by buffering goods from manufacturers to consumers to fulfil fluctuations in demand (Ries, Grosse, and Fichtinger 2017). According to Tate (2018), the next generation of warehousing features and characteristics, including agility and adaptability to market demands, modular and networked systems, learning and intelligent agents, data as an asset, virtual system models, and digital supply chain visibility, can potentially determine efficiency for the future supply chain. Therefore, the efficiency of warehouses and their activities will become much more critical in the following decade to help a company gain competitive advantages over competitors (Dekhne et al. 2019).

Warehouse operations, i.e. picking, packing, storing, and retrieving activities, are considered the most expensive tasks (and most critical tasks) in the warehouse as

they require high labour- and capital-intensive (Ballestín et al. 2013). To improve system performance, the operations are typically assigned to working robots equipped with smart and modern technologies (Kong et al. 2020; Dolgui, Sgarbossa, and Simonetto 2022). For example, multi-robot collaboration can lower operating costs (Nof 2007; Sayyed and Buss 2015) by improving repeatability, speed, and fatigue resistance (Liu and Wang 2018) while increasing higher performance (Nof 2007; Sayyed and Buss 2015) by allowing robots to work faster and in parallel (Brogårdh 2007; Cao et al. 2019).

On one hand, the advanced warehouse technologies can pave a way for the transition to Automation 5.0, which aims to enable robots to connect with their dynamic environments via a cyber-physical system in order to prepare for Work-of-the-Future, the new working environment in which robots and humans work collaboratively (Dusadeerungsikul and Nof 2021a). On the other hand, they introduce new challenges for researchers and engineers in terms of developing an effective system protocol to optimise novel available resources and deliver optimal performance.

Regarding this transition, future autonomous warehouse robots should be able to collaborate with their

peers to enable higher capabilities such as (1) processing shared information and decisions from their environment, (2) sharing workflows with their peers to overcome data scarcity and lateness, (3) improving efficiency by integrating real-time information, and (4) reducing work-related errors and conflicts for system integrity (Wang, Chen, and Xie 2010). With these new warehouse robot capabilities, the development of Cyber Collaborative Warehouse (C2W), a future warehouse with cyber augmentation and collaboration, will essentially raise warehouse performance to the next level.

A great deal of research has gone into developing a policy for optimising smart and/or cyber augmentation warehouse operations (He, Aggarwal, and Nof 2018). Table 1 contains an example of recent research into procedures and policies for improving warehouse operations.

As presented in Table 1, despite the fact that warehouse operations by autonomous agents have received considerable attention, the majority of the approaches predominantly discussed in the literature deal with system structures, namely allocation, scheduling, routing, and operation strategies. Although there may be advantages to integrating humans and robots into the system (De Lombaert et al. 2022), to date, there have been limited studies systematically addressing the issue

of collaborative protocol for multi-robot collaboration with human experts in the design of the C2W, leaving the essential connection among robots, humans, and dynamic environment unexplained.

This article, therefore, aims to fill the gaps by developing a new Task Administration Protocol (TAP) called Cyber Collaborative Protocol for Dual-Cycle Task in Future Warehouse (CCP-DC). The CCP-DC, which enhances the work by Dusadeerungsikul et al. (2021), includes a mathematical model, algorithms, and collaboration procedure between agents. In addition, this article relaxes an assumption about the operation tasks (storage and retrieval) of the previous work and integrates dual-cycle operation strategy to improve C2W performance. The protocol has been designed for robot collaboration intended for operation, knowledge, and information exchange to increase C2W's capabilities and collaboration abilities to minimise total operation cost and total operation time.

The remaining parts of this article are organised as follows. The following section describes the characteristics of C2W and defines the problem in C2W. Section 3 explains the design of CCP-DC to solve the given problem. Section 4 analyses and summarises the experiments executed to validate the performance of CCP-DC. Lastly,

Table 1. Current and recent research (sample) of improving warehouse operations.

Warehouse operations	Approach(es)	Reference
Routing and pathfinding of warehousing agent(s)	Single warehouse picker online routing for multiple picking tasks Collision free path planning algorithm for warehouse robots Order batching, routing, and assigning integrated system to minimise operation time Joint order batching and picker routing with a probabilistic model	Chen et al. (2014) Kumar and Kumar (2018) Gils et al. (2019) Yousefi et al. (2020)
Warehouse design	Design of storage capacity in a warehouse with the dedicated storage policy Multiple levels shelf design to minimise operation cost Design guideline for case-picking warehouse Layout design for just-in-time warehouse Hierarchical design methodology decomposing problem into a set of subproblems Multi-deep compact robotic mobile fulfillment system layout design Product-to-cluster and cluster-to-zone allocation model, minimising robot's travel time	Lee and Elsayed (2004) Önüt, Tuzkaya, and Doğaç (2008) Thomas and Meller (2015) Horta, Coelho, and Relvas (2016) Sprock, Murrenhoff, and McGinnis (2016) Yang, Jin, and Duan (2021) Mirzaei, Zaerpour, and de Koster (2022)
Warehousing system and management	A top-down methodology based decision-support system for warehouse Internet of Things integrated warehousing system in a dynamic environment Pick-and-pass warehousing system RFID-supported warehousing management Storage policy that optimises performance for a multi-dock unit-load warehouse	Accorsi, Manzini, and Maranesi (2013) Ready, Gunasekaran, and Spalanzani (2014) Pan, Shih, and Wu (2015) Alyahya, Wang, and Bennett (2016) Yu, Yu, and Yu (2022)
Package storage and retrieval processing	Storage assignment method based on bill of material Dynamic storage and retrieval algorithms for tasks with a due date Self-organised order picking system Adaptive storage assignment with multiple objectives Order picking assignment based on travel distance estimation Agents collaboration for storing packages Mathematical framework for Robotic Mobile Fulfillment Systems in e-commerce Agents collaboration for dual-cycle operations	Xiao and Zheng (2010) Ballestín et al. (2013) Hong, Johnson, and Peters (2015) Yan et al. (2015) Buonamico, Muller, and Camargo (2017) Dusadeerungsikul et al. (2021) Rimélé et al. (2022) (This article)

section 5 concludes with a discussion of the findings and potential further research directions.

Problem description

In this section, we describe the main characteristics of Cyber Collaborative Warehouse (C2W), the cyber-physical warehousing system enabling effective multi-agent collaboration. We present the relevant agents, packages, and operation cost of C2W, which define the environment with which we are working.

Characteristics of cyber collaborative warehouse (C2W)

This article considers a rectangular warehouse with parallel and crossing storage aisles. Warehouse storage

locations are on both sides of the aisle, with Internet of Things/ Internet of Services (IoT/IoS) devices attached. The primary operations in C2W are package storage and retrieval with the objectives to store and retrieve all packages with minimum cost (and time). The C2W comprises multiple agents working together with cyber augmentation. Agents in C2W can be categorised into three types; Operating agent, Intelligent agent, and Data fusion agent. The roles and responsibilities of each type of agent are shown in Table 2. In addition, Figure 1 illustrates C2W system architecture.

Table 2. Agents and their roles in C2W.

Type of Agents	Example	Roles
Operating agents	Warehouse robots	Move and operate in a warehouse (i.e. store or retrieve packages)
Intelligent agents	Human agents	Solve the real-time and unexpected issue
Data fusion agent	IoT/IoS	Collect and transmit real-time data, identify system errors

Robot team in C2W

In this study, we will focus on operating agents in C2W. Multiple robots with different capabilities are selected to enhance the flexibility of C2W and improve cost-effectiveness. Such that, two unique robots (R_1 and R_2) are operating in C2W. Therefore, we will have three possible robot team options: (1) Only R_1 , (2) Only R_2 , and (3) Collaborative team ($R_1 + R_2$). Table 3 presents robots needed for different robot teams. Note that, the word *robot team* represents all three options in Table 3, not only option three (A_3).

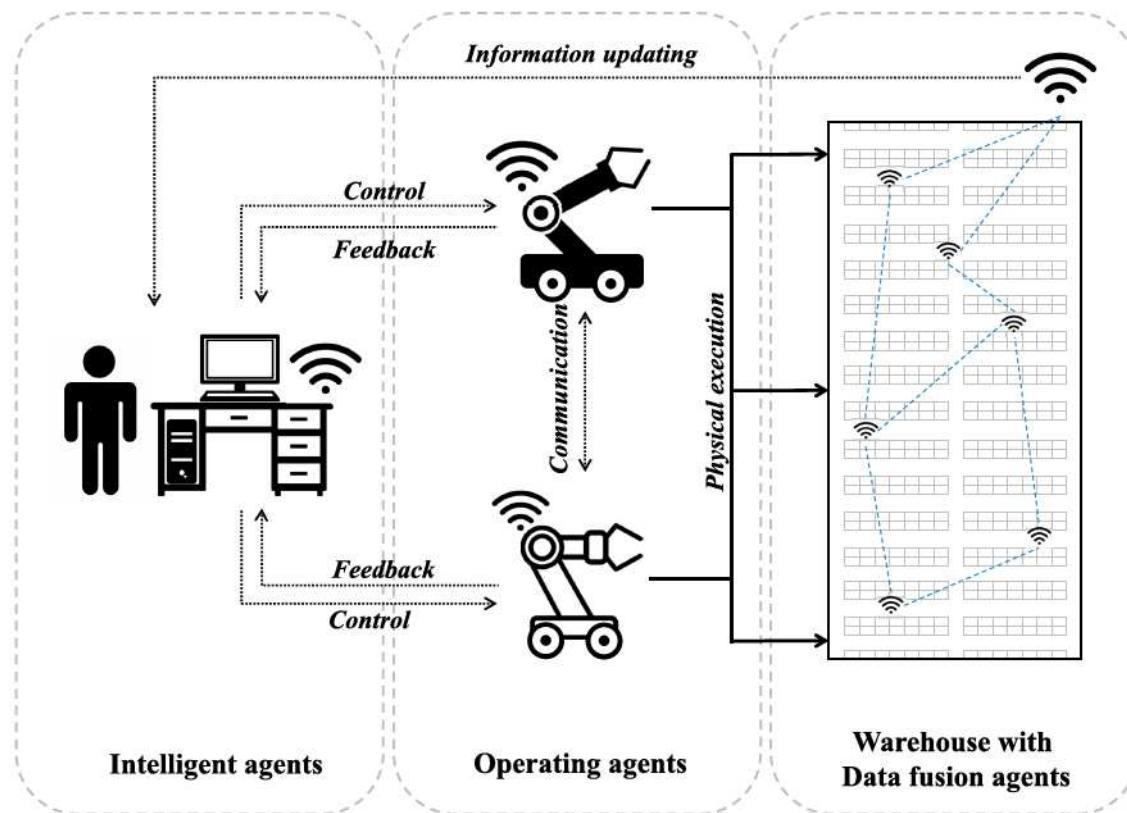


Figure 1. Cyber Collaborative Warehouse (C2W) (Modified from Dusadeerungskul and Nof (2021b)).

Table 3. Collaboration team in C2W.

Robot team	Robot 1 (R_1)	Robot 2 (R_2)
Team 1 (A_1)	✓	—
Team 2 (A_2)	—	✓
Team 3 (A_3)	✓	✓

Package in C2W

According to the defined robot team, there will be at most five possible package types in C2W. The five package types are derived from the complete possible combinations of working robots as follows and presented in Table 4.

Package types 1 (P_1) is the simplest and most common task in C2W as it can be executed by either R_1 , R_2 , or the collaboration team, ($R_1 + R_2$). Therefore, A_1 , A_2 , or A_3 can be assigned for storing or retrieving this package task.

Package type 2 (P_2) requires R_1 to store or retrieve the package because the package needs handling equipment from R_1 (i.e. R_1 handling specification constraint). Therefore, A_1 or A_3 can be assigned for executing this package task.

Package type 3 (P_3) requires R_2 to store or retrieve the package because the package needs handling equipment from R_2 (i.e. R_2 handling specification constraint). Therefore, A_2 or A_3 can be assigned for executing this package task.

Package type 4 (P_4) is a package that has space limitation constraints; therefore, only one robot can be assigned to execute the package task (not the collaboration team). Therefore, A_1 or A_2 can be assigned for executing this package task.

Package type 5 (P_5) is a package with weight or volume constraint; therefore, the collaboration team must execute the package task. Hence, only A_3 can be assigned to this package type.

Operation cost and performance in C2W

Operation cost is derived from operation time and the cost of the specific robot team. The relationship

of operation cost and its components have shown in Equation (1) where c_{na} is a cost for executing package n by robot team a , k is a conversion factor of robot team a to perform task p (p can be either storage or retrieval task), and t_{ija} is the travel time from i to j by robot team a .

$$c_{na} \sim k_{ap} t_{ija} \quad (1)$$

In other words, when a particular robot team needs to traverse for a longer distance, it will incur a higher operation cost. In addition, with the same package, when multiple robots work as a team, it will cost more than a team with a single robot. Furthermore, the operation cost of collaborative robot (c_{nA_3}) will be strictly higher than a single robot cost ($c_{nA_1} + c_{nA_2}$) because of the addition of collaboration cost. It, however, will have better performance and faster completion time because of collaborative operation. The assumption implies a time-cost trade-off in the C2W agents. For example, given a P_1 , cost of A_1 or A_2 to store or retrieve the package is strictly less than A_3 , but A_3 can complete the task in a shorter time. The same explanation also applied to P_2 and P_3 . Lastly, the cost of storing packages and the cost of retrieving packages are not necessarily equal in C2W.

Cyber collaborative protocol for dual-Cycle task in future warehouse (CCP-DC)

The newly designed TAP, called Cyber Collaborative Protocol for Dual-Cycle Task in Future Warehouse (CCP-DC), is discussed in this section. The CCP-DC has improved from work by Dusadeerungsikul et al. (2021) as it relaxes an assumption of operation task in C2W. Because of the relaxation, the dual-cycle operation, a strategy to reduce dead-heading (an empty trip of a robot) by interleaving the storage and retrieval process (Bartholdi and Hackman 2008), can be employed. Therefore, all tasks can be completed faster (less delay) and with lower cost.

CCP-DC design

The CCP-DC was designed with two phases, Global level (θ) and Local level (ε), following Collaboration Requirement Planning (CRP) in Collaborative Control Theory (Nof 2007; Nof et al. 2015).

θ is a planning level with high computation power. The objective of θ is to assign robot teams to store packages. θ with mathematical model receives information from human agents, IoT/IoS, and package information. Then, θ generates an initial plan for C2W with minimising total operation cost.

Table 4. Package type in C2W.

Package type	Robot team option(s)	Explanation
P_1	A_1, A_2 , or A_3	Either R_1 , R_2 , or $R_1 + R_2$ can store or retrieve the package.
P_2	A_1 or A_3	R_1 is compulsory for storing or retrieving the package.
P_3	A_2 or A_3	R_2 is compulsory for storing or retrieving the package.
P_4	A_1 or A_2	Either R_1 or R_2 can store or retrieve the package (cannot be both of them).
P_5	A_3	Both R_1 and R_2 must work collaboratively ($R_1 + R_2$) for storing or retrieving the package.

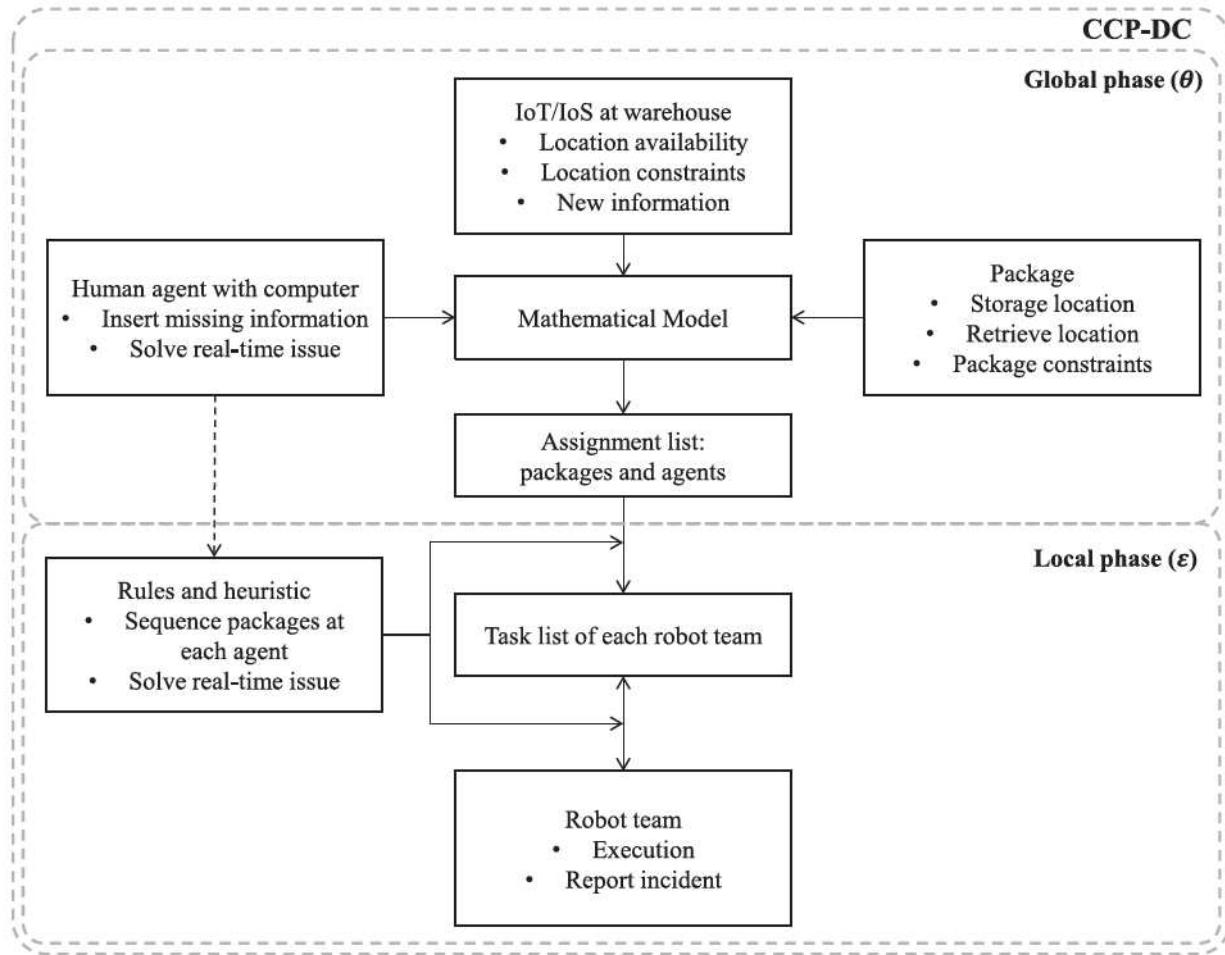


Figure 2. CCP-DC, Cyber Collaborative Protocol for Dual-Cycle Task in Future Warehouse.

On the other hand, ϵ which performs at the local agent level, has two limitations; limited computational power and limited acceptable time delay. Hence, at ϵ , simple rules or heuristics will be utilised for solving both expected and unexpected tasks performed by the robot team. ϵ sequences tasks of each robot team so that the total operation time is minimised. In addition, ϵ also assigns packages to retrieval tasks to create a dual-cycle operation. The connection between θ and ϵ is shown in Figure 2.

$a \in A$ is a set of robot teams. ($|A|$ represents a total number of the robot teams.)

c_{na} = cost for storing or retrieving package $n \in N$ by robot team $a \in A$

- Decision variable

$x_{na} = 1$ if robot team $a \in A$ is assigned to store or retrieve package $n \in N$; 0 otherwise

- Auxiliary variable

K = Load balancing factor

- Objective

$$z : \min \sum_{n \in N} \sum_{a \in A} c_{na} x_{na} \quad (2)$$

- Constraints

$$\sum_{a \in A} x_{na} = 1; \forall n \in N \quad (3)$$

CCP-DC components

Global phase

Mathematical model.

- Sets and parameters

$p \in P$ is a set of package types.

$n \in N$ is a set of packages. ($|N|$ represents a total number of the packages and $|N_p|$ represents a total number of the packages for each type.)

$$\sum_{n \in N} x_{na} = K; \forall a \in A \quad (4)$$

$$K \geq \frac{|N|}{|A|} \quad (5)$$

$$K \geq |N_p|; \forall p \in P \quad (6)$$

$$K \in \mathbb{Z}^+ \quad (7)$$

$$x_{na} \in \{0, 1\} \quad (8)$$

The objective of the mathematical model is to assign packages to robot teams to store in C2W to minimise total operation cost. Constraint (3) ensures that all packages are assigned to a robot team. Constraint (4)–constraint (6) is the load balancing constraints that ensure that the system does not overload a particular robot team. The number of packages assigned to each robot team should be as close as possible, to balance the load. On the other hand, if the number of P_2 or P_3 which requires a particular robot to operate exceeds the average number of packages per robot team, there will be a possibility that the particular robot team will have more loads than others, denoted by constraint (6).

The reason for having load balancing constraints is that when the system overloads a robot team, the total operation time, another objective of C2W, is affected. Therefore, load balancing constraints will be an essential part of improving the total operation time of the system.

The output from the mathematical model in θ is the assignment of packages to robot teams to minimise the total operation cost of the system. The C2W, however, requires the sequence of each package at each robot team. Therefore, the local phase (ε), which aims to minimise total operation time with the dual-cycle operation, is necessary.

Local phase (ε)

The ε has an objective of minimising total operation time by sequencing packages for each robot team. Because, at

ε , computational power and time are limited due to local agent capacity, maintaining a complex mathematical model that can generate an exact solution but not deliver the solution on time might not be a suitable approach. Therefore, at ε , to effectively and smoothly execute the operation, a new algorithm called Dual-cycle operation algorithm for C2W (DCC) is developed. DCC aims to not only sequence packages at each robot team but also create a dual-cycle operation to minimise the total operation time of the system and collaborate robot teams in C2W at the same time. The detail of the algorithm is discussed as follows.

Dual-cycle operation algorithm for C2W (DCC)

The DCC comprises of two sub-modules: (1) Sequencing of packages algorithm (M_1), and (2) Online selecting and inserting package algorithm (M_2). The first sub-module (M_1) aims to sequence packages at each robot team, and the second sub-module (M_2) aims to select and insert packages to develop a dual-cycle operation in C2W. Each sub-module is explained as follows.

- Sequencing of packages algorithm (M_1)

The following algorithm is M_1 which aims to sequence packages to store at each robot team. In addition, Algorithm 1 and Figure 3 present a pseudo-code and conceptualised output of M_1 .

- Online selecting and inserting packages algorithm (M_2)

After completing M_1 , each robot team will obtain a list of packages to store and their sequence. Next, to improve the system efficiency of C2W, a dual-cycle concept is deployed by M_2 . The following algorithm is developed to select a package for retrieval to minimise total operation time. In addition, Algorithm 2 and Figure 4 illustrate pseudo-code and conceptualised schedule from M_2 .

					<i>C_Schedule_{max}</i>				
<i>A₁</i>	<i>R₁</i> busy as it is a part of <i>A₃</i>				<i>NCP_{A₁1}</i>	<i>NCP_{A₁2}</i>	<i>NCP_{A₁3}</i>	...	<i>NCP_{A₁m₁}</i>
<i>A₂</i>	<i>R₂</i> busy as it is a part of <i>A₃</i>				<i>NCP_{A₂1}</i>	<i>NCP_{A₂2}</i>	<i>NCP_{A₂3}</i>	...	<i>NCP_{A₂m₂}</i>
<i>A₂</i>	<i>CP₁</i>	<i>CP₂</i>	...	<i>CP_n</i>	<i>A₃</i> not available				
<i>C_Schedule</i>					<i>NC_Schedule</i>				

Figure 3. Conceptualised schedule from M_1 .

Algorithm 1: Sequencing of packages algorithm (M_1)

Step 1 Separate package to store into two types:
 - Collaborative package or CP (Packages that are assigned to A_3) and
 - Non-collaborative package or NCP (Packages that are assigned to A_1 (NCP_{A_1}) or A_2 (NCP_{A_2}))

Step 2 Among CP , sequence packages by executing package task that has smallest t_{jA_3} first, called collaborative schedule ($C_Schedule$)

Step 3 Compute maximum makespan of $C_Schedule$ ($C_Schedule_{max}$)

Step 4 Set release date of NCP to $C_Schedule_{max}$

Step 5 Among NCP assigned to A_1 sequence packages by executing the package task that has the smallest t_{jA_1} first, called non-collaborative schedule A_1 ($NC_Schedule_{A_1}$)

Step 6 Among NCP assigned to A_2 sequence packages by executing the package task that has the smallest t_{jA_2} first, called non-collaborative schedule A_2 ($NC_Schedule_{A_2}$)

Step 7 Combine $C_Schedule$, $NC_Schedule_{A_1}$, and $NC_Schedule_{A_2}$ to generate storage schedule in C2W

Algorithm 2: Online selecting and inserting packages algorithm (M_2)

Step 1 Separate packages to retrieve into two types:
 - Collaborative package or CP' (Packages that require A_3) and
 - Non-collaborative package or NCP' (Packages that do not require A_3)

Step 2 During M_1 operate $C_Schedule$, if there is a package in CP'

Step 2.1 Among CP' , select a package that has the smallest t_{jA_3} relative to the current location

Step 2.2 Retrieve the package and deliver it to the destination

Step 2.3 Resume to the schedule from M_1

Step 3 During M_1 operate $NC_Schedule_{A_1}$, if there is a package in NCP'

Step 3.1 Among NCP' , select a package that has the smallest t_{jA_1} relative to the current location

Step 3.2 Retrieve the package and deliver it to the destination

Step 3.3 Resume to the schedule from M_1

Step 4 During M_1 operate $NC_Schedule_{A_2}$, if there is a package in NCP'

Step 4.1 Among NCP' , select a package that has the smallest t_{jA_2} relative to the current location

Step 4.2 Retrieve the package and deliver it to the destination

Step 4.3 Resume to the schedule from M_1

Step 5 After M_1 is completed, if there is a package in CP' or NCP'

Step 5.1 Among remaining NCP' sequence packages by executing package retrieval that has the largest t_{jA_1} or t_{jA_2} to an available agent

Step 5.2 Among remaining CP' sequence packages by executing package retrieval that has the smallest t_{jA_3} first

CCP-DC workflow and Task Administration Protocol

The CCP-DC workflow is developed to connect the protocol elements. CCP-DC has derived from TAP, one of the key tools for developing a collaborative system (Ko and Nof 2010, 2012; Moghaddam and Nof 2013; Scavarda et al. 2015; Tkach, Edan, and Nof 2017; Yoon and Nof 2010). TAP, a workflow optimisation protocol, manages systems with multiple agents to deliver system optimal performance. In addition, an emerging type of TAP is the cyber collaborative protocol which is cyber-augmented TAP for the collaborative system or cyber collaborative protocol (CCP). The CCP has been applied in various

fields to design a complex cyber-physical system such as agriculture robotic systems and multi-robot collaborative operations (Dusadeerungskul et al. 2019).

CCP-DC workflow collaborates protocol's components by activating or deactivating system agents and algorithms. The workflow starts with receiving operation information and a tasks list. Then, the mathematical model in θ is utilised to obtain the assignment of packages and robot teams. In this process, as all information is received in advance and the mathematical model requires an amount of computational time, θ can be executed before the physical packages have arrived. Then, after the

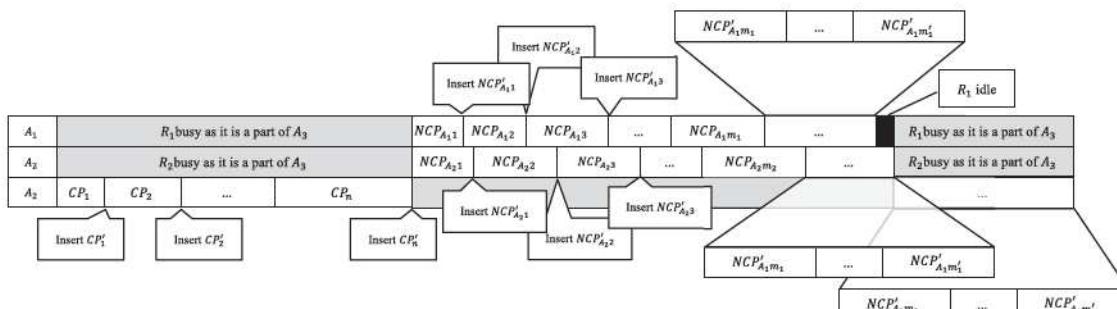


Figure 4. Conceptualised schedule from M_2 .

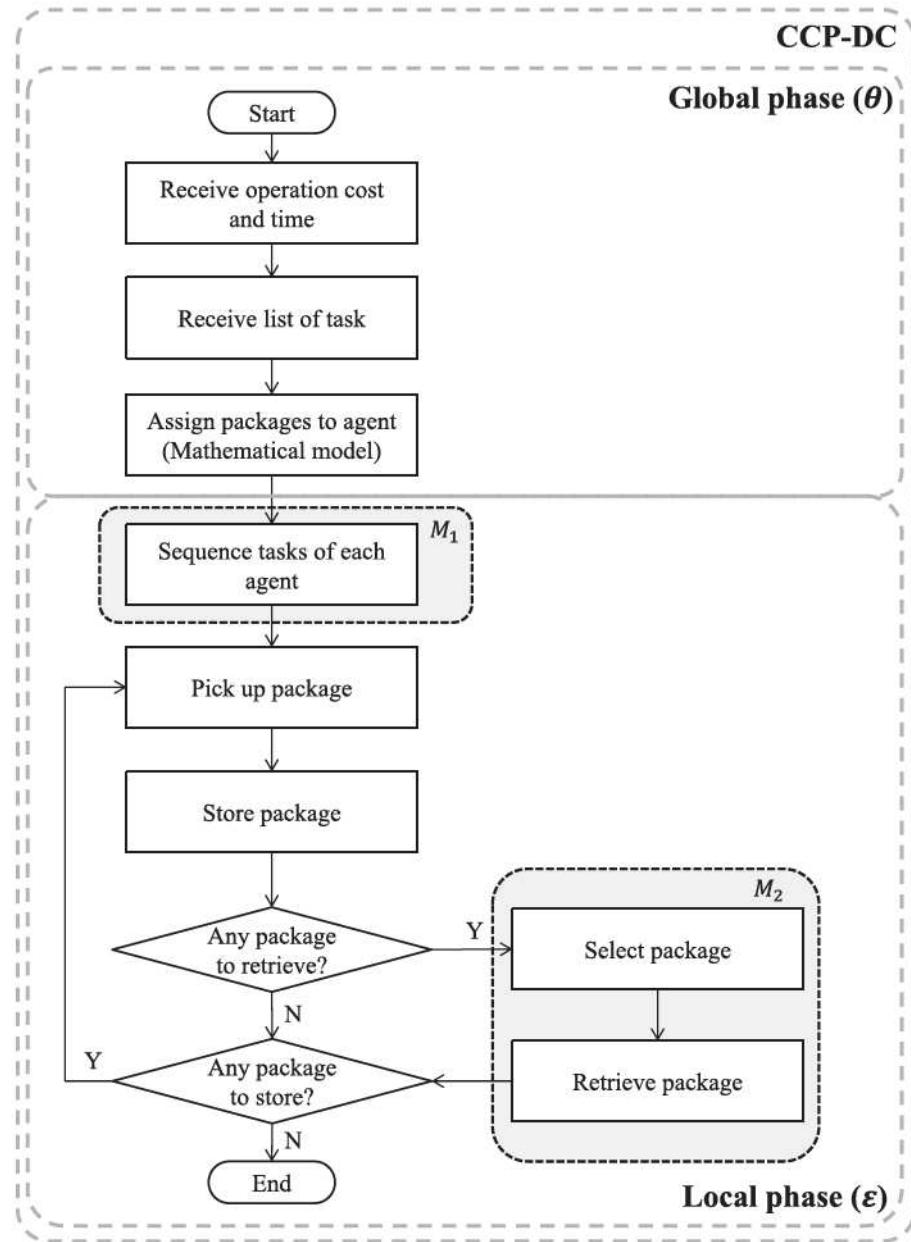


Figure 5. CCP-DC workflow.

physical packages have been received, ε will be executed. Note that, for the warehouse operating continuously, θ and ε can be performed in parallel. Put differently, while ε is executing the current package tasks, θ can optimise the new task list for the next round, minimising the waiting time between θ and ε . Figure 5 presents the CCP-DC workflow.

Experiments and results

In this section, the test and validation of CCP-DC are explained and compared against alternative protocols. The computer simulation experiments were constructed by coding in MATLAB. Storage and retrieval tasks were randomly generated and assigned to the system. Three

experiments were conducted to measure the protocol performance in various situations. The first experiment presents the operation with an equal number of storage and retrieval packages. Then, the second experiment illustrates the case where there are more packages to store than to retrieve. Lastly, the third experiment shows a situation where there are fewer packages to store than to retrieve.

Experiments design

In C2W, operation tasks which consist of storage and retrieval tasks, are executed by multiple agents. In the experiments, three robot teams are available (A_1 , A_2 , and A_3) with different capabilities and costs of operation.

Note that, as an assumption in the experiment, the storage cost is lower than the retrieval cost because of handling difficulties. A total of 100 randomly generated tasks are loaded to the system with the distribution of tasks as shown in Table 5. The proportion between storage and retrieval tasks in the different experiments is set differently to observe the impacts of the proportion of task types. All parameters used in the experiments are presented in Table 6. In addition, three protocols compared in experiments are (1) CCP-DC, (2) Current practice, and (3) Baseline protocol. The CCP-DC is a newly designed protocol. The second protocol combines First Come First Served policy with dual-cycle operation, representing the

current warehouse practice that utilises simple operation rules. The third protocol is considered as a baseline, utilising only First Come First Served policy, to indicate the impacts of both θ and ε . The performance of each operation protocol is determined by two metrics; total operation cost and total operation time. Lower total operation cost and time are preferred, indicating the more efficient system protocol.

Table 5. Tasks in experiments.

	Storage tasks	Retrieval tasks	Total tasks
Experiment 1	50	50	100
Experiment 2	65	35	100
Experiment 3	30	70	100

Table 6. Parameters in experiments.

Parameters	Robot team	Operation tasks	
		Storage	Retrieval
Travel speed (meter/second)	A_1	$N(2.5, 0.5)$	$N(2.5, 0.5)$
	A_2	$N(2.5, 0.5)$	$N(2.5, 0.5)$
	A_3	$N(3, 0.5)$	$N(3, 0.5)$
Operation time (second)	A_1	$N(45, 10)$	$N(60, 10)$
	A_2	$N(45, 10)$	$N(60, 10)$
	A_3	$N(60, 10)$	$N(45, 10)$
Fixed operation cost (\$)	A_1	$N(1, 0.1)$	$N(1.2, 0.1)$
	A_2	$N(1, 0.1)$	$N(1.2, 0.1)$
	A_3	$N(3, 0.1)$	$N(3.6, 0.1)$
Operation cost per distance (\$/meter)	A_1	$N(0.1, 0.01)$	$N(0.1, 0.01)$
	A_2	$N(0.1, 0.01)$	$N(0.1, 0.01)$
	A_3	$N(0.25, 0.01)$	$N(0.25, 0.01)$

Experiment 1: equal number of storage packages and retrieval packages

The first experiment investigates the balanced situation where the numbers of packages to store and retrieve are equal. This situation represents C2W that operates continuously in such a balance and has unlimited package tasks to complete.

Experiment results

After 30 operation runs, Figure 6 presents results with the standard deviation bars of total operation cost and total operation time to complete 50 storage and 50 retrieval package tasks. As shown in Figure 6, CCP-DC yields the lowest operation cost and operation time compared to alternative protocols. Note that the detailed results are summarised in Appendix 1.

One-way ANOVA and Post Hoc Tukey HSD are utilised to assess the three procedures' statistical differences. The results show that with a 99% confidence level, CCP-DC yields better performance in terms of total operation cost and total operation time compared to the two alternative protocols.

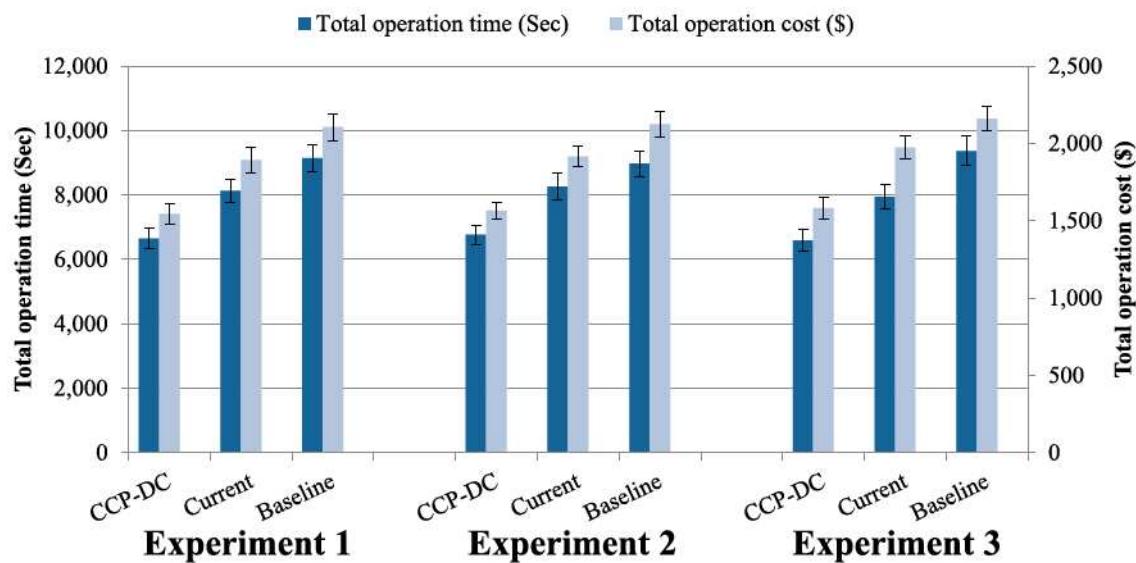


Figure 6. Comparison of the 30 operations runs results with standard deviation bars, and the CCP-DC outperforms others in all experiments with 99% confidence level.

Experiment 2: number of storage packages is greater than number of retrieval packages

The second experiment is when the number of packages to store is larger than the number of packages to retrieve. This situation represents C2W with incoming package flow larger than outgoing flow. An example of this situation is a warehouse used for storing inventories ahead of a peak season.

Experiment results

Figure 6 presents results with a standard deviation bars of total operation cost and total operation time after 30 operation runs. The system was loaded with 65 packages to store and 35 packages to retrieve. Compared to Experiment 1, the total operation cost and time of three procedures are increased as the imbalance between incoming and outgoing flow in C2W reduces the number of dual-cycle operations. Nevertheless, CCP-DC still yields the lowest total operation cost and total operation time compared to the alternative protocols. Note that the detailed results of the Experiment 2 are presented in Appendix 2.

One-way ANOVA and Post Hoc Tukey HSD are also used to analyse the statistical difference between the three protocols. The results show that with a 99% confidence level, CCP-DC yields better performance in terms of total operation cost and total operation time compared to the two alternative protocols.

Experiment 3: number of storage packages is fewer than number of retrieval packages

The third experiment is where the package to store is fewer than the package to retrieve. The situation represents C2W with incoming package flow smaller than outgoing flow. An example of this situation is a warehouse serving high demand volume, and the inventories in the warehouse become lower.

Experiment results

The results with standard deviation bars after 30 operation runs are presented in Figure 6. The system was given 30 packages to store and 70 packages to retrieve. As the imbalance of package flow, and with an assumption that the retrieval process has a higher operation cost, the total operation cost and operation time increase compared to Experiments 1 and 2. The reason is that some packages cannot be assigned for the dual-cycle operation. Figure 6, however, presents that the CCP-DC delivers the lowest total operation cost and total operation time compared to the alternative protocols. In addition, the detailed results of the Experiment 3 are summarised in Appendix 3.

One-way ANOVA and Post Hoc Tukey HSD are utilised to assess the statistical difference between the three operation procedures. At 99% confidence level, the results show that CCP-DC has significantly lower total operation cost and total operation time compared to the two alternative protocols.

Conclusion and discussions

This work contributes to the design of future cyber-augmented warehouses by defining the C2W and developing an effective protocol for collaborative operation. The main assumption of the C2W is the cost and time trade-off. Therefore, a newly developed protocol called CCP-DC aims to effectively balance system cost and time by collaboration between operating agents (e.g. warehouse robot teams). The CCP-DC separates tasks into two levels; Global level (θ) and Local level (ϵ). Each operation level has its advantages and limitations. θ has more computational power but is less flexible, while ϵ has limited power and time but enables more flexibility to the system. Hence, at θ , the mathematical model, shown to assign packages to robot teams optimally, is maintained. On the other hand, at ϵ , algorithms called Dual-cycle operation algorithm for C2W (DCC) which has two sub-module (1) Sequencing of packages algorithm (M_1), and (2) Online selecting and inserting package algorithm (M_2) is utilised. The mathematical model and algorithms are connected by CCP-DC workflow. The computer simulation experiments were conducted to validate the newly designed protocol with the alternatives. Two main performance metrics, total operation cost and total operation time, are measured. Results show that the newly designed protocol, CCP-DC, outperforms the alternatives in all three tasks scenarios with 99% confidence level.

Researchers can pursue further research in the following directions in the future.

- (1) Consider a system with more robots: Two robots might not cover all warehouse requirements, and a new robot with different capabilities may be required. Designing a new protocol including more robots with new collaboration capacity is challenging for researchers.
- (2) Examine system conflicts and errors: The system might have conflicts and errors that lead to an unfavourable performance. Identifying, preventing, and solving conflicts and errors before they severely impact the entire system will improve system resilience, an important factor in future warehouses.
- (3) Research on a system with unexpected situations: The system might face an unplanned situation that

needs to be solved in real-time. Researchers can design and develop a protocol involving new intelligent agents such as human agents who can serve as real-time problem-solvers in C2W.

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Data availability statement

There is no data set associated with this work. The quantitative details of the model used and the numerical experiments have been provided in the article.

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Appendices

Appendix 1: Detailed results of the experiment 1

Table A1 presents means with a standard deviation of total operation time and cost from the Experiment 1, where in flow and out flow are balanced. The percentage difference in Table A1 is calculated from the change of CCP-DC compared to baseline, highlighting impact of both phases of CCP-DC as well as dual-cycle operation strategy.

Table A1. Experiment 1 results.

	CCP-DC	Current practice	Baseline	%Difference
Total operation time (Sec)	6,650.63 (327.32)	8,129.38 (343.78)	9,145.83 (419.92)	27.28%
Total operation cost (\$)	1,545.08 (67.46)	1,893.13 (80.25)	2,106.33 (86.29)	26.65%

Note: Standard deviations are given in parentheses.

Appendix 2: detailed results of the experiment 2

The means and standard deviation of the Experiment 2, where number of storage packages is greater than number of retrieval packages, are presented in Table A2. Note that the percentage difference in Table A2 is the relative change of CCP-DC compared to baseline.

Appendix 3: detailed results of the experiment 3

The results (means and standard deviation) of the Experiment 3, where the number of packages to store is fewer than the number of packages to retrieve, are presented in Table A3. The percentage difference in Table A3 presents the relative change of CCP-DC compared to baseline.

Table A2. Experiment 2 results.

	CCP-DC	Current practice	Baseline	%Difference
Total operation time (Sec)	6,766.69 (306.52)	8,265.56 (426.27)	8,977.08 (393.77)	24.62%
Total operation cost (\$)	1,565.49 (56.34)	1,915.69 (85.07)	2,124.93 (85.89)	26.33%

Note: Standard deviations are given in parentheses.

Table A3. Experiment 3 results.

	CCP-DC	Current practice	Baseline	%Difference
Total operation time (Sec)	6,587.88 (343.53)	7,947.79 (282.70)	9,370.83 (452.37)	29.70%
Total operation cost (\$)	1,582.86 (80.32)	1,975.04 (76.61)	2,161.53 (81.58)	26.77%

Note: Standard deviations are given in parentheses.