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Collaboration Requirement Planning Protocol for HUB-CI in Factories of the Future

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Abstract

Rapid advances in production systems' models and technology continually challenge manufacturers preparing for the factories of the future. To address the complexity issues typically coupled with the improvements, we have developed a brain-inspired model for production systems, HUB-CI. It is a virtual Hub for Collaborative Intelligence, receiving human instructions from a human-computer interface; and in turn, commanding robots via ROS. The purpose of HUB-CI is to manage diverse local information and real-time signals obtained from system agents (robots, humans, and warehouse components, e.g., carts, shelves, racks) and globally update real-time assignments and schedules for those agents. With Collaborative Control Theory (CCT) we first develop the protocol for collaborative requirement planning for a HUB-CI, (CRP-H), through which we can synchronize the agents to work smoothly and execute rapidly changing tasks. This protocol is designed to answer: Which robot(s) should perform each human-assigned task, and when should this task be performed? The primary two phases of CRP-H, CRP-I (task assignment optimization) and CRP-II (agents schedule harmonization) are developed and validated for two test scenarios: a two-robot collaboration system with five tasks; and a two-robot-and-helper-robot collaboration system with 25 tasks. Simulation results indicate that under CRP-H, both operational cost and makespan of the production work are significantly reduced in the two scenarios. We summarize with the implications and future plans for integrating HUB-CI and CRP-H in a cyber-augmented physical simulation model.

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1. Introduction

Advancements in production system technology, artificial intelligence and machine vision have challenged engineers and researchers to prepare and invent the Factory of the Future (FoF). Ability to handle information generated by IoT/IoS devices, utilizes new technologies, and deal with increased complexity of the system will indicate the characteristics of future factories [11]. If factories cannot deal effectively with such changes, loss/wastage of time, effort, and money are the natural consequences, and which will decrease their overall competitiveness in their respective industries.

In this article, we consider a typical warehouse operation as a case study. Robots are commonly used today in warehouses to perform tasks such as picking, packing, storing, and retrieving packages. Moreover, IoT/IoS devices can improve work performance by minimizing data collection and data validation time. Without a model to manage massive information generated in real-time, however, and to optimize and harmonize system agents, the system will work ineffectively, with potential conflicts and errors. To address the problem, HUB-CI, which is a brain-inspired protocol model is needed. Its objective is to manage massive information about distributed agents in real-time, and optimize and harmonize operations instructed by human operators. The important features of this hub are to receive commands from human agents via a user interface, and develop a plan for robots which are managed by Robot Operating System (ROS) middleware. In addition, a protocol for HUB-CI will manage local information which is received from system agents (humans, robots, warehouse racks, etc.) and update tasks globally. By having a protocol which can enable collaboration among agents in the system, the total operation cost and time can be minimized. To accomplish the above objective, a collaboration requirement protocol for HUB-CI (CRP-H) is designed and developed in the research reported here.

Section 2 summarizes background and previous work related to the problem. Section 3 presents a new method, called collaborative requirement planning protocol for HUB-CI (CRP-H). Two case studies for which CRP-H is applied are presented in section 4. Finally, Section 5 discusses conclusions and future research directions.

2. State of the art

2.1. Smart warehouse and IoT/IoS

Warehouse operation is a critical activity in supply chains to attain excellence in terms of customer service, lead times and cost [5]. The ever-increasing needs for effective interaction and collaboration require real time communication, and information gathering and validation. Each agent, as an intelligent and autonomous entity, must be able to detect and process information from its environment and share it with its peers. To overcome difficulties due to a shortage or lateness of comprehensive resource information, we consider warehouse management systems with RFID technology implemented in an IoT/IoS system, through which we can continuously monitor parameters such as shelf or rack inventory levels, robot positions and availabilities. In addition to the projected improvement in efficiency by integrating real-time information into the decision-making process, we can decrease work-related errors, conflicts and operation costs for task allocation and scheduling, in comparison to systems without IoT/IoS.

2.2. HUB based collaboration

HUB-CI is a tool designed for cyber augmented collaboration between physical and virtual agents. The collaboration is not restricted to only the virtual domain. The key innovation of HUB-CI is that it can enable and facilitate physical collaboration between several groups of human users along with relevant cyber-physical agents [14], whereas previous HUBs collaborate jobs on virtual materials and simulations [6]. HUB-CI has been designed to comprise algorithms and protocols to improve the productivity and efficiency of a distributed system of networked agents via augmented collaboration.

2.3. The need for Human Robot Collaboration

The main reason for adopting multi-robot control in industry is the possibility of reducing production cost by having robots working faster and in parallel [1]. Shorter processing time through collaboration means higher efficiency for the operation. When there is an overlap in machine capability, the system reliability is also improved through redundancy. The benefit is especially significant at process bottlenecks, in which case single robot failure can bring down the whole system. Moreover, the overlap of machine capability during collaboration adds another dimension of flexibility due to the additional tasks that can be performed by cooperating machine sets [12]. Some even suggested that the combination of skillset may be able to accomplish tasks that cannot be done by any single one. Another argument is based on the relative simplicity in design. Having small, simple robots can be simpler and cheaper to implement, than having a single powerful and complicated robot [4].

2.4. Multi-robot collaboration

The Handbook of Industrial Robotics defines a collaborative multi-robot system as a system where robots exploit the ability to complete tasks independently, or through collaboration. In such systems, tasks can be assigned either to individual robots, or cooperative teams of robots with enhanced capabilities [7]. By considering collaborative teams as task handlers, we can expand the scope of tasks being serviced, through key performance indicators such as cost, time, and volume of work. In this research, we tackle the integration of Human-Robot Collaboration in a storage-retrieval process at a smart warehouse and provide the results of efficient task allocation and scheduling. Parker et al. [10] suggest the following challenges need to be addressed when designing multi-robot systems: (1) How to ensure collaborative teams of robots complete the tasks successfully on their own? and (2) How to make robot teams adapt autonomously to dynamic changes in the environment? We attempt to create a model which attempts to answer these challenges.

2.5. Collaboration Requirement Planning

Collaborative Requirement Planning (CRP) is a hierarchical decision-support strategy for multi-agent collaboration. The concept was originally coined by Rajan and Nof (1996): “It is the process of generating a consistent and coordinated global execution plan for a set of tasks to be completed by a multi-machine system based on the task cooperation requirements and interactions” [12]. The CRP methodology aims to address deficiencies mentioned previously by 1) seeking optimized collaborative solution; 2) administer a global production plan [8] [13].
A machine job consists of a set of tasks, and CRP has two components. The first one, CRP I, takes the product and machine description as inputs and generates the cooperation requirement matrix (CRM), whose elements represent the performance capability of the machine sets for the potential tasks. Based on machine availability, CRP-II also considers real-time operational constraints. CRP-II takes the CRM and given constraints to determine the assignment of tasks to machine sets for processing [12].

2.6. Human in the loop systems

The convergence of embedded computing, Information and Computing Technologies (ICT) and distributed systems has ushered a new dimension for the future of manufacturing, with the development of the concept of Cyber-Physical Systems (CPS). CPS can be defined as smart systems encompassing computational and physical elements, integrated with the virtual world of Information Technology and thus creating an Internet of Things and Services [3].
“Achieving effectively networked, cooperating and human-interactive systems will be the integral factor in the adoption of CPS. In the future, networked, cooperating human-interactive systems will optimize the power of human operations through high levels of situation awareness and adaptability” [2].
Human-in-the-loop (HIL) CPS are being investigated and applied to an increasing number of applications. In HIL-CPS, we address the potential of integrating a human decision maker in the manufacturing or control decision, and by integrating human intelligence we can enhance the system responsiveness. Through HIL-CPS, human operators

can monitor various aspects of the use-case scenario and provide inputs when necessary. For example, in the warehouse case scenario studied in our research, a user can suggest possible task schedules, or select the optimal one based on personal expertise. We can also consider human input for teleoperation and remote access control in robotic systems, where users can manually control the robots, or access the on-board sensors for improved assessment of the current situation.

3. Methodology

3.1. Task Description

The warehouse system consists of human operators, robots, and warehouse shelves. The main task which we study in this article is package storage operation. Human operators command the system using a visual interface. Complex workflows are programmed using a visual programming (VIPO) language. Through VIPO, operators can express the workflows in the spatial context of the manufacturing area. The output is an intermediate script, which expresses a task for a robot to perform. That script is then passed to HUB-CI. HUB-CI is the brain model which can manage tasks in real-time by optimizing and harmonizing the agents in system. Optimization (by CRP-I) has an objective to minimize the total operation cost of the system. The operation cost for each task by each robot or team of robots is calculated by using the Collaborative Requirement Matrix (CRM). CRM will be updated continuously with any new information from IoT/IoS agents and human operators. An initial plan will be generated when the operation starts. Not only the new information from local agents impacts CRM, it might be unexpected events such as robot delay, or mismatched items that change operation cost in CRM. Hence, the harmonization phase is necessary. Harmonization (CRP-II) is the real-time control and adaptation to new information in CRM. Harmonization will deal with the changes from the initial plan. Plan and updated plan from HUB-CI will be executed in Robot Operating System (ROS) and the plan will be distributed to locations of warehouse shelves, robots, and human users. Fig. 1 shows the operation described above.

3.2. CRP-H Protocol Design

For effective control based on distributed information, HUB-CI relies on a protocol called CRP-H which is Task Administration Protocol (TAP) for managing CRP-I and CRP-II. Collaboration Requirement Planning (CRP) which is one of the key design principles in Collaborative Control Theory (CCT) is utilized for designing CRP-H.
As mentioned above, CRP-H has two components, Optimization (CRP-I) and Harmonization (CRP-II). In optimization process, it has two main algorithms; matching algorithm, and grouping algorithm. The matching algorithm follows a Best Matching (BM) procedure, while grouping algorithm has an objective to maximize the saving from the extra capacity of a robot or robot-helper. Then, the initial plan which assign task(s) to robot(s) is generated. Optimization will have the objective to minimize the overall operation cost from the initial data. In addition, harmonization part is to schedule and sequence tasks of each robot (or team of robots) by utilizing scheduling algorithm. The schedule will update continuously according to the new information received from system agents (humans, robots, and warehouse shelves). The objective of harmonizing part is to minimize the makespan of the system with respect to updating CRM. Fig. 2 depicts the workflow of the CRP-H.

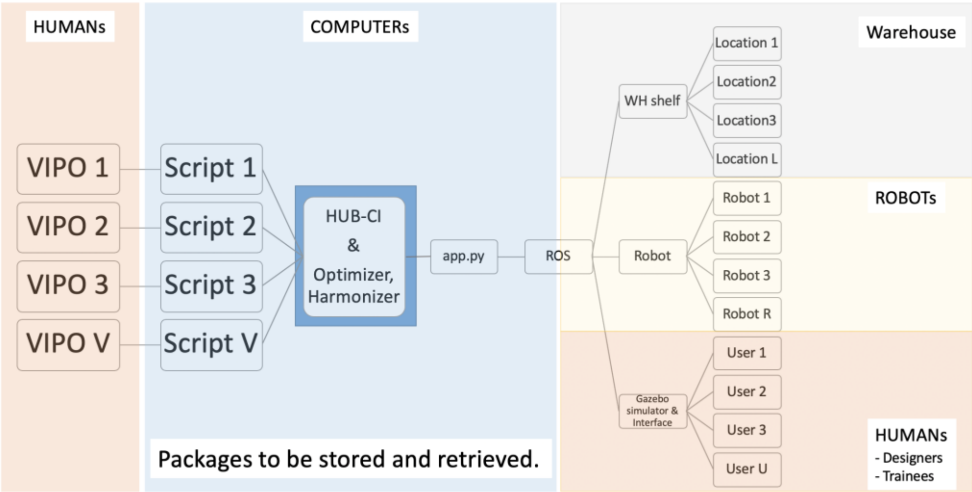

Fig. 1 Warehouse operation as a case study for factory of the future

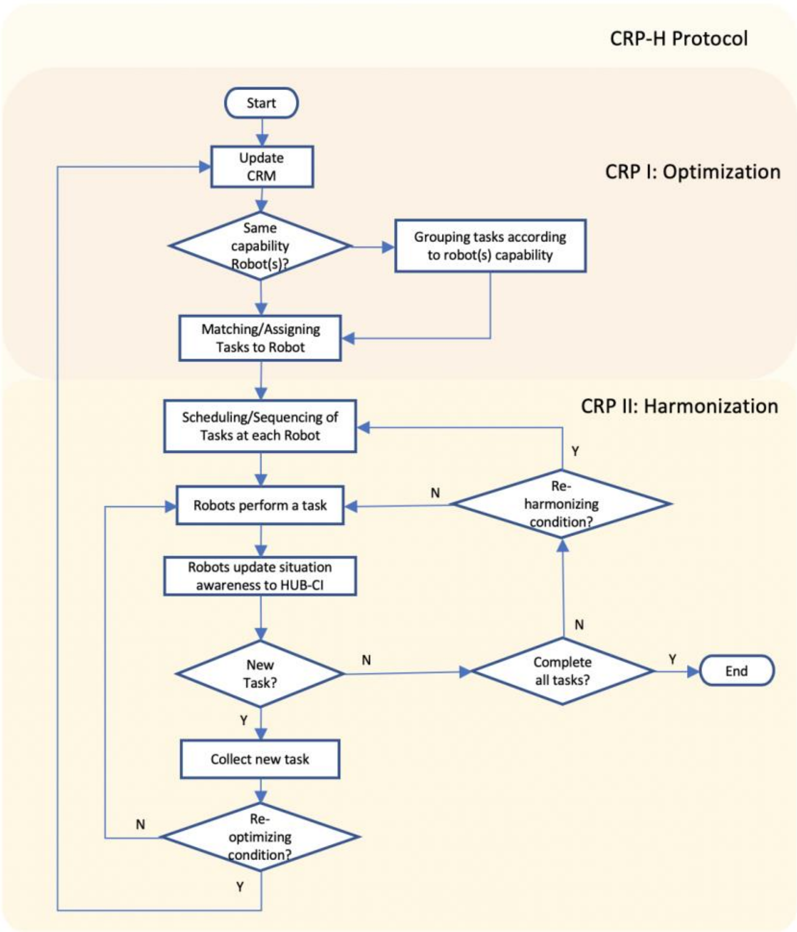

Fig. 2 CRP-H workflow

4. Experiments and Results

For the experiments, we consider two cases with different collaborative groups:

1. Case 1: Two robots, 1 group, 5 tasks
2. Case 2: Two robots, 1 helper, 2 groups, 25 tasks

For both cases, we run the simulation for the warehouse scenario with the storage tasks.

4.1. Case 1

In case 1, we assume that our model has two individual robots, R_1 and R_2. The possible collaborative group in this case is when both R_1 and R_2 work to complete the task together. Hence, any task can be performed in three ways: either by R_1, R_2, or a combination of R_1 and R_2. Given these performance options, we make the assumption that the collaborative tasks incur higher costs for faster processing times. The output parameters measured are the overall cost and the makespan for 5 tasks.

For the experiment, we simulated the system using MATLAB. In tune with Collaborative Resource Planning [9], we dedicate a Collaborative Resource Matrix (CRM) which is a real-time reflection of the status in the system. In our case, the CRM is a dynamic cost matrix for the current state of the system, which includes operational cost and distance-based cost updates for each robot task completion. We also design an allocation matrix based on the *intlinprog* MATLAB solver and BM fashion, which provides us with an optimal set of task allocations for the tasks in our system. Scheduling tasks is based on the Parallel Machine problem, and we use the Longest Processing Time first (LPT) rule as a scheduling algorithm to schedule and find the system makespan. We select the LPT rule because the heuristic is better at balancing loads to agents than other scheduling algorithms such as Shortest Processing Time first (SPT) rule, so it yields a better makespan. In our results, we will compare our outputs with the case of random task assignments and schedules as a control scenario. Note that in Case 1, all robots (R1 and R2) are identical, so the grouping algorithm is not required.

4.2. Case 2

For this case, we consider an additional helper robot (H) as a part of the system. The helper robot cannot perform a task individually, but it can work in collaboration with other robots and provide greater carrying capacity, i.e., a Robot-and-Helper group can carry more than a single package (task) at once. Our assumptions in this case are similar to the assumptions in Case 1: Collaborative tasks cost more, but service more quantities of tasks at a slower rate. We define three types of tasks based on their storage location for simplicity considering the routing of collaborative tasks. Tasks can be performed in four ways: R_1, R_2, R_1+H and R_2+H. We again measure the overall cost and makespan for 25 tasks.

In this experiment, the assignment of tasks to collaborative groups depends on their individual processing time. If a task is assigned to the collaborative group, since we have added capacity, the task preceding it (based on sorted processing times, within the same location group) is also added to the collaborative group. Hence, to an extent, we reduce the number of runs performed by the robots, since the combined set of tasks performed by the collaborative group is considered as a single task (by grouping algorithm). We dedicate another CRM to dynamically update the current costs in the system, which is dynamic depending on the traversing distance for the robot and operational cost for each task. As in Case 1, we use BM procedure as well as integer programming solver to solve the initial assignment which created allocation matrix (tasks to robots). Lastly, we use LPT to schedule the tasks as a scheduling algorithm. The results and observations for both experiments are given in the next section

4.3. Results

Fig. 3 compares the result of experiment 1 with 100 replications. Table 1 summarizes the measurement from the simulation. In term of operational cost, the CRP-H is slightly lower than the control group on per task basis. In addition, while standard deviation of CRP-H is slightly higher than the control group, the average makespan of CRP-H is ~45% less than the control group. Two t-tests were conducted to investigate the statistical relationship between the two operational costs and the two makespans. At the significance level of 0.05, the both null hypotheses were rejected. Therefore, the CRP-H outperforms the control group both in terms of operational cost and makespan.

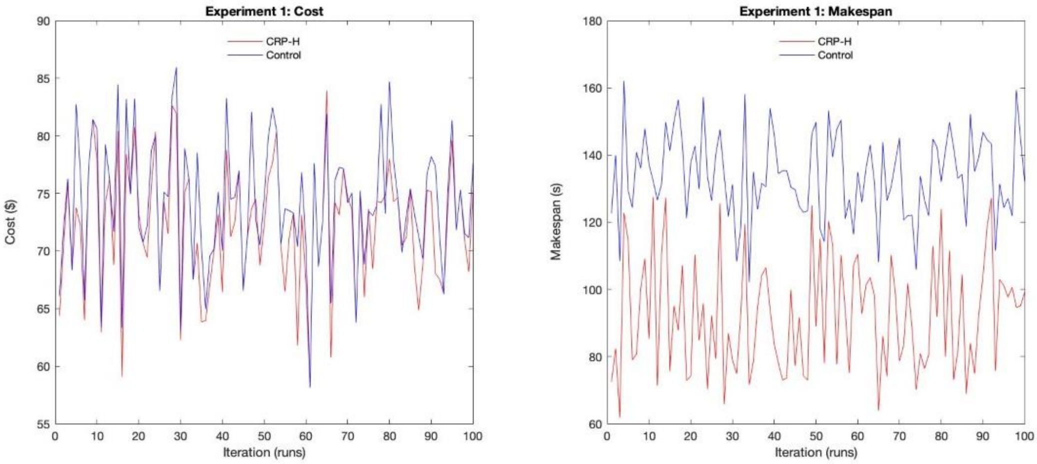

Fig. 3 Experiment 1: Operational cost (left), Makespan (right)

Table 1. Result of Experiment 1

	CRP-H	Control
Average operational cost ($)	72.07	74.21
SD of operation cost ($)	5.59	5.39
Average makespan (second)	92.30	134.00
SD of makespan (second)	17.04	12.72

Fig. 4 compares the result of experiment 2 with 100 replications. Table 2 summarizes the measurement from the simulation. The introduction of the helper robot in experiment 2 allowed us to test more complex scenarios. CRP-H shows significantly better performance than the control group in both makespan and cost. Furthermore, the standard deviation of makespan and cost for CRP-H are also lower, showing better control consistency in the results.

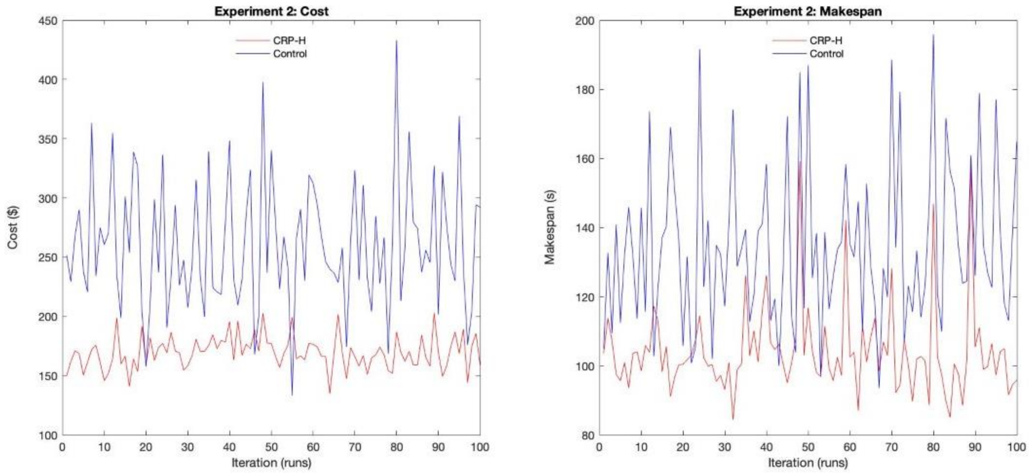

Fig. 4 Experiment 2: Operational cost (left), Makespan (right)

Table 2. Result of Experiment 2

	CRP-H	Control
Average operational cost ($)	169.70	260.20
SD of operation cost ($)	13.71	53.97
Average makespan (second)	104.00	134.20
SD of makespan (second)	12.66	23.41

5. Conclusion and Discussion

Based on preliminary tests of the model, observations indicate that the Collaboration Requirement Planning for HUB-CI (CRP-H) protocol delivers superior performance in terms of Operational Cost and Makespan, when compared to a system logic that randomly assigns tasks to robots and instructs random scheduling. The outcomes of this research are based, so far, on a model that considers a relatively smaller system design: Two collaborative groups, and two robots, with a relatively small number of tasks. A significant aspect of this work is that it incorporates robots of different capabilities, capacities and functions, as anticipated in future warehouses.

Future work in this area would address the following problems:

1) Scalability of the CRP-H to include larger collaborative groups of robots and human operators;

2) Incorporation, design and testing of the Human-in-the-loop concept, as described earlier as this article, and is the expected nature of future work.

3) Use of learning-based algorithms in conjunction with the CRP-H protocol.

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