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Human-robot interactive disassembly planning in Industry 5.0*

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Abstract— **Industry 5.0 sets off a new wave of the industrial revolution by highlighting human-centric intelligent manufacturing. Human-cyber-physical system (HCPS) is the cornerstone of Industry 5.0. It seamlessly integrates humans, cyberspaces, and physical assets to optimize the entire product lifecycle while ensuring the well-being of all stakeholders along the product value chain. Understanding the role of humans is of great importance. Disassembly plays a crucial role in achieving the sustainability required in Industry 5.0. The mass personalization of products requires the flexibility to accommodate frequent changes in disassembly. Human-robot interaction within the same workplace transcends boundary limitations and empowers flexibility for disassembly processes. This paper proposes a HCPS framework for human-robot interactive disassembly with two significant paradigms, namely human-in-the-loop (HitL) and human-on-the-loop (HotL). According to the HotL paradigm, a multi-objective optimization model for human-robot interactive disassembly is constructed considering the disassembly task complexity and operator ergonomics. An improved multi-objective hybrid grey wolf optimization approach is proposed to obtain the Pareto front that reveals the optimal human-robot interactive disassembly sequence. A HitL experiment for disassembling an automated vehicle control box is presented to illustrate the feasibility of the proposed method.**

Index term— **Industry 5.0; human-cyber-physical system; human-robot interaction; disassembly planning**

I. Introduction

Industry 5.0 is a new trend supported by European Union [1] to convert manufacturing paradigms from technology-driven to human-centric. It aims to complement human capabilities rather than substitute humans with automation. The cognition abilities and tacit knowledge owned by humans can in turn to support manufacturing by dealing with flexible, unexpected, and uncertain tasks. Human-robot interaction (HRI) at the same workstation breaks the fence of industrial robots and yields significant insight in achieving human-centric Industrial 5.0 [2], [3].

Due to the shortage of global resources and the vision to reduce environmental pollution, remanufacturing has attracted much attention to facilitate sustainable development. Disassembly plays a crucial role in remanufacturing [4] as it involves the process of breaking down end-of-life products into valuable components that can be reused in the future. As the mass personalization in Industry 5.0 results in muti-varieties and small batch products, the flexibility of disassembly approach is valued to accommodate frequent changes resulting from various product characteristics. HRI within the same workplace overcomes boundary limitations and addresses the shortage of either humans or robots by complementing each other. It empowers flexibility in the disassembly to meet different requirements.

Even if many studies explore the feasibility of HRI in the assembly scenario [5]–[7], the research about HRI disassembly is still in its infancy. Different from the assembly process that assembles all the parts in sequence, the disassembly process can selectively choose components with the aim of maximizing recycling benefits and minimizing costs. Xu et al. [8] allocated the disassembly task to either a human or a robot by evaluating the disassembly difficulty and proposed a discrete Bees algorithm to obtain the disassembly sequence. Parsa et al. [9] employed the PROMETHEE II method to determine the components that should be disassembled. A quantitative scoring algorithm is presented to evaluate each disassembly task so that the executor can be determined. Lee et al. [10] proposed a disassembly sequence planning algorithm in HRI while taking limited resources and human workers' safety into consideration. Hjorth et al. [11] summarized potential enabling technologies that can support HRI disassembly. Lee et al. [12] proposed a real-time HRI sequence planner to assign disassembly tasks by considering disassembly rules and the safety of human operation. However, most studies deemed disassembly sequence plans and task allocation as different aspects without a comprehensive analysis of the mathematical model. And the allocation of tasks is simply determined based on some evaluation criteria without considering the ergonomics of operators.

Taking the human roles into full consideration, this paper proposes a human-cyber-physical system (HCPS) framework for HRI disassembly by highlighting human-in-the-loop (HitL) and human-on-the-loop (HotL) paradigms. According to the HotL paradigm, a multi-objective optimization model for HRI disassembly is constructed considering the disassembly task complexity and operator ergonomics. An improved multi-objective hybrid grey wolf optimization (MOHGWO) approach is proposed to obtain the Pareto front that reveals the optimal HRI disassembly plan. And a HitL experiment for disassembling a control box of an automated vehicle is presented to illustrate the feasibility of the proposed approach. The rest of this paper is organized as follows: Section II illustrates the proposed HCPS framework. Section III introduces the multi-objective optimization for HRI disassembly. A case study is shown in Section IV and the conclusions are shown in Section V.

II. HCPS Framework for HRI Disassembly

HCPS is the extension of the cyber-physical system by integrating humans into the whole system rather than deeming them as external users or monitors of the system [13]. The cognition and action abilities of humans, e.g., perception,

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reasoning, and agility, are separately contributed to different levels of the system, which leads to HitL-CPS and HotL-CPS paradigms. By cohesively combining humans, cyberspace and physical assets, HCPS presents significant potential to achieve the human-centric goals highlighted in Industry 5.0. As for the human-robot interactive disassembly scenario, the HCPS framework is shown in Fig. 1.

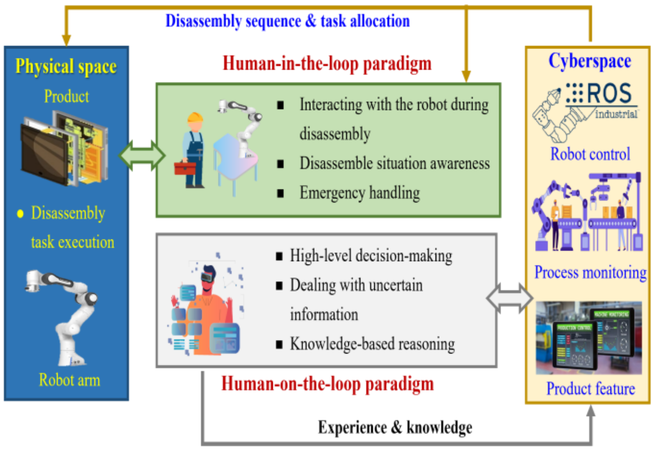


Fig. 1. The proposed HCPS framework

The HitL-CPS paradigm refers to direct interactions between a human operator and a robot to execute disassembly tasks in a shared working cell. Both the perception and actuation abilities of the operator and robot are valued in this paradigm. The robot receives the disassembly task from cyberspace and senses relevant data (e.g., the position of the parts) for further motion control from cyberspace. In addition to perceiving task instructions, the operator can generate situation awareness to deal with unprecedented disassembly problems in the workstation. The operator is delegated to disassembly tasks that require high flexibility and elaborate actions while the robot is assigned to achieve repetitive and high-load tasks. Thus, the musculoskeletal disorders of operators can be reduced to a great extent through the HitL-HCPS paradigm.

The HotL-CPS paradigm focuses on high-level decision-making and knowledge-based interaction between human experts and cyberspace. Since all the product features can be obtained through the HitL-CPS paradigm and revealed in cyberspace together with CAD models or design specifications, experts can generate structured data for guiding disassembly sequence generation and task allocation. According to the recycling value of product components and the historical operation data of operators and robots in cyberspace, the multi-objective optimization model for disassembly planning can be constructed based on experts' knowledge and then solved by the computational ability of cyberspace. Subsequently, the optimal disassembly plan can be decided while ensuring the operator's ergonomics and disassembly benefit at the same time.

III. MULTI-OBJECTIVE OPTIMIZATION FOR HRI DISASSEMBLY

According to the HotL-CPS paradigm, the mathematical representation of HRI disassembly planning is formed based on experts' knowledge. An improved MOHGWO is illustrated to solve it efficiently in cyberspace.

A. Evaluation of task complexity and operator ergonomics

In order to effectively assign a disassembly task to an operator or a robot, the capacity and limits of them should be evaluated by experts in regard to task characteristics. Since human and robot has different skills, disassembly complexity-based method [9] are applied to assist task allocation. Table I lists eight evaluation criteria and their corresponding levels regarding disassembly complexity. These values reveal the difficulty of a component to be handled during disassembly, and they are determined based on engineering practices [9], [14]. However, traditional methods allocate a task to either an operator or robot by simply comparing aggregated evaluation value to a fixed threshold without considering the disassembly sequence and human ergonomics. Therefore, the disassembly complexity C_j of the task j is deemed as one of the key parameters in the proposed mathematical model for obtaining a more considerable and effective disassembly plan.

$$C_j = \sum_{i=1}^{8} v_i, \, i \in \text{evaluation criteria} \tag{1}$$

Table I The evaluation criteria for disassembly complexity

Component shape		**Component weight**		**Grasp difficulty**	
Symmetric	0.8	Light	2.0	Low	2.0
Semi-symmetric	1.2	Moderate	2.2	Moderate	3.5
Asymmetric	1.4	Heavy	2.4	High	4.0
Tool requirement		**Operation complexity**		**Operation force**	
No tool	1.0	Low	1.0	Low	1.0
Common tool	2.0	Moderate	4.5	Moderate	2.0
Specialized tool	3.0	High	6.5	High	4.0
Positioning accuracy		**Fastener accessibility**			
No accuracy	1.2	Shallow and broad	1.0		
Moderate accuracy	2.0	Moderate deep and narrow	1.6		
High accuracy	5.0	Very deep and narrow	2.0		

In Industry 5.0, one of the primary goals of HRI disassembly is to enhance the operator's capabilities and prevent any physical harm they may sustain during the process. It is important to assess the ergonomics of the operator as they perform a disassembly task. As the disassembly tasks mainly require upper body movement, the acknowledged stress index [15] is adopted to quantify ergonomics and avoid work-related musculoskeletal disorders. Table II shows the strain index and its scales [15]. The rating of each index is matched to a corresponding multiplier value. A value larger than 1 means such a condition will lead to bad ergonomics (improving the risk of musculoskeletal disorders), and vice versa. When the value is equal to 1, it will not influence the ergonomics. For instance, if the speed of work is very slow, slow, or fair, it will not result in physical harm to the operator. Thus, the values regarding these conditions are set as 1. The comprehensive ergonomic score Q_{hj} of disassembly task j can be calculated based on the stress index:

$$Q_{hj} = \prod_{y} r_y, \, y \in \text{strain index} \tag{2}$$

Table II Strain index for operator's ergonomics evaluation

Intensity of exertion		Duration of exertion		Efforts per minute	
Light	1.0	Very short	0.5	Very low	0.5
Kind of hard	3.0	Short duration	1.0	Low effort	1.0
Hard	6.0	Fair duration	1.5	Fair effort	1.5
Very hard	9.0	Long duration	2.0	High effort	2.0
Near maximal	13.0	Very long	3.0	Very high	3.0
Body posture		**Speed of work**			
Very good	1.0	Very slow	1.0		
Good posture	1.0	Slow	1.0		
Fair posture	1.5	Fair	1.0		
Bad posture	2.0	Fast	1.5		
Very bad	3.0	Very fast	2.0		

B. Multi-objective optimization model

By considering the goals of maximizing recycling profit and minimizing costs during HRI disassembly, a multi-objective optimization model for disassembly planning is constructed as follows:

$$\text{Max} \quad f_1 = \sum_{j=1}^{M}\sum_{i=1}^{N} b_i g_{ij} d_j \tag{3}$$

$$\text{Min} \quad f_2 = \sum_{j=1}^{M}\left(C_{rj} r_j + C_{hj} h_j\right) + \sum_{j=1}^{M} Q_{hj} h_j \tag{4}$$

$$\text{Min} \quad f_3 = \sum_{j=1}^{M}\left(t_{rj} r_j + t_{hj} h_j\right) + \sum_{k=1}^{M}\sum_{j=1}^{M}\left(s_{kj} r_k h_j + s_{kj} h_k r_j\right) t_c \tag{5}$$

$$\text{s.t.} \quad d_j = \sum_{k=1}^{M} s_{kj}, \quad \sum_{k=1}^{M} s_{kj} \le 1, \quad j = 1,2,\cdots,M \tag{6}$$

$$\sum_{j=1}^{M} d_j \ge 1 \tag{7}$$

$$e_{jm}\left(d_j + d_m\right) \ge -1, \quad \forall d_j, d_m = 1 \tag{8}$$

$$d_m \le \sum_{j=1}^{M} f_{jm} d_j, \quad m = 1,2,\cdots,M \tag{9}$$

$$\sum_{k=1}^{M} s_{kj} \ge \sum_{l=1}^{M} s_{jl}, \quad j = 1,2,\cdots,M \tag{10}$$

$$r_j = h_j = 0, \quad \forall d_j = 0 \tag{11}$$

$$r_j = 0, \quad \forall C_{rj} = \infty \tag{12}$$

$$h_j = 0, \quad \forall C_{hj} = \infty \tag{13}$$

$$r_j + h_j = 1, \quad \forall d_j = 1 \tag{14}$$

$$d_j, s_{kj}, r_j, h_j \in \{0,1\}, \quad j,k = 1,2,\cdots,M \tag{15}$$

where d_j, s_{kj}, r_j, h_j are decision variables. d_j refers to the execution of a disassembly task j. s_{kj} is the sequence index of disassembly tasks. r_j and h_j reveal whether a disassembly task j is allocated to a robot or an operator. Other nominations are illustrated in the Appendix. Objective function f_1 aims to maximize the revenue obtained by sequential disassembly tasks. Objective function f_2 aims to minimize the disassembly costs which consist of disassembly complexity and ergonomics scores. Objective function f_3 aims to minimize the operation time. Eq. (6) is the constraint that ensures each task will be executed no more than one time. Eq. (7) constrains that at least one disassembly task should be executed. Eq. (8) removes exclusive tasks in the disassembly sequence. Eq. (9) ensures the disassembly precedence. Eq. (10) indicates the equilibrium relation of in-degree and out-degree of a task. Eq. (11) – (14) constraint the allocation of a selected task to either a robot or operator. Eq. (15) illustrates that all decision variables are Boolean values.

C. MOHGWO for disassembly planning

In order to solve the multi-objective optimization problem obtained from HotL-CPS paradigm, an improved MOHGWO approach is applied in cyberspace to determine the disassembly sequence and task allocation results. Regarding the features in HRI disassembly, a four-vector hybrid encoding scheme is proposed to represent a grey wolf. As shown in Fig. 2, discrete values in the first vector represent alternative disassembly tasks while the second vector depicts the execution of tasks in binary values. Therefore, the disassembly sequence in Fig.2 can be decoded as 3-4-1-8-5-7. Furthermore, the next two vectors in binary values represent the allocation of a selected task to a robot or an operator. The safety-rated monitored stop mechanism is applied in this study to ensure safe interaction by assigning a disassembly task to either a robot or an operator.

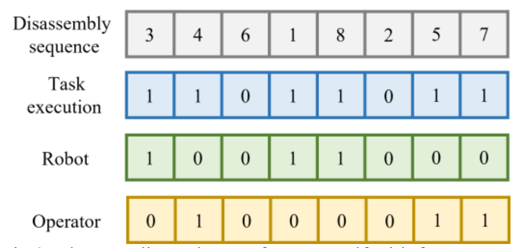


Fig.2. The encoding scheme of a grey wolf with four vector

Random initialization of grey wolves is applied in most GWO-based methods [16] but it can only deal with continuous values within explicit ranges. A novel random initialization method with four steps is proposed in this work adapting to the hybrid four vectors and satisfying all the constraints defined in the mathematical model. The initialization process of grey wolves is as follows: (1) Generating the first two vectors randomly in discrete values and binary values respectively as the initial disassembly sequence. (2) Removing exclusive disassembly tasks based on the exclusive matrix $E = \left\{ e_{jm} \middle| j,m = 1,2,\cdots,M \right\}$ decided by experts:

$$e_{jm} = \begin{cases} -1 & \text{if the task } j \text{ is exclusive with } m \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

(3) Adjusting the sequence of selected tasks to ensure the precedence defined in the precedence matrix $F = \left\{ f_{jm} \middle| j,m = 1,2,\cdots,M \right\}$:

$$f_{jm} = \begin{cases} 1 & \text{if the task } j \text{ is the immediate task of } m \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

As for a selected task, if all the precedent tasks are executed, the sequence of it can be settled. Otherwise, the task that should be immediately executed before it should be added or changed to its left side in the first vector. The corresponding position in the second vector should be set as 1 as well. (4) Allocating the determined disassembly tasks to either a robot or an operator to generate the last two vectors.

After the initialization, the leading α, β, and δ wolves can be determined based on the dominant relations regarding objective functions. An archive with the leader selection strategy [17] is applied to store and update leading grey wolves for guiding the behaviors of the wolf pack during iteration. Different from traditional GWO that updates the position of grey wolves in continuous ranges, this work combines discrete and binary updating strategies [18], [19] conforming to the features of the four-vector hybrid coding scheme. After updating the four vectors in a grey wolf, the dominant relationships among newly generated wolves and the archive are determined. Non-dominated grey wolves are saved in the archive and then decoded as alternative disassembly plans after iteration. Experts can choose the optimal disassembly plan through HotL-CPS paradigm and assign related tasks to the robot and operator while the HitL-CPS paradigm is applied to ensure the execution of on-site disassembly works.

IV. Case Study for Interactive Disassembly

A case study on disassembling a customized control box of automated vehicles is presented to illustrate the feasibility and practicability of the proposed approach. Different from the assembly, the disassembly does not aim to obtain all components but to recycle valued parts with minimum costs. Thus, determining the suitable disassembly sequence and task allocation is important to ensure human-centric requirements highlighted in Industry 5.0. The nine components of the control box and the HRI workstation is shown in Fig. 3.

(a) (b)

Fig. 3. (a) HRI workstation. (b) The components in the customized control box of automated vehicles.

According to the feature of the control box, 14 alternative disassembly tasks and 20 parts during the disassembly process can be determined by experts through the HotL-CPS paradigm. Fig. 4. adopts AND/OR graph to represent the disassembly process in cyberspace. And Table III explains the specific disassembly tasks.

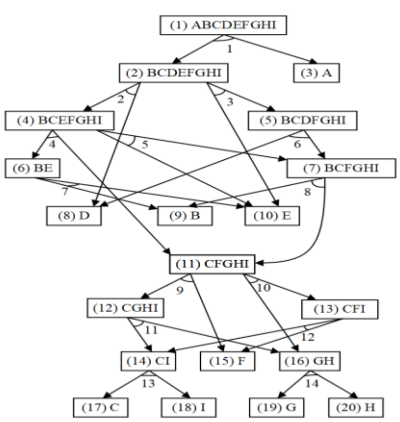
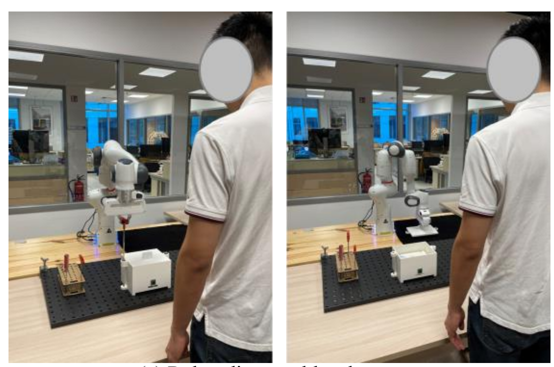


Fig. 4. The AND/OR graph for control box disassembly

Table III The alternative disassembly tasks listed in the AND/OR graph

No	Disassembly task description	No	Disassembly task description
1	Remove the cover of the box	8	Remove middle plate
2	Recycle IMU part	9	Recycle camera
3	Recycle GPS part	10	Remove the Raspberry Pi cover
4	Remove the middle plate with GPS	11	Remove Raspberry Pi cover after camera
5	Recycle GPS after IMU	12	Remove camera after Raspberry Pi cover
6	Recycle IMU after GPS	13	Remove Raspberry Pi
7	Separate GPS and middle plate	14	Remove fan

By applying the improved MOHGWO, the multi-objective optimization model for HRI disassembly can be solved and the non-dominated Pareto front can be obtained in cyberspace. The solutions in the Pareto front can be deemed as the optimal disassembly plans because they have the best performance on three different objective functions. Experts select the most suitable disassembly plan from the Pareto front to make a good trade-off among recycle benefit, disassembly cost, and operator ergonomics. Then allocating different tasks to the designated operator and robot. The disassembly plan chosen in this case study is: task 1 (disassemble cover A by the robot) – task 2 (disassemble IMU D by the operator) – task 4 (disassemble the middle plate C by the robot without disassembling the GPS unit E) – task 9 (disassemble the cover and fan of the Raspberry Pi by the operator) – task 12 (disassemble the camera by the operator) – task 13 (disassemble the Raspberry Pi by the operator). The disassembly plan can be executed through HitL-CPS paradigm. Fig. 5 shows the interactive disassembly process at the workstation.



(a) Robot disassembles the cover

(b) Operator disassembles the IMU

Fig. 5. HRI disassembly process in the workstation

The proposed approach incorporates the concepts of HitL and HotL, enabling the integration of robots/operators within a shared working environment and experts/decision-makers within the manufacturing company. The HotL paradigm empowers domain experts to carry out knowledge-intensive tasks such as constructing AND/OR graphs and mathematical models. These experts can leverage the abundance of information available in cyberspace to support their high-level decision-making processes. Furthermore, this approach offers significant cost savings in operator training, as operators are not required to devise complex disassembly sequences; instead, they simply execute specific disassembly tasks. In situations where abnormalities or unexpected events occur during the HRI disassembly process, operators can directly handle them using the HitL paradigm.

V. Conclusion

This paper proposes a HCPS framework for HRI disassembly by illustrating the HitL and HotL paradigms. According to the HotL paradigm, a multi-objective optimization model for HRI disassembly planning is proposed with the goals of maximizing recycling profit, minimizing disassembly costs, and ensuring operator ergonomics. A MOHGWO approach with four-vector hybrid encoding scheme and improved initializing/updating strategies is presented to solve this problem and obtain a suitable disassembly plan. Moreover, the HitL-CPS paradigm is applied to ensure the execution of on-site disassembly works. A case study on the HRI disassembly of a customized control box is illustrated. Future studies may focus on applying computer vision-based methods to evaluate real-time operator ergonomics during disassembly and optimize it by adjusting robot postures.

Appendix

Table A Notations of variables in the HRI disassembly model

Symbol	Definition
f_{jm}	The parameter in the precedence matrix F
e_{jm}	The parameter in the exclusive matrix E
g_{ij}	The parameter in the transition matrix G
C_{rj}	The disassembly complexity of a robot to execute task j
C_{hj}	The disassembly complexity of a human to execute task j
t_{rj}	The time consumed when a robot executes task j
t_{hj}	The time consumed when a human executes task j
t_c	The time consumed in the transition between a human and robot
Q_{hj}	The ergonomic score of a disassembly task j
b_i	The profit of recycling a component i

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